Quantifying Impacts of Future Climate on the Crop Water Requirement, Growth Period, and Drought on the Agricultural Watershed, in Ethiopia

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ABSTRACT: Quantifying the influence of climate change on the crop growth period, water requirement, and drought conditions is essential for integrated crop production system planning. In this study, the effects of climate models from the Coupled Model Inter-comparison Product (CMIP5) on Crop Water Requirement (CWR), Length of Growth Period (LGP), and drought conditions were quantified for Lake Hawassa watershed in Ethiopia. In this study, two regional climate models were selected that showed better performance on the evaluation criteria after applying a quantile mapping bias correction procedure. The impact analysis was conducted for two Representative Concentration Pathways (RCPs) (RCP4.5 and RCP 8.5). Drought analysis was performed using the standardized anomalies of rainfall (S-index). The future growing season of the area is projected to be between April 15 and May 1 on average for all years. The total crop water requirement was projected to increase to a value of 3,258.7 mm on average under both the RCP4.5 and RCP8.5 scenarios for all the stages at the end of 2080s from its baseline value of 3,180.4 mm. In addition, the drought forecast analysis shows extreme drought with S-index values <-1.6 in the 2050s and 2080s under RCP 8.5. Of all the time periods, the 2050s recorded the smallest number of years (10 out of 30 years) with a positive S-index value, indicating projected precipitation shortages during these time periods under RCP 8.5. With this result, the combined impacts of climate change on crop production factors are expected to be high in the region. The results suggest an early warning for the study region considering low economic and technological development as in many developing parts of the world. Therefore, understanding the future changes in climate variables and their impacts can be an important input for developing a better plan for adaptation and mitigation measures.

KEYWORDS: CMIP5, drought, growth period, Lake Hawassa Watershed, water requirement

TYPE: Original Research

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Introduction

Climate change is expected to cause variations in future precipitation and temperatures, which are important variables for crop production. Climate change will alter several variables affecting crop production, soil moisture, drought, and evapotranspiration (Gomez-Gomez et al., 2022; Kay & Davies, 2008; Secci et al., 2021). Future climate variability is projected to affect water management at many locations (IPCC, 2022). Possible declines in crop production, water availability, and drought due to climate change and variability are the subject of many recent studies globally and in the region (Adhikari et al., 2015; Alemayehu & Bewket, 2016; Kassaye et al., 2021; Masia et al., 2021; Muluneh et al., 2017; Shiferaw et al., 2015; Stringer et al., 2021; Waaswa et al., 2022). Studies have also shown the regional impact of climate change on water resources, by reducing future open water volume (Tesfalem et al., 2018; Zeray et al., 2007). The increasing drought amount and projected increment in potential evapotranspiration could directly affect the crop growing season and the related water requirements of the crop (Parmar et al., 2022; Ray et al., 2018). Similar to many other developing regions, crop production in Ethiopia mainly in Lake Hawassa watershed is dependent on rainfall. In Lake Hawassa watershed, the influence of climate variability and change is not well quantified, and the response of Maize water requirement to climate change is not well known. In addition, rainfall distribution in the region is highly variable and difficult to quantify due to lack of sufficient data (Abraham, Liu, et al., 2022).

The General Circulation Models (GCM) have been widely used in climate change studies. Regional Climate Models (RCMs) have been used to dynamically downscale GCM output to scales more suitable to end regional applications (Mengistu et al., 2021; Shrestha et al., 2014). Compared to GCMs, RCMs provide better information and representation of different topographies at finer temporal and spatial scales (Giorgi et al., 2008). The Coordinated Regional Climate Downscaling Experiment in Africa (CORDEX), which is produced under the Coupled Model Inter-Comparison Project Phase 5 (CMIP5), has provided many regional climate models and their scenarios in the Representative Concentration Pathways (RCP). The evaluation and application of CORDEX outputs were widely reported for the water resource impact assessment in Ethiopia (Alehu et al., 2022; Ashaley et al., 2020; Asnake et al., 2021; Mengistu et al., 2021; Tesfaye et al., 2020).

Independent of other factors, Crop Water Requirement (CWR) and Length of Growth Period (LGP) are influenced by potential evapotranspiration. LGP is defined as the period between which optimum soil moisture is achieved for the water requirements of a given crop (FAO, 1978). Under normal conditions, crop productivity can be maintained when soil moisture meets the evapotranspiration needs of the crop. When the moisture drops, the crop will become under moisture stress that marks the cessation period. Different methods have been proposed to estimate the length of growth periods in Sub-Saharan Africa. Some of these methods are rainfall-dependent (Anyadike, 1993; Matthew et al., 2017), while others depend on rainfall, temperature, and evapotranspiration (Odekunle et al., 2005; Omotosho, 2002). The common method adopted from the FAO approach defines the LGP as the number of days in a year when rainfall exceeds half of potential evapotranspiration (FAO, 1978). The FAO-Penman-Monteith method requires detailed information on data such as air temperature, humidity, radiation, and wind speed for the potential evapotranspiration estimation (Merugu & Mathyam, 2015). The LGP can also be affected by other factors such as soil type, soil depth, water retention, release characteristics, air temperatures, and daylight hours (Merugu & Mathyam, 2015). According to the FAO (1978) in any region the crop growing season can have three characteristics, the beginning period, humid periods, and end of the growing period. The beginning of the growing season is when the rainfall is equal to half of the potential evapotranspiration, which is considered the normal rainy season. The Humid period is when the rainfall exceeds the potential evapotranspiration; and end of the growth period is when the rainfall falls below half of the potential evapotranspiration, which marks the dry period.

The water requirement of crops is the amount of water needed to meet evaporative demand. Crop water demand is largely determined using the FAO Penman-Monteith method (Allen et al., 1998) to estimate reference evapotranspiration (ET_o) (Sawant et al., 2017). A study was conducted to estimate the actual water requirements of crops and identified the time when water deficit start to occur and its magnitude (Li et al., 2005). In addition, an approach using the FAO-Penman–Monteith method depending on meteorological measurements has accurately predicted the crop evapotranspiration, being in close agreement with field measurements using lysimeter (Möller & Assouline, 2007). For estimating evapotranspiration for future climates, the Hargreaves method can be applied (Hargreaves & Samani, 1982). The crop coefficient (K_c) affects the amount of water required for a certain crop at different growth stages.

Drought is another indicator of future climatic variability. Drought can affect future crop production and can result in severe stress to the plant water requirement (Parmar et al., 2022; Ray et al., 2018). Studies have been conducted in Ethiopia to assess the impact of climate change on drought and its historical variability (Degefu & Bewket, 2015; Gidey et al., 2018). The common approach for assessing drought is through the standardized anomalies of rainfall (Agnew & Chappell, 1999). Furthermore, the associated classification of drought indices such as extreme drought, severe drought, moderate drought, and no drought conditions would help in the decision-making of crop production. Since lake Hawassa watershed in Ethiopia is located in the Sahel we applied the classification of drought indices by Agnew and Chappell (1999) that uses the standardized anomalies of rainfall. A similar drought index called "Standardized Anomaly Index (SAI)" and more recent collection of drought indices are also available from WMO and GWP (2016) and their full description is shown by Katz and Glantz (1986).

In Ethiopia, nearly 85% of the population shares the wide-ranging characteristics of agriculture, which depends on rainfall. In terms of economy, 30% of the overall GDP and 60% of agricultural GDP results from cereal production. Cereals production accounts 86% of the total crop by covering 80% of the cropped land among which Maize, Wheat, and Teff altogether constitute 56% from the total grain production (CSA, 2015). Climate change is posing treat to the cereal crop production. Recent studies have shown impacts of climate change on maize production (Alemayehu & Bewket, 2016; Muluneh et al., 2017) and the related economic impact due to decline in production (Araya et al., 2015; Muluneh et al., 2015). Previous studies have also shown impact of climate change on maize productivity on the national scale using the multi-model GCM outputs (Kassaye et al., 2021; Thomas et al., 2019). However, this study investigates the impacts of climate change on maize water requirement and growth period on a specific region using highly performing regional climate models that can fully and explicitly leverage the use of ensemble mean.

This study analyzed the impact of climate change on Maize water requirement, growth period, and drought for Lake Hawassa watershed in Ethiopia. Lake Hawassa watershed in Ethiopia is one of the region that is highly known for Maize production by small farm holders and by large-scale private farm enterprises. This study applied two well-performing regional climate models from the RCM groups from the outputs of CORDEX Africa. The two regional models (CNRM5 and CSIRO MK-3-6-0) sufficiently modeled the historical climate using the standard evaluation criteria. Previous studies have tested the applicability of different RCM models for analyzing the effects on crop growth period, and water requirements (Kwawuvi et al., 2022). However, in this study, the impact of climate change on crop growing period and water demand is accurately shown using the specific RCM with the best performance for Lake Hawassa watershed. We have hypothesized that the best performing climate model for both temperature and precipitation could provide reasonable estimates of future change in the crop water requirement, growth period, and drought than using ensemble mean, which is a common approach. In this study, impact analysis was conducted on the two RCPs, these are RCP4.5 the stabilization scenario and RCP8.5 being the worst-case scenario. The length of the growth period was estimated using the standard approach of the FAO (1978). Analysis of the influence of future climate impact on crop water requirements would have implications for future food security in the region. In addition, the future drought expected in the region can be an input for regional scale decision-making and better preparedness. Therefore, this study particularly quantifies the future opportunities and traits in the food production systems that enables for conducting an accurate planning for a resilient production in for Lake

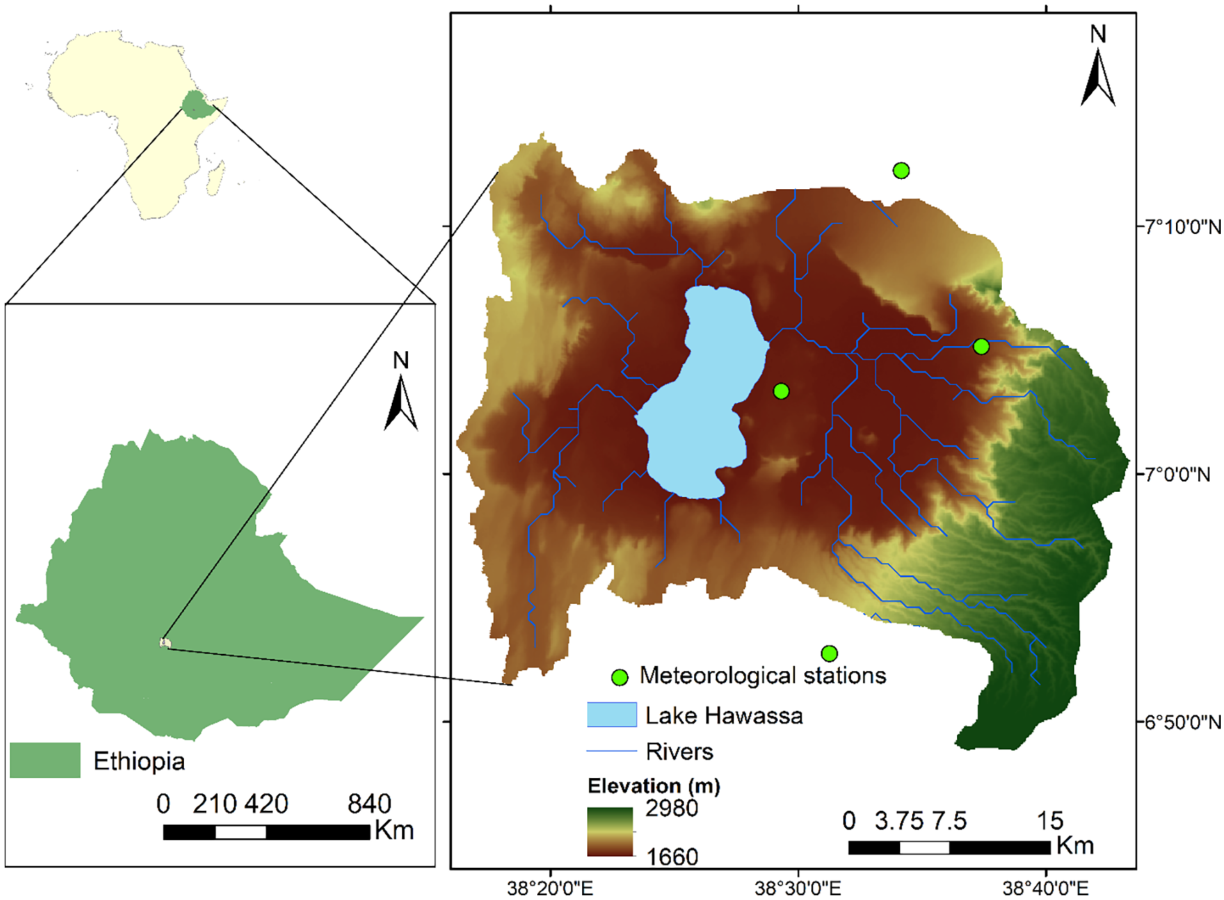

Figure 1. The study area showing Lake Hawassa Watershed, its elevation, and river network.

Hawassa watershed. The remainder of the paper is outlined as follows: Section 2 shows material and methods including the study area description, data sources, a climate model description and evaluation and analysis of onset date, cessation date, and length of growth periods: Section 3 contains the results and discussion: Section 4 is the summary of conclusions.

Materials and Methods

Study area description

Lake Hawassa watershed is located within the Rift Valley Lake Basin of Ethiopia. The total area of the watershed is approximately 1,376 km² where the lake covers an area of 99 km² and the remaining 1,276 km² of the watershed is occupied by land surface (Figure 1). The area has a bimodal rainfall pattern and with average maximum and minimum temperature of 20°C and 11°C respectively. The analysis from four meteorological stations for the period 1987 to 2017 showed that the mean annual rainfall of the watershed was 1,097.5 mm and June to September contributes 44% to the mean annual precipitation .

Rainfed agriculture of annual crops is the major crop production scheme in the region in addition to a small area of mechanized farms. Agricultural land, at the household level, is mainly used for Maize, Sorghum, and root crop production. In Lake Hawassa watershed majority of lowland area is occupied by seasonal and perennial agricultural land, grassland, and wetland, whereas the upland terrain is predominantly covered by wooded bush, and woodlands (Abraham, Muluneh, et al., 2022; Degife et al., 2019). The watershed is composed of several small ungauged streams (Abraham et al., 2021) draining the upland terrain toward grassland and agriculture dominated lowland area (Abraham, Muluneh, et al., 2022; Girma et al., 2020). However, recently due to population increment, deforestation, and progressive replacement of other land use by agricultural land and built-up land have been shown (Abraham, Muluneh, et al., 2022; Gebeyehu Admasu, 2015).

Data sources and availability

For this study, we have used observed meteorological variables from the National Meteorological Service Agency of Ethiopia (NMSA), for the historical periods to compute the reference evapotranspiration (ET_O) as shown in Table 1. Future climate variables were obtained from CORDEX Africa (Coordinated Regional Climate Downscaling Experiment in Africa) project for the two climate models (CSIRO MK-3-6-0, and CNRM5). The model results are available for the RCP4.5 and RCP8.5 scenarios. These models are selected because regional models

Table 1. The Historical and Future Climate Data With Their Temporal Scale and Sources.

DATA TYPE	DATA DESCRIPTION	TIME PERIOD	TEMPORAL SCALE	DATA SOURCE
Meteorology	Precipitation, temperature, relative humidity, solar radiation, and wind speed	1987–2017	Daily	NMSA
CNRM5	Precipitation, maximum and minimum temperature	1980–2005	Daily	https://esgf-node.llnl.gov/search/esgf-llnl/
CSIRO MK-3-6-0	Precipitation, maximum and minimum temperature	1980–2005	Daily	https://esgf-node.llnl.gov/search/esgf-llnl/

cover smaller areas so they can have a higher spatial resolution, for the same number of grid points as a global model.

Climate model validation and bias correction

The two climate change models applied for this study were derived from the Regional Climate Models (RCM) from the CORDEX Africa project. The regional climate model has a resolution of 0.48° and it is widely used in most African countries (Ashaley et al., 2020; Mengistu et al., 2021). This study compared several climate models with a reasonable spatial resolution to retrieve data for two climate variables (rainfall and temperature) at a monthly scale. Before using climate models to simulate future climate fluctuations, it is necessary to evaluate how well models represent the historical and present climate.

Climate models usually provide bias in representing the local scale climate variables. This study has applied a quantile mapping bias correction technique (Gudmundsson et al., 2012) to adjust the bias in the downscaled temperature and precipitation product. The quantile mapping technique has an advantage to account the GCM biases in many statistical moments. Similar to many other statistical downscaling techniques, the biases remaining to the historic observations were assumed constant also for the projection periods. Several previous studies have used the quantile mapping technique for downscaling monthly average precipitation and temperature (Hayhoe et al., 2008; Maurer & Duffy, 2005; Wood et al., 2004). The RCM products of CNRM5 and CSIRO MK-3-6-0 datasets were bias corrected with daily observed temperature and precipitation datasets from 1980 to 2005. The quantile mapping was done separately for each month. Evaluation was done using efficiency measures of Coefficient of Determination (R^2), Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970), and the Kling–Gupta efficiency KGE (Gupta et al., 2009), between the bias corrected RCM products and observed precipitation and temperature at the monthly scale.

Historical and future crop evapotranspiration (ET_C)

This study applied the Penman-Monteith method (equation (1)) to calculate the daily potential evapotranspiration using rainfall, maximum and minimum temperature, relative humidity, sunshine hours, and wind speed (Allen et al., 1998). The future potential evapotranspiration was estimated by the Hargreaves method (equation (2)) due to the availability of only minimum and maximum temperatures for the future period.

$$\mathrm{ET_o} = \frac{0.408\Delta\left(R_n - G\right) + \gamma \frac{900}{T+273} U^2\left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34U^2\right)} \tag{1}$$

In the above equation, ET_o is the reference potential evapotranspiration (mm day^{-1}), R_n is Net radiation at the crop surface (MJ m^{-2} day^{-1}), G is Soil heat flux density (MJ m^{-2} day^{-1}), T is Mean daily air temperature at 2 m height (°C), U_2 is the Wind speed at 2 m height (m s^{-1}), e_s is Saturation vapor pressure (kPa), e_a is Actual vapor pressure (kPa), e_s–e_a is the Saturation vapor pressure deficit (kPa), Δ is Slope of vapor pressure curve (kPa °C^{-1}), and γ is Psychrometric constant (kPa °C^{-1}).

$$PET = 0.0023^{*}Ra^{*}\left(T_{max} - T_{min}\right)^{0.5} {}^{*}(T_{mean} + 17.8) \tag{2}$$

Where PET is the potential evapotranspiration rate (mm/day), T_{min} and T_{max} represent the minimum and maximum temperature, and T_{mean} is the daily mean temperature. Table 2 shows the reference potential evapotranspiration (ET_o) for the historical period.

Crop water requirement for Maize grown in the study area was estimated from historical records (1980–2010) and the future model outputs. For this study, the water requirement of Maize was derived through a crop coefficient that integrated the combined effects of crop transpiration and soil evaporation into a single crop coefficient (K_c), as shown in equation (3) (Allen et al., 1998).

$$ET_c = K_c{}^{*}ET_o \tag{3}$$

where; ET_o is reference evapotranspiration rate, K_c is crop coefficient, ET_c is crop evapotranspiration defined as the evapotranspiration from a disease-free, well-fertilized crop, grown in large fields, under optimum soil water conditions, and achieving full production.

Determination of crop coefficient (K_C)

Crop coefficient in this study was determined using the FAO-56 method (Allen et al., 1998). The daily K_C values can be

Table 2. Long-Term Average Monthly Potential Evapotranspiration From Hawassa Stations (1980–2010).

MONTH	JANUARY	FEBRUARY	MARCH	APRIL	MAY	JUNE	JULY	AUGUST	SEPTEMBER	OCTOBER	NOVEMBER	DECEMBER
ET_o (mm/month)	122.6	123.6	145.1	134.2	134.1	128.2	113.3	115.5	111.6	132.2	120.2	121.7

determined by assuming K_C constant during the initial and mid-season stages and assuming a linear relationship between K_C values at the previous stage and at the beginning of the next stages in the crop development and late-season stages. The daily K_C values during the crop development and late-season stages are calculated using equation (4) (Allen et al., 1998).

$$Kc, \mathrm{i} = Kc(prev) + \left[\frac{\mathrm{i} - \sum Lprev}{\mathrm{Lstage}}\right]\left(Kc(next) - Kc(prev)\right) \quad (4)$$

where, K_{Ci} = daily K_C value; K_C (prev) = K_C values at the previous stage; K_C *(next)* K_C values at the next stage; L_{prev} = length of previous stages; L_{stages} = length of the estimated growing stage.

Table 3 shows the K_C values for Maize in different growth stages that are grown in a tropical region having an average rooting depth of 60 cm. However, this study considered only the first three growth stages (the Initial, Development, and Late-Season) due to the sensitivity of these growth stages to water demand. In addition, the average annual water requirement for the future periods of 30 years (2020s, 2050s, and 2080s) was analyzed to depict the change in the future periods.

Onset date, cessation date, and length of growing period (LGP)

In this study, the onset date, cessation date, and LGP of a growing season were determined from the relationship between rainfall and potential evapotranspiration (PET). However, the LGP is not only dependent on the rainfall amount, rather it can be influenced by other factors such as the type of soil, water retention, air temperatures, and daylight hours (Merugu & Mathyam, 2015). Among the several methods developed to determine the LGP (Ashok Raj, 1979; Sivakumar et al., 1993), this approach uses a method dependent on rainfall and PET (FAO, 1978; Velayutham et al., 1999). This approach was selected due to limited availability of other factors (soil, water retention, air temperatures, and daylight hours) in the required scale in the study region. In this regard, the onset date is when rainfall $\geqslant 0.5 \times$ PET, and the offset date is when rainfall $\leqslant 0.5 \times$ PET and LGP is the difference between offset date and onset date. Accordingly, the onset date is the beginning of cropping period where optimum soil moisture is available for crop production. On the other hand, the cessation date is when the crop is under stress to absorb water due to moisture deficit in the soil.

Estimation of drought index

This study has used the standardized anomalies of rainfall (*S*) to analyze the different drought classes. This study applied the standardized anomalies of rainfall (*S*) to calculate and assess the frequency and severity of droughts (Agnew & Chappell, 1999) as shown in equation (5).

Table 3. *Kc* Values Taken From FAO (Allen et al., 1998).

STAGES	INITIAL	DEVELOPMENT	MID-SEASON	LATE-SEASON	TOTAL
Kc	0.3	1.2	1.2	0.35	
Days	20	35	40	30	125

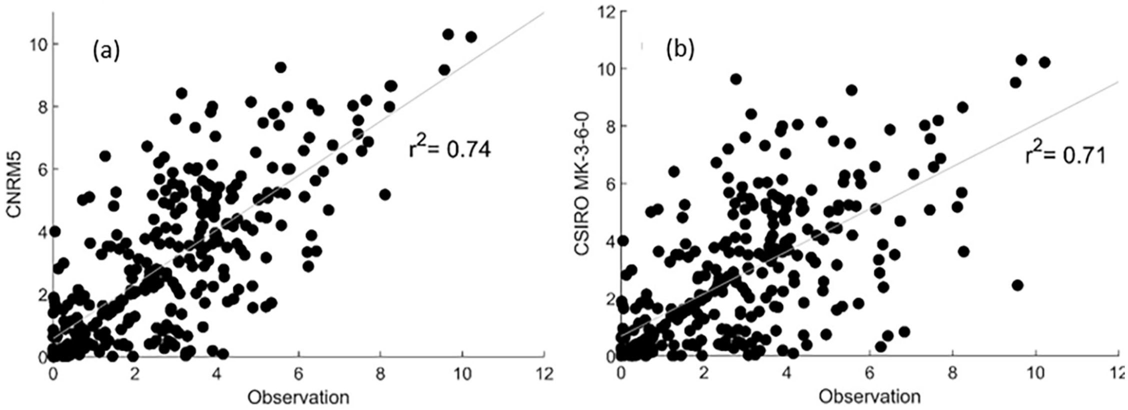

Figure 2. Performance of the two climate models using a correlation coefficient: (a) for CNRM5 and (b) for CSIRO MK-3-6-0 for the baseline period (1980–2005).

Table 4. Performance of Two RCM Models Before and After Bias Correction on Monthly Scale Using Different Metrics.

		PRECIPITATION		MEAN TEMPERATURE	
RCMs	Monthly evaluation	Before correction	After correction	Before correction	After correction
CNRM	R^2	.62	.74	.73	.78
	NSE	0.63	0.70	0.76	0.78
	KGE	0.68	0.76	0.78	0.79
CSIRO MK-3-6-0	R^2	.61	.71	.76	.78
	NSE	0.61	0.67	0.77	0.79
	KGE	0.64	0.70	0.79	0.81

$$S = \frac{\left[P_t - P_m\right]}{\sigma} \quad (5)$$

Where S is the standardized rainfall anomaly, P_t is the annual rainfall in year t, P_m is the long-term mean annual rainfall over a given period of observation, and σ is the standard deviation of rainfall throughout the observation period. The drought severity classes are categorized in this study as extreme drought ($S < -1.65$), severe drought ($-1.28 > S > -1.65$), moderate drought ($-0.84 > S > -1.28$), and no drought ($S > -0.84$).

Results and Discussions

Bias adjustment and validation of climate models

Evaluation of the monthly bias adjusted precipitation and temperature shows adequate performance (Figure 2 and Table 4). Correlation coefficients between the observed and the two RCM models were significantly improved by bias correction on monthly comparisons (Figure 2a and b and Table 4). The two climate models such as CNRM5 and CSIRO MK-3-6-0 perform well on reproducing rainfall at a coefficient of determination (R^2) value of .74 and .71 respectively (Figure 2a and b). Furthermore, the climate models have shown a reasonable capacity in simulating rainfall and temperature on a monthly basis for the remaining evaluation criteria (Table 4). From these the KGE has shown better performance for both precipitation and temperature for the two climate models. However, we note that the monthly bias correction has improved precipitation better than the mean temperature.

The two complementary models were also tested for their performance in simulating daily rainfall at the regional scale. The calculated daily means (Figure 3a) and variances (Figure 3b) show acceptable simulation of the historical period. For

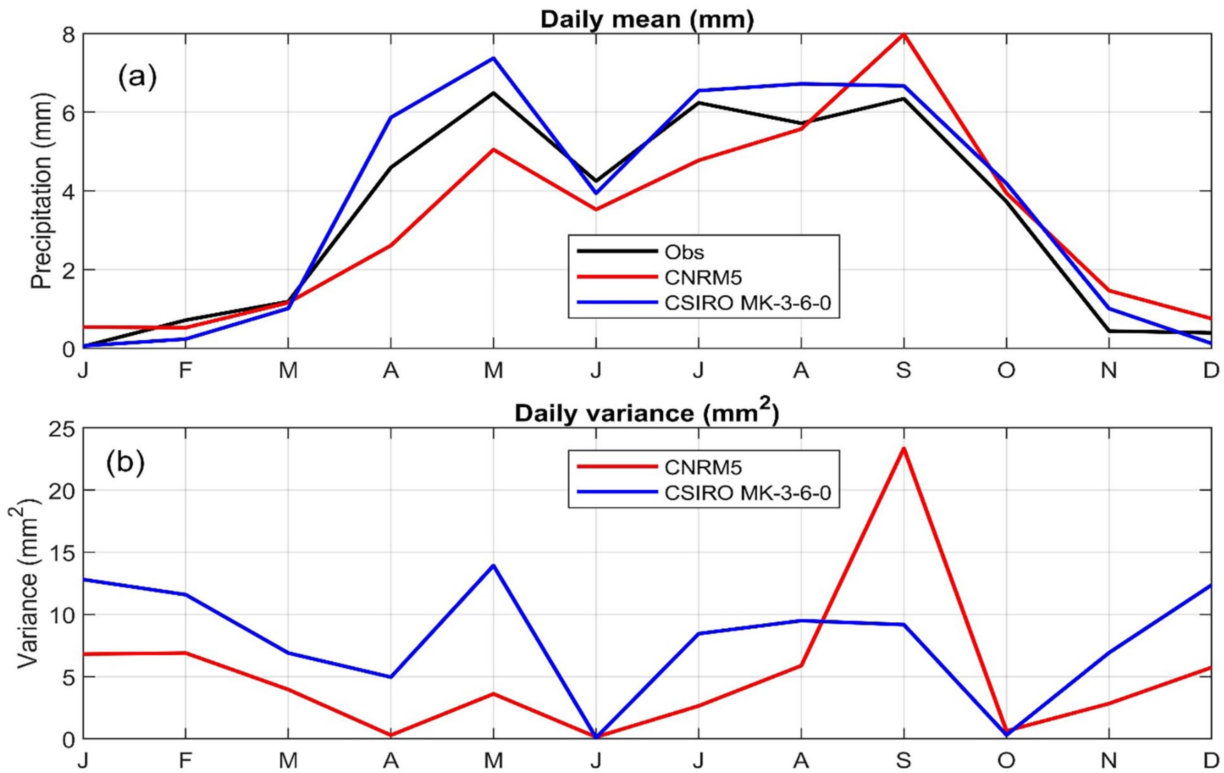

Figure 3. Comparison between the statistical properties of the observed daily rainfall for the period 1980 to 2005 and the two RCM outputs: (a) shows the daily mean precipitation and (b) shows the daily variance.

the CNRM5 and CSIRO MK-3-6-0 models, the annual variability in mean monthly rainfall is acceptable. The CSIRO MK-3-6-0 model was well reproduced in most months, while other months such as April, May, and August showed a slight deviation. In addition, the CNRM5 model has a general tendency to underestimate the monthly variance in most months of the year, although there is an overestimation in some months, such as September to December. The CNRM5 models have the lowest daily variance, whereas the CSIRO MK-3-6-0 model exhibited a greater daily variability (Figure 3b).

Maximum and minimum temperature

Figure 4 shows that both models underestimated the maximum temperature. Likewise, both models overestimated the minimum temperature except for CNRM5 April estimation. The analysis shows that the maximum temperature is well captured by CSIRO MK-3-6-0 and the minimum temperature is better captured by CNRM5. In addition, the models can more accurately reproduce the monthly and seasonal maximum and minimum temperature values because their monthly and seasonal variations are less than the projected monthly maximum and minimum temperature for a future period (Figure 4). In this regard, the CNRM5 model groups reproduced the minimum temperature with greater probability than the CSIRO MK-3-6-0 model. In addition, the CSIRO MK-3-6-0 model is better able to track the mean maximum temperature than the CNRM5 model. Therefore, for further estimation of potential evapotranspiration, both models were used considering their average values.

Projected rainfall under the CNRM5 model

Projected rainfall in the study regions was analyzed for three periods of the 21st century (2020s, 2050s, and 2080s). The rainy season (June, July, and August) for the future periods shows a decrease under the RCP4.5 scenario for the 2020s, 2050s, and 2080s periods, but the dry seasons (October–December and January–April) show an increase in rainfall during the same periods. For the rainy season at the end of the 21st century, a maximum decrease was observed in June from 172.9 to 155.7 mm/month under the RCP4.5 scenario (Figure 5a). Projected rainfall under the RCP8.5 scenario shows a change in the wet season (Figure 5b) from the baseline period. A reduction in wet season rainfall was observed under the RCP8.5 scenario for the 2020s, 2050s, and 2080s time periods, while future dry season rainfall increased. The decline in future rainfall during the wet season will reduce maize productivity in the region whose cultivation depends on rainfall from this season.

Projected potential evapotranspiration for future water requirement

In the future, PET will experience declines primarily during the wet seasons of June, July, August, and September. However,

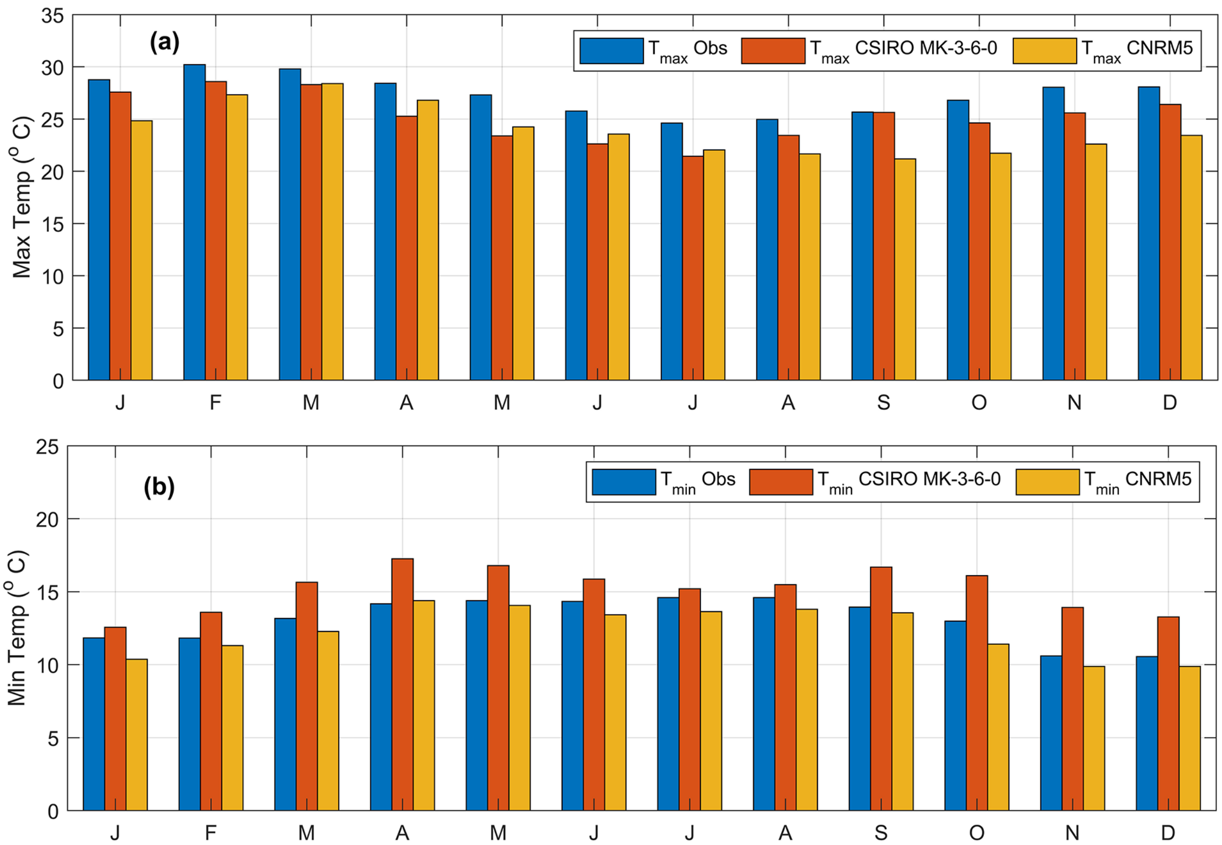

Figure 4. Comparison of CNRM5 and CSIRO MK-3-6-0 models with the observed (a) maximum and (b) minimum temperatures in the historical period.

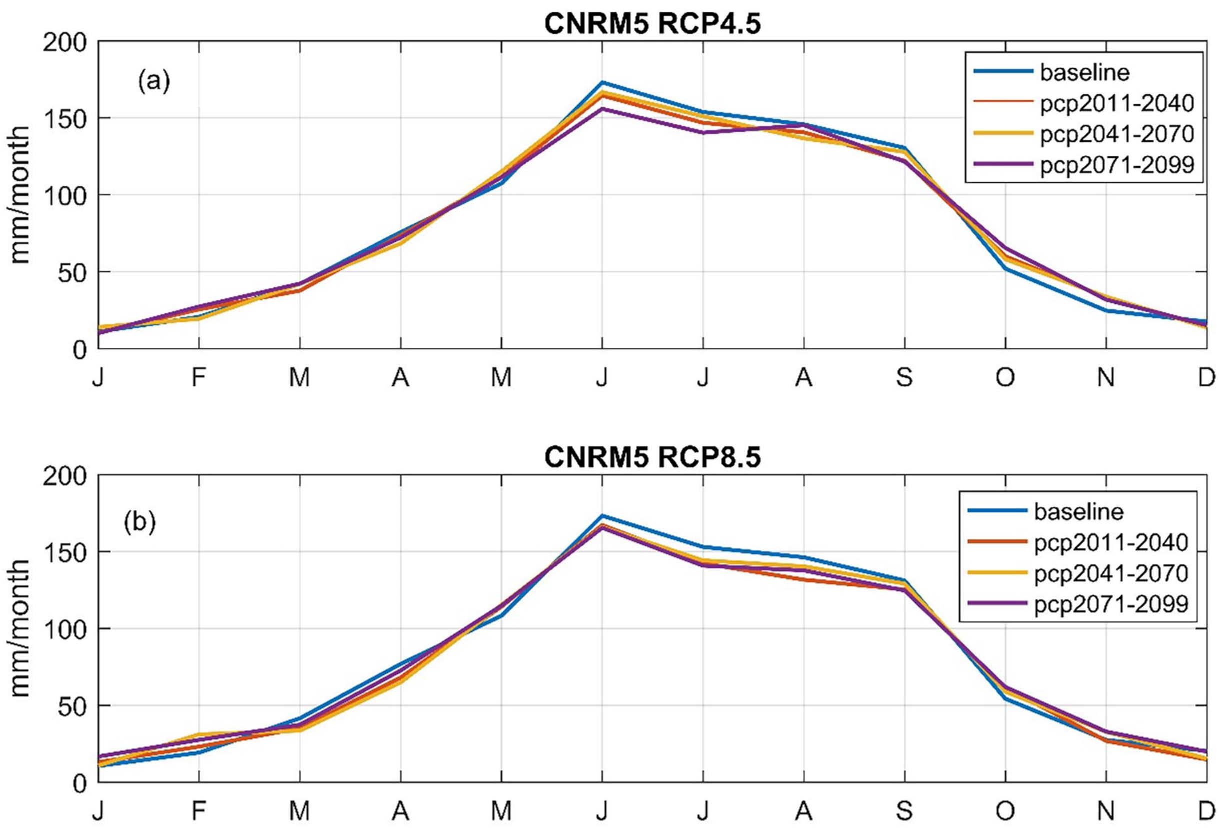

Figure 5. Projected monthly rainfall under the CNRM5 model for RCP4.5 (a) and RCP8.5 (b) scenario for future periods.

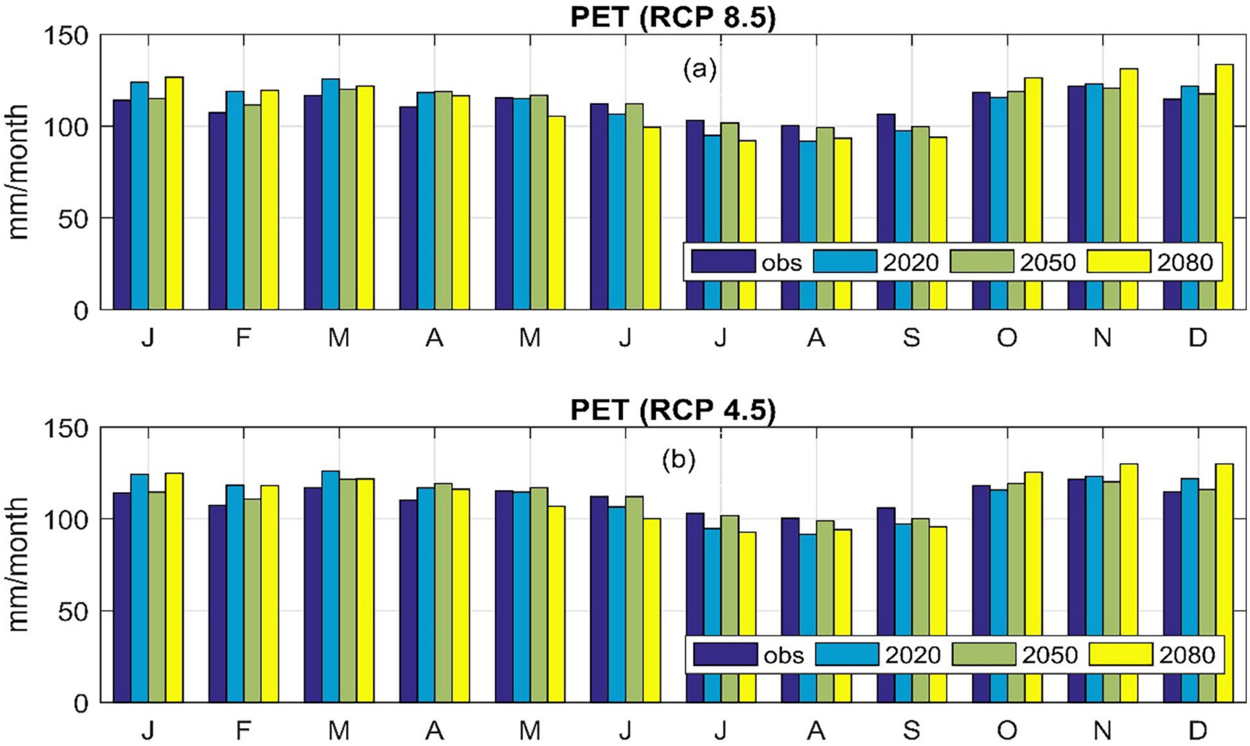

Figure 6. Projected PET at different time horizons for: (a) RCP8.5 and (b) RCP4.5.

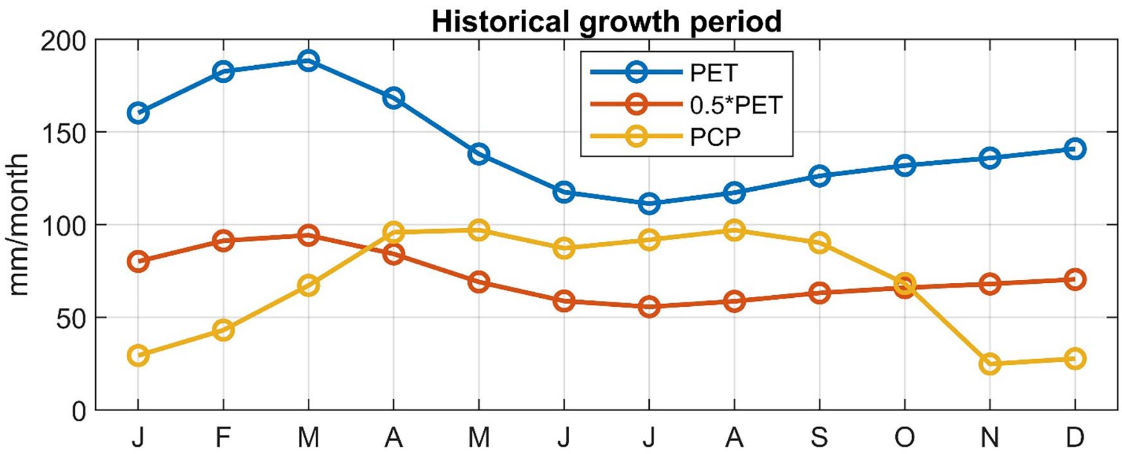

Figure 7. The historical (1980–2010) length of growth period of maize over Lake Hawassa watershed.

regional dry months January to April and October to December are projected to show a relative increase for RCP8.5 in the 2020s (Figure 6a). Similarly, in the wet seasons (June, July, August, and September), PET was reduced for most future periods. In addition, the same increase from PET is projected for most dry months (January, February, March, April, and through October, November, and December) at RCP4.5 (Figure 6b).

Historical and future growth periods under the CNRM5 model

From the PET estimated by the Penman-Monteith method, the overlap between half of PET and monthly historical precipitation (PCP) was used to determine regional LGP. The result shows that, on average, late March was the beginning month and October was the ending month of the area with a maximum LGP of 190 days for the 1980 to 2010 period (Figure 7).

Following the same procedure, the CNRM5 model results for precipitation and average temperature from the two model groups and the Hargreaves method were used to project the onset, offset, and LGP of the area for the future time horizons. Figure 8a and b show the length of growth periods for the 21st century under the RCP4.5 and RCP8.5 scenarios, respectively. The result shows that for the 2020s period, the area is expected to have an average of April 1 to 15 as the onset time and early October as the exit time. Therefore, the area will have a maximum LGP of 180 days with wet periods of almost 3 months

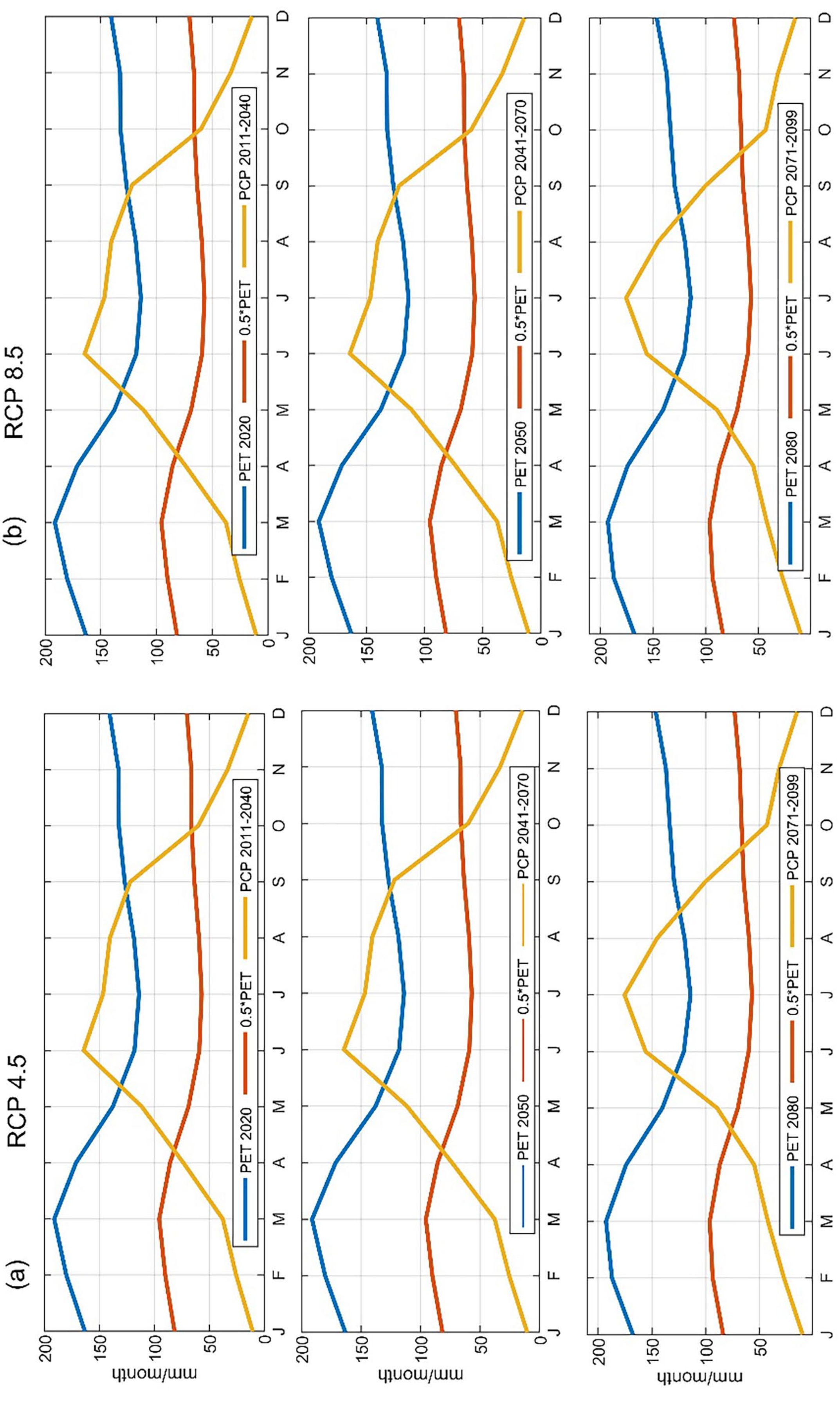

Figure 8. Future growing season of Lake Hawassa watershed for the years 2020s, 2050s, and 2080s under CNRM5 (a) left panel for RCP4.5 and (b) right panel for 8.5 scenario.

(Figure 8a). In the 2050s, the LGP is almost the same as in 2020s, with the LGP onset date being April 1 to 15 and the LGP end date being the end of September. During this period, the maximum LGP is reduced to 150 days. At the end of the 21st century (2080s), LGP is lowest in the area with an average LGP of 140 days under the RCP4.5 scenario.

The future shift in Maize LGP under the RCP8.5 scenario is shown in Figure 8b. Based on this assessment the period of the 2020s, on average April 1 to 15 is likely to be the onset time and the end of September is the cessation time of the area. Consequently, the area will have a maximum LGP of 165 days with humid periods of nearly 3 months in June, July, and August (Figure 8b top panel). The 2050s period is nearly identical to the 2020s period, where the wet period begins April 1 to 15 and ends in late September. During this period, the maximum LGP is reduced to 150 days. At the end of the 21st century (2080s), LGP is lowest in the area with an average LGP of 138 days under the RCP8.5 scenario (Figure 8b, bottom panel).

The future growing season of the area averages between April 15 and May 1 as the beginning of the growing season and the end of September as the end of the growing season for all years, with LGP between 150 and 160 days. Even though the future is estimated to be suitable for rainfed agriculture, the short wet period is an indicator of the occurrence of water stress in the future time horizons. Comparing the historical and future growing seasons of the area, there is a time when the two local seasons "*Bega*" (between October and February) and "*Belg*" (from March to May) are not usable for rainfed agriculture. However, in the future, it is assumed that the local rainy season "*Kiremt*" (from June to September) is suitable for rainfed agriculture. There is also a considerable change in the initial period from April to May and the offset period from September to October, and a shortening of the growing season is an early warning that requires a transformation of traditional agricultural practices and optimal use of expected rainfall for future periods.

Maize water requirement under changing climate

Water requirements of Maize at each growth stage by scenario are shown in Table 5. Accordingly, under RCP4.5 scenarios, Maize would require 518.1 mm by 2020s, and 528.4 mm by 2080s respectively for the initial growth period. For the same scenario (RCP4.5), the Maize shows an increment in the CWR from 2,072.4 to 2,213.25 mm (6.79%) from the 2020s to the 2080s respectively. During the late season, there was also a remarkable increment in the CWR of Maize up to the end of the 21st century. Therefore, an average increase in crop water demand was projected for the RCP4.5 emissions scenarios compared to the baseline period. In this case, the increase in CWR is mainly due to the increase in projected evapotranspiration from the two climate models used in this study (CNRM5 and CSIRO MK-3-6-0). Similarly, the RCP8.5 scenario for the development stage shows an increase from 2,083 to 2,155 mm (3.45%) between 2020s and 2080s. This projection for the study region indicates additional water demand to supplement the rainfed agriculture system.

As discussed in the projection PET (*Section 3.4*), the highest and lowest PET were in March and December, respectively. This result is almost consistent with the water requirement of Maize for the same period. During the baseline period, the total water requirement for Maize production was about 3,180.4 mm and increased to 3,258.7 mm (2.46%) by the end of the 2080s for all stages on average from both RCP4.5 and RCP8.5. This difference in the water demand of Maize is possibly due to the difference in the length of the growing period between the two periods. It was discussed that under the RCP4.5 scenarios, future LGP shows a reduction primarily due to an increase in PET.

Future drought conditions in the region

The standardized rainfall anomalies (S) are presented here to describe the different classes of drought index for the region using the CNRM5 model under both scenarios (RCP4.5 and RCP 8.5). Under the RCP4.5 scenario, most of the standardized anomalies of rainfall (S) are negative indicating a water deficit during the 2020s (Figure 9a). The results from the 2011 to 2040 time frame show that 2015 was an extreme drought year, and 2027 is predicted to be an extreme drought year, while 2031 and 2038 will be severe drought years. This finding is in agreement with the study by Mohammed and Yimam (2021) and Teshome and Zhang (2019) that showed the increase of extreme drought events in Ethiopia. The increase in extreme drought will ultimately affect crop and livestock production, influence the water balance, and ecology (Mohammed et al., 2018). The analysis reveal other 26 years with $S > -0.84$, that show no drought years. The result also shows that 15 out of 30 years have a positive anomaly, with a maximum in 2026 (+2.8), indicating that the area received good rainfall in these years, and 15 years with negative anomalies show a rainfall deficit in the area for the period 2011 to 2040. In the 2050s (2041–2070), there is no case leading to extreme drought (Figure 9b). However, in 2041, 2061, and 2069, severe drought was observed in 3 years. The same analysis was projected for the 2080s, where there is only one case of severe drought in 2074. However, out of 30 years, 15 years have a positive S-index, indicating good precipitation coverage across years (Figure 9c).

Figure 9d to f also shows the standardized rainfall anomalies under the RCP8.5 scenario for the three periods of 2020s, 2050s, and 2080s. Under this scenario, few cases of extreme drought occurred in the 2050s and 2080s. In addition, the 2050s recorded the fewest years (only 10 years) with a positive S-index value in relative terms, indicating projected scarcity of rainfall during these periods (Figure 9e). In comparison, years in the 2080s have more positive S-index than other periods. Despite high variability of rainfall in the region (Fekadu, 2015) good amount of positive anomalies were also shown that indicate the likely occurrence of sufficient rainfall in Lake Hawassa watershed (Figure 9f).

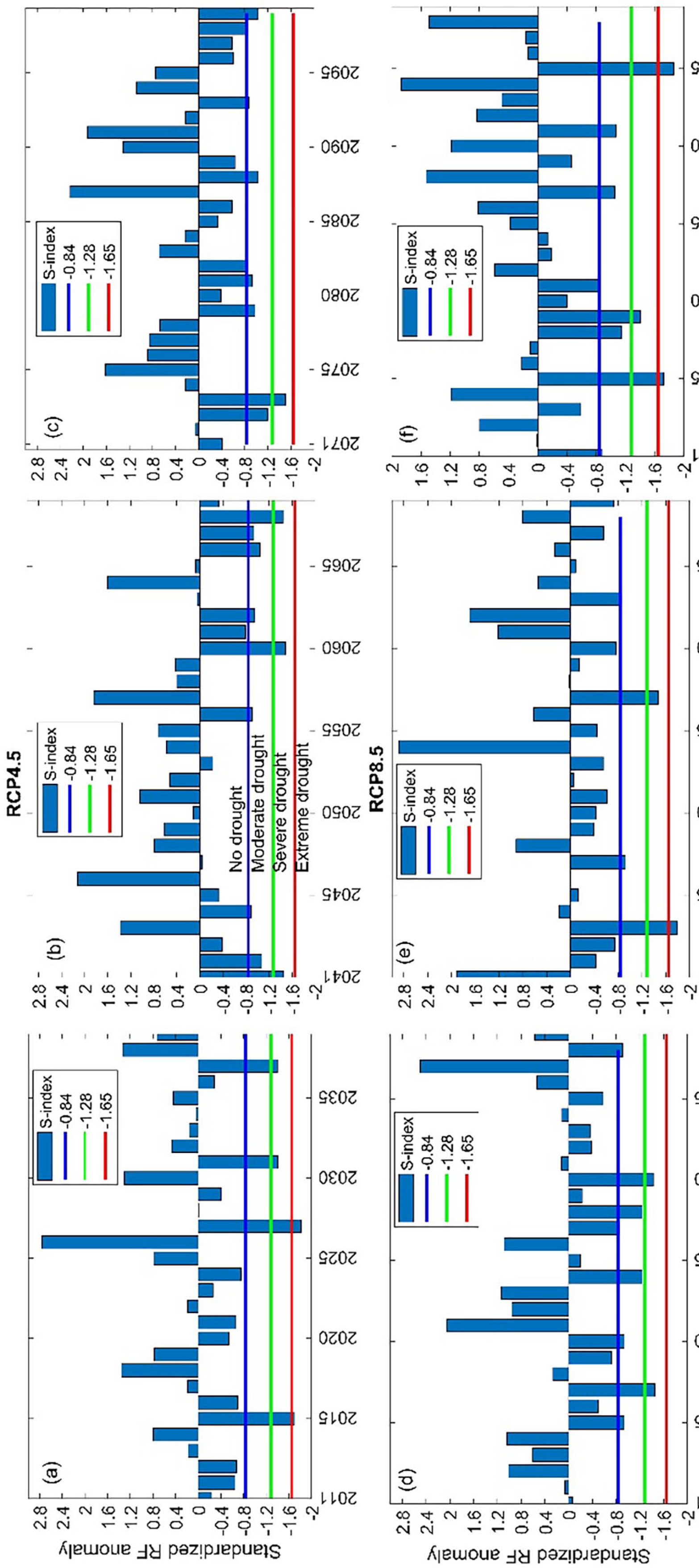

Figure 9. Standardized rainfall anomalies of future rainfall of the periods 2020s, 2050s, and 2080s for the CNRM5 model under RCP4.5 (a–c) and RCP8.5 (d–f) scenarios.

Table 5. Annual Future CWR (mm/growing stages) of Maize Under Different Development Stages for RCP4.5 and RCP8.5 Scenarios.

FUTURE PERIODS	RCP4.5			RCP8.5		
	INITIAL STAGE	DEVELOPMENT STAGE	LATE STAGE	INITIAL STAGE	DEVELOPMENT STAGE	LATE STAGE
2020s	518.1	2,072.4	604.4	520.9	2,083.7	607.7
2050s	522.1	2,096.4	632.3	532.1	2,128.3	620.8
2080s	528.4	2,213.3	653.3	538.9	2,155.7	628.7

The implication of the future LGP and CWR for crop production in the region

The study analyzed the historical growth period of the Lake Hawassa watershed which is under progressive anthropogenic influences similar to other places in Ethiopia (Abraham & Nadew, 2018; Gebeyehu Admasu, 2015). Analysis of LGP from the best-fitting climate model (CNRM5) for the region was overlaid to show a possible shift in LGP. Here, the CNRM5 model for precipitation best describes the fit, while the temperature estimate for both models (CNRM5 and CSIRO MK-3-6-0) shows a regionally acceptable result. For the Lake Hawassa watershed, the analysis showed that the LGP for the future period shows a decrease in the values of the base periods (4–5 months). Decrease in the LGP will reduce the productivity of small farmers, which are already exposed to the varying degrees of vulnerability due to climate change induced extremes (Shiferaw & Legesse, 2015). Considering the low economic and agricultural development in the region, the result suggests an early warning to develop a coping and mitigation option to develop adaptive farming systems. In addition, the reduction in LGP also affects maize production and could lead to a change in the crop type suitable for the region. The Thornton et al. (2010) study showed that moderate yield losses can be offset in the near future through plant breeding and agronomic approaches, while more severe yield losses could require a change in cropping patterns, even a switch to livestock-oriented production, or abandonment of the crop altogether.

Another point to consider is that maize production in rainfed regions will be more problematic and the lower LGP will most likely rely on crops that have a shorter LGP in these regions. In addition, the increase in CWR could make maize production more problematic. The analysis (*Section 3.6*) showed that CWR will increase in both scenarios compared to baseline period values. These increases are due to an increase in future temperature in the area, which would serve as a proxy for estimating evapotranspiration. Specifically, in these regions, crop production depends on a rainfed system that is inherently volatile, which will lead to an increase in uncertain crop production in the future. To cope with these scenarios, water needs to be conserved in fields at the household level, and the efficiency of irrigation systems needs to be improved. Adaptive irrigation system especially suited to the drought prone regions have been demonstrated to increase crop productivity (Grewal et al., 2021). In addition, the shift in cropping patterns (Burke et al., 2009) that require less water or are resistant to water stress in the future should be considered. Consequently, development of improved germplasm and farmer access to improved seed should be planned to strengthen breeding strategies and offset projected yield declines (Burke et al., 2009; Thornton et al., 2010).

Conclusions

The effects of climate change are being felt in many sectors. Quantifying its effect on the crop production factors such as LGP and CWR will allow better preparation. In this study, the impact of climate change and its consequences on the length of growing seasons and water requirements of maize were quantified. Two regionally downscaled climate models (CNRM5 and CSIRO MK-3-6-0) were used for the study, which reproduce precipitation and temperature data well over the historical period after correcting for biases. The onset time for the average of all future periods is between April 15 and May 1 and the end of September is the cessation time with LGP ranging between 150 and 160 days. Predictions for the future growing season of the area show, two local seasons such as "*Bega*" (October–February) and "*Belg*" (March–May) could remain mostly not operational for the rainfed agriculture. However, the local rainy season "*Kiremt*" (June–September) is anticipated to remain suitable for rainfed agriculture under both the RCP4.5 and RCP8.5 scenarios.

According to both RCP4.5 and RCP8.5 scenarios, the baseline total crop water requirement of 3,180.4 mm was expected to rise to an average value of 3,258.7 mm for all stages by the end of the 2080s. Similarly, under the RCP8.5 scenario, the development stage of Maize has shown the largest increment of water requirement for the period of 2020s to 2080s that suggest additional water demand to supplement the rainfed agriculture system. Most of the standardized anomalies of rainfall (S) are negative under the RCP4.5 scenario indicating a water deficit during the 2020s. In addition, no extreme drought occurred in 2050s, but a severe drought class was indicated in 2041, 2061, and 2069 under the RCP4.5 scenario. In contrast, there was only one instance of severe drought in the 2080s. The same analysis shows that few cases of extreme drought occurred under the RCP8.5 scenario in the 2050s and 2080s, but a precipitation shortage was projected for 2050s for this period.

Overall, this study showed the impact of two different climate models on maize production. Therefore, given the expected uncertainties in climate models, it is recommended that future analysis of climate data include multiple models. In addition, LGP estimates should be interpreted cautiously due to the limited availability of other large-scale data, and future studies should include finer spatial quantification of LGP by incorporating measured data such as soil moisture, water retention, air temperatures, and daylight hours.

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Author Contributions

TA conceptualized the method, analysis, interpretation of the result, and write-up of the paper. AM, provided support in developing the manuscript and commented on previous versions of the manuscript.

Consent for Publication

All authors read the manuscript and agreed for publication.

Data Availability

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

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