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Evaluating Climate Change Impact of Rainfed Maize Production Yield in Southern Ethiopia

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Abstract

A developing country like Ethiopia suffers a lot from the effects of climate change due to its limited economic capability to build irrigation projects to combat climate change's impact on crop production. This study evaluates climate change's impact on rainfed maize production in the Southern part of Ethiopia. AquaCrop, developed by FAO that simulates the crop yield response to water deficit conditions, is employed to assess potential rainfed maize production in the study area with and without climate change. The Stochastic weather generators model LARS-WG of the latest version is used to simulate local-scale level climate variables based on low-resolution GCM outputs. The expected monthly percentage change of rainfall during these two-time horizons (2040 and 2060) ranges from -23.18 to 20.23% and -14.8 to 36.66 respectively. Moreover, the monthly mean of the minimum and maximum temperature are estimated to increase in the range of 1.296 ^{0}C to 2.192 ^{0}C and 0.98 ^{0}C to 1.84 ^{0}C for the first time horizon (2031-2050) and from 1.86^{0}C to 3.4^{0}C and 1.56^{0}C to 3.18^{0}C in the second time horizon (2051-2070), respectively. Maize yields are expected to increase with the range of 4.13% to 7% and 6.36% to 9.32% for the respective time horizon in the study area provided that all other parameters were kept the same. In conclusion, the study results suggest that rainfed maize yield responds positively to climate change if all field management, soil fertility, and crop variety improve were kept the same to baseline; but since there is intermodal rainfall variability among the seasons planting date should be scheduled well to combat water stress on crops. The authors believe that this study is very likely important for regional development agents (DA) and policymakers to cope up with the climate change phenomenon and take some mitigation and adaptation strategies.

Keywords: AquaCrop model, Climate change, LARS-WG, Yield estimation.

1. Introduction

A warmer world would likely affect all aspects of our environment. Amongst all sectors (energy, agriculture, water, fisheries, livestock, etc.), agriculture is the most sensitive and vulnerable to climate change (IPCC, 1990). Climate change is now a leading issue on the environmental and socioeconomic agenda worldwide (Crossman et al., 2013). It is the primary determinant of agricultural production and hydrology balance (Adams et al., 1998). There is testimony from the scientific community of the globe that there is climate change now and 97% of climate scientists agree that it is being driven primarily by human activity (IPCC 2001b, Wang et al., 2019). Climate change, however, is expected to make agricultural development in Africa more challenging in many places (E. Blanc., 2012). Ethiopia is one of the most likely vulnerable countries in Sub-Saharan Africa facing climate change extreme events (drought and floods) as a result of climate variability and change, that would influence largely the agricultural sector (Gezie, M., 2019). The study in five regions (Amhara, Tigray, Benishangul Gumuz, Oromia, and Southern Nation Nationality and People (SNNP) of Ethiopia indicated that all the regions are negatively affected by climate change at varying levels (Baylie, M. M., & Fogarassy, C., 2021).

The Federal Democratic Republic of Ethiopia Ministry of Agricultural (2011) report on agriculture sector program plan adaptation to climate change depicted that Ethiopia agriculture would face many adverse impacts that are caused by the unpleasant appearance of climate variable change. Yet there are indications by which these impacts will continue to influence the socio-economic activities of the community at a larger scale. Deressa et al., (2008) study that used biophysical and social vulnerability indices of the Ricardian approach suggests that a decline in rainfall and an increase in temperature are more likely tends to damage Ethiopian agriculture. The second (IPCC, 1996) report predicted that tropical and subtropical regions would experience higher losses in crop production, while temperate climates might gain in productivity with climate warming. Issues of hunger and famine in Ethiopia are associated with low cereal crop production like maize as a result of poor rainfall what happens nowadays in Ethiopia once again. It is apparent, therefore; that tropical/subtropical parts of the nation wholly rely on rainfed farming. Ethiopia's food production could be greatly impacted by climate changes.

Maize is the second-largest most widely produced cereal crop next to teff in area coverage in Ethiopia and the most important commodity used to alleviate poverty in the country (CSA, 2015). Solomon et al., (2021) researched the Impact of Climate Change on Agricultural Production in Ethiopia at the national level and found that crop production will be adversely affected during the coming four decades and the severity will increase overtime period. The future prediction of the study indicates that the production of teff, maize, and sorghum will decline by 25.4, 21.8, and 25.2 percent, respectively by 2050. Timothy et al., (2019) researched the Climate change impacts on crop yields in Ethiopia and suggest that climate change will likely have only relatively small effects on average yields of maize. However, Kassaye et al., (2021) study on the Impact of climate change on the staple food crop yield in Ethiopia suggest that the yield of teff and maize will be expected to increase by 20.2 and 17.9% respectively at the end of the twenty-first century with increasing temperature and rainfall decline. Ironically, Abera et al., (2018) indicate that maize yields will decrease by up to 43 and 24% by the end of the century at Bako and Melkassa stations, respectively, while simulated maize yield in Hawassa will increase by 51%. In contrast to this, the study in the central rift valley of Ethiopia predicted that maize production will decrease on average by 20 % under climate change by 2050 (Kassie et al.,2015). The study in the Gambella region also suggests that rainfed maize production will decrease under three RCPs (2.6, 4.5, and 8.5) in the future but only it will decrease under RCP8.5 after 2040–2069 (Degife et al., 2021).

General circulation models (GCMs) are greatly supportive of the assessment of potential climate change impacts on multiple sectors on a global scale. However, a horizontal resolution of GCMs is typically between 250 and 600 km, which cannot meet the requirements of most local impact studies (Phuong et al., 2020). Hence, many dynamical and statistical downscaling methods have arisen to overcome these key disadvantages of GCMs. By creating General Circulation Models (GCM), climate conditions can be assessed for long-time scales. However, the output of these models does not have enough spatial and temporal accuracy to study the effect of climate change on agricultural and hydrological systems (Pervez and Henebry.,2014; Tripathi et al., 2006; Valizadeh, J.et al.,2014; Boe et al., 2007, Chen et al., 2011). Thus, applying suitable downscaling models can improve the results of climate change studies (Arshad, et al., 2019; Miao et al., 2019, Dahm et al., 2019; Adnan et al. 2019).

Several studies have been conducted to evaluate the impacts of climate change on crop production using crop simulation models. In this study AquaCrop model FAO (Food and Agriculture Organization) was used (Steduto et al., 2009) which has been widely used and tested in different climate change impact studies worldwide in general and Ethiopia, in particular, have a user-friendly interface and are openly accessible. It is widely used and validated for different crops in Ethiopia (Msowoya et al.,2016; Gebremedhin, Y., 2015; Feleke et al., 2021; Tsegay et al., 2011). Feleke et al., (2021) study suggest that the AquaCrop model accurately simulated maize canopy cover and yield for all varieties. Due to the inconsistent results concerning the impact of climate change on the crop yield obtained among the different studies (Abera et al., 2018; Kassaye et al., 2021; Kassie et al.,2015; Degife et al., 2021) and none of them applied the combination of Global Circulation Models (GCMs) and AquaCrop whereby LARS-WG is used as a downscaling tool, the main objective of this study is to estimate the effect of climate change in the near future 2040 (2031-2050) and midterm 2060 (2051-2070) on maize yield production in the southern part of Ethiopia using the AquaCrop model in combination with Global circulation models. The study contains four sections: Section 1: is an introduction, section 2: Material and methods, Section 3: Results and Discussions, and Section 4: is the conclusion.

2. Material and methods

2.1. Study Area

This study was conducted in the Southern part of Ethiopia in Sidama regional state at Hawassa district that covers the latitudinal area from $6^0\,40'0''$N to $7^0 20'0''$N and the longitudinal area $38^0 20'0''$ E to $38^0\,40'0''$ E (**Fig.1**). The main staple food crops in the zone are maize, haricot beans, *kocho*, and sweet potato, all produced in relatively small amounts. Chat is an income-generating crop in the higher-altitude areas of the zone, but it is not typical of the zone as a whole (USAID, 2005). There are many types of soils in Hawassa district but the soil type prevailing in the study area is Andosols (a black or dark brown soil formed from volcanic material, with an A horizon rich in organic material). The soil property of the area is characterized by the wilting point of 18.5% and field capacity of 34.8% with no restrictive soil layer and soil salinity stress (K.N.Disasa et al., 2019). Sidama region is technically falling into the borderline area between the *kolla* and *woina dega* agro-ecological zones, with altitudes in the range of 1400 – 1700 meters above sea level. Average annual rainfall is in the range of 700- 1200mm per year and falls during two rainy seasons, the *belg* (autumn) and *kremt* (summer) rains. Hawassa district has an annual average rainfall of 955mm with a mean annual temperature of 20^0C. The main rainy season generally extends from June to October.

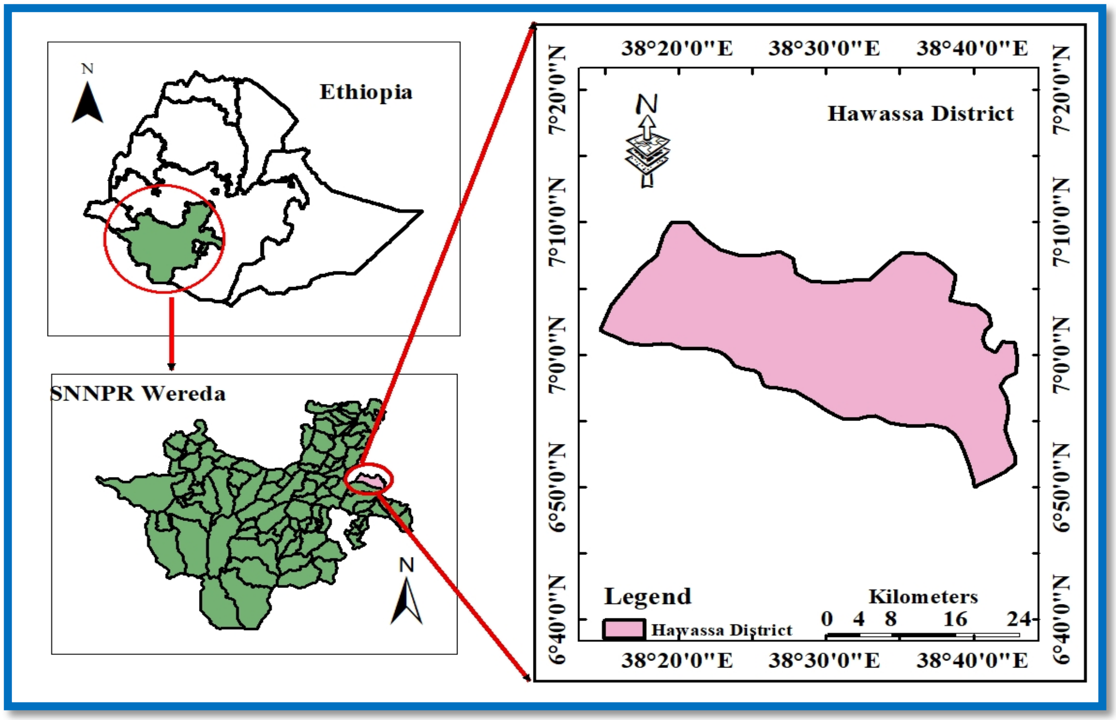


Figure 1. Map of the study area

2.2. Global Circulation Models Downscaling models

Stochastic weather generators, as one of the most typical and popular downscaling methods, have been widely applied for local-scale weather simulation based on low-resolution GCM outputs at a single site (Vallam and Qin 2018; Wilby et al., 2002; Zhang 2005). At low cost and with less computationally demanding frameworks, it is simple to use weather generator models to quickly model future multiple-year weather data series at the daily time scale at a particular station. LARS-WG, as one of the downscaling models, is used for the simulation of climate information under current and future circumstances. Different studies reported the superiority of LARS WG over SDMS (Pourtouiserkani et al., 2014, Semenov, M.A.and Barrow, E.M 2002; Rajabi et al., 2010). Several studies in the world demonstrated the successful prediction of different climatic variables using LARS-WG, including the prediction of temperature and precipitation, and LARS WG has excellent downscaling performance in maximum and minimum temperature than precipitation (Sepideh Karimi et al., 2015; K.N.Disasa et al., 2019; Karimi et al., 2015; Awal et al., 2016; Agarwal et al., 2014; Qi et al., 2016).

Accordingly, the new parallel approach that developed by IPCC, AR5., (2014) to replace the Special Report on Emissions Scenarios (SRES) with Representative Concentration Pathways (RCPs) to shorten the time between the development of emissions scenarios and the use of the resulting climate scenarios in impact research is used in this study. The RCPs also provide an important reference point for new research within the integrated assessment modeling (IAM) community by standardizing on a common set of year-2100 conditions and exploring alternative pathways and policies that could produce these outcomes (Moss et al., 2010, Van Vuuren et al., 2011).

In the new parallel approach radiative forcing trajectories are not associated with unique socioeconomic or emissions scenarios, and instead can result from different combinations of economic, technological, demographic, policy, and institutional futures. Four pathways lead to radiative forcing levels of RCP 8.5, RCP 6, RCP 4.5, and RCP 2.6 W/m2 by end of the 21st century. Each of the RCPs covers the 1850–2100 periods, and extensions have been formulated for the period thereafter up to 2300 (Van Vuuren et al. 2011). A subset of 18 GCMs from the CMIP5 multi-model ensemble was incorporated into the LARS-WG weather generator (Semenov MA and Stratonovitch P.2015) under two RCPs (RCP 8.5 and RCP 4.5). For this study, only five GCMs (**Table 1**) from the CMIP5 are used under two RCPs (Ahmadi, M., et al., 2021).

2.3. Description of LARS-WG

Long Ashton Research Station Weather Generator is neither a predictive nor forecasting tool but is simply a means of generating time-series of synthetic weather statistically identical to the observations (Semenov, M. A. et al., 2002). Its latest version (LARS-WG Version 6.0, to date version) was used for this study to simulate future weather data (maximum and minimum temperatures, precipitations, and Solar radiation) for the near term, and mid-term in the study area. The model simulates weather data at a single site under current and future conditions (Racsko et al., 1991). It uses Minimum temperature (°C), Maximum temperature (°C), Precipitation (rainfall) (mm), and Solar radiation (MJ/m2/day) as input to generate synthetic data in daily time series. In the absence of solar radiation, the model accommodates the use of sunshine hours. LARS-WG automatically converts the sunshine hours to solar radiation using an algorithm that was described by Rietveld (1978).

Table 1. Global Circulation Models used in this study

GCM Name	Name of the research center	Grid Resolution	RCPs 4.5	RCPs 8.5
EC-EARTH	European community Earth-System	1.125°× 1.125°	✓	✓
GFDL-CM3	Geophysical Fluid Dynamics Laboratory	2.00° × 2.50°	✓	✓
HadGEM2-ES	UK Meteorological Office	1.25° × 1.88°	✓	✓
MIROC5	Japan Agency for Marine-Earth Science & Technology	1.39° × 1.41°	✓	✓
MPI-ESM-MR	Max Planck Institute for Meteorology	1.85° × 1.88°	✓	✓

The ability of LARS-WG to simulate reliable data depends on the availability of observed data. The model simulates future weather data based on as little as a single year of observed weather data. Semenov and Barrow (2002) recommend the use of daily weather data of at least between 20-30 years for better results. Weather data for long periods are significant in the way that they capture some of the less frequent events like droughts and floods. This study used daily historical observed weather data of at least 30 years from the (1981-2010) periods as baseline data.

2.3.1. LARS-WG Calibration and validation

It is very likely important to calibrate LARS-WG before generating future scenarios that are common for most statistical downscaling models. Calibration of LARS-WG is carried out by a function on the main menu called "Site Analysis". The process is done to determine the statistical characteristics and site parameters of the observed weather data. Once LARS-WG has been calibrated, its ability to simulate future weather data in the representative study site is assessed. Validation is a process that is used to determine how well a model can simulate potential future climate variables.

The Q test function was used to determine the ability of LARS-WG to rationally estimate future climate variables. This was achieved using three statistical tests; chi-square test (X^2), t-test, and K-S (Kolmogorov-Smirnov) which is the output Q test function to test the performance of LARS-WG. The chi-square test will be used to determine the existence of any significant difference between the simulated and observed frequencies in the meteorological data. A t-test was used to check the existence of any reliable difference between the means of the generated and observed data sets. Additionally; a K-S test was used to decide if a sample comes from a population with a specific distribution. The Kolmogorov-Smirnov (K-S) statistic Δ is the absolute maximum differences between observed cumulative probability P (X_m) and the theoretical cumulative probability F(X_m).

$\Delta = max|F(x_m) - P(x_m)|$---1

The observed cumulative probability is computed using Weibul's formula P(X_m)= $\left\lfloor \frac{(n+1-m)}{(n+1)} \right\rfloor$ and theoretical cumulative probability is obtained for each ordered observation using the selected distribution. Where n is sample size and m is ordered sequence or rank (K.N.Disasa et al., 2019).

Moreover, observed and simulated data time series of the monthly mean precipitation, the maximum and minimum temperature is checked by using the coefficient of determination (R^2), Root Mean Square Error (NRMSE), Nash–Sutcliffe efficiency (NSE) (Birara, H.et al.,2020; Amhadi, M. et al.,2021).

The coefficient of determination (R^2) is used to determine the proportion of variance in the simulated variable that can be explained by the observed variable. The higher the value for the goodness of fit of the model.

$$\boldsymbol{R^2} = \frac{\sum_{i=1}^{n}(s_i-\bar{o})^2}{\sum_{i=1}^{n}(o_i-\bar{o})^2} \text{---} 2$$

RMSE is used to measure the difference between simulated and observed values. The lower the value the higher accuracy of the model to predict.

$$\mathbf{NRMSE} = \sqrt{\frac{\sum_{i=1}^{n}(o_i - s_1)^2}{n}} \text{--} 3$$

The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance between simulated and observed data. The more the value approaches 1 the high the predictive skill of the model.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(s_i-o_i)^2}{\sum_{i=1}^{n}(o_i-\bar{o})^2} \text{--} 4$$

where Oi is the observed data, Si is the simulated data.

2.4. Introduction to AquaCrop

AquaCrop is the FAO crop model to simulate yield response to water (Raes et al., 2009; Steduto et al., 2009). It is a very likely friendly tool that would be used for a wide range of users and applied for the prediction of crop yield under current and future climate change scenarios. AquaCrop appears to use ground canopy cover instead of leaf area index and mostly focuses on water hereby using water productivity values normalized for atmospheric evaporative demand and of carbon dioxide concentration. This helps the model to use in diverse locations and seasons under future climate scenarios. An empirical production function is mostly suggested to use to estimate crop yield response to water to overcome the difficulty of crop responses to water deficits. Among the empirical function approaches, FAO Irrigation & Drainage Paper 33 (Doorenbos and Kassam, 1979) represented an important source to determine the yield response to water of field, vegetable, and tree crops, through Equation 5:

$$\left(\frac{Y_x-Y_a}{Y_x}\right) = K_y\left(\frac{ET_x-ET_a}{ET_x}\right) \text{---} 5$$

Where Yx and Ya are the maximum and actual yield, ETx and ETa are the maximum and actual evapotranspiration, and ky is the proportionality factor between relative yield loss and relative reduction in evapotranspiration. AquaCrop develops from Doorenbos and Kassam (1979) approach by separating the Evapotranspiration *(ET*) into soil evaporation *(E)* and crop transpiration (T_r) and the final yield *(Y)* into biomass *(B)* and harvest index *(HI*). The separation of *ET* prevents the confounding effect of the non-productive consumptive use of soil evaporation water (E). This phenomenon is very likely important when the canopy does not cover the ground completely. The separation of *Y* into *B* and *HI* allows the distinction of the basic functional relations between environment and B from those between environment and HI. These relations are fundamentally different and their use avoids the confounding effects of water stress on B and HI. The changes described led to **Equation 6** at the core of the AquaCrop growth engine:

$$B = WP.\sum T_r \text{---} 6$$

Where T_r the crop transpiration (mm) and WP is is the water productivity parameter (kg of biomass per m^2 and per mm of cumulated water transpired over the time period in which the biomass is produced). This step from *Eq.5* to *Eq.6* has a fundamental implication for the robustness of the model due to the conservative behavior of WP (Steduto et al., 2007). It is worth noticing though that both equations are different expressions of a water-driven growth engine in terms of crop modeling design (Steduto, 2003).

2.4.1. Components of AquaCrop

AquaCrop contains five sections (Atmosphere, Crop, Soil, Field Management, Irrigation management) which are used to calculate crop growth. Moreover, it also requires five weather data (daily minimum air temperatures, daily maximum air temperatures, daily rainfall, *ETO* and mean annual carbon dioxide concentration in the bulk atmosphere). *ETO* calculator the Penman-Monteith method as described by FAO (Allen et al., 1998) is used for estimation of Evapotranspiration (*Eq.7*)

$$\boldsymbol{ET_o} = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_{2(e_s-e_a)}}{\Delta+\gamma(1+0.34u_2)} \text{--} \mathbf{7}$$

Where ET_o reference evapotranspiration (mm/ day)

R_n net radiation at the crop surface (MJ/m^2 /day)
G soil heat flux density (MJ/ m^2 /day)
T mean daily air temperature at 2 m height (^{0}C)
U_2 wind speed at 2 m height (m/s)
e_s saturation vapor pressure (kPa)
e_a actual vapor pressure (kPa)
$e_s - e_a$ saturation vapor pressure deficit (kPa)
Δ slope vapor pressure curve (kPa/ ^{o}C)
γ psychometric constant (kPa/ ^{o}C)

AquaCrop calculations are performed always at a daily time-step. However, input is not required at a daily time-step, but can also be provided at 10-daily or monthly intervals. The model itself interpolates these data to daily time steps. The only exception is the CO2 levels which should be provided at the annual time-step and are considered to be constant during the year.

2.4.2. Climate change in AquaCrop

In this particular study climate change is conducted only by adjusting the precipitation data file and the temperature data file under current and future climate scenarios but the impact of enhanced CO2 levels is not considered. The impact of enhanced CO2 levels is calculated by AquaCrop itself. AquaCrop uses the so-called normalized water productivity (WP*) for the simulation of aboveground biomass. The WP is normalized for the atmospheric CO2 concentration and the climate, taking into consideration the type of crop (e.g. C3 or C4). The C4 crops assimilate carbon at twice the rate of C3 crops. A C4 plant is a plant that cycle's carbon dioxide into four-carbon sugar compounds to enter into the Calvin cycle.

2.4.3. Calibration of AquaCrop

Calibration of AquaCrop has been achieved by comparing the actual maize production (as provided by the Department of Agriculture of southern nations, nationality, and peoples of Ethiopia regional state, Sidama zone) with the maize yield simulated by the model. Input data for various crop and soil parameters used in the model are obtained from the South Region Agricultural Research Institute and Wondo Genet Agricultural Research Center Hawassa Maize Research Sub Center of Ethiopia. By comparing the actual and simulated maize yields crop parameters (CCo, canopy development, root deepening, flowering and yield formation, canopy expansion relative to water stress, stomata closure relative to water stress, etc..), field management(soil fertility stress percentage for biomass production in respective to canopy, biomass, water productivity, and percentage soil surface covered) and soil characteristics (characteristics of soil horizon, soil surface, restrictive soil layer, and capillary rise) are adjusted through trial and error, until the closest match between recorded and simulated maize yield was achieved. Data (recorded maize yields, rainfall, minimum and maximum temperature) from Hawassa station for the year 2018 has been used to calibrate the mode l(Msowoya et al.,2014).

2.4.4. Validation of AquaCrop

Having calibrated AquaCrop, it was significant that the model is validated to evaluate its performance in simulating crop yields. Model validation is important to determine if the model can replicate the data, and analyze the effectiveness of model calibration and compare synthetic data with those done in previous studies. Loague and Green (1991) indicate that there are numerous statistical indicators for evaluating the performance of AquaCrop, nonetheless, Willmott (1984) argues that each of the statistical indicators has its weaknesses and strengths. To effectively evaluate the performance of the model, the use of ensemble statistical indicators is appropriate (Willmott, 1984). In an analysis of the performance of AquaCrop, the following lists of statistical indicators were used (Msowoya et al., 2016): prediction error (Pe), coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and Nash and Sutcliffe (Ns) (Nash and Sutcliffe, 1970). Ns and R^2 indicate the predictive power of the model whilst Pe, MAE, and RMSE are used to signify the amount of error associated with the model prediction (Abedinpour et al., 2012).

Calibrated crop parameters, management practices, and soil types and conditions remained constant. Maize yields for years 2012 to 2017 were used to compare with those simulated by the model within the same time period.

$$\boldsymbol{R^2} = \left[\frac{\sum(\boldsymbol{O_i}-\bar{\mathbf{0}})(\boldsymbol{S_i}-\bar{\boldsymbol{s}})}{\sqrt{\sum(\boldsymbol{O_i}-\bar{\mathbf{0}})^2\sum(\boldsymbol{S_i}-\bar{\mathbf{0}})^2}}\right]^2 \text{---} 8$$

$$\boldsymbol{N_s} = \mathbf{1} - \frac{\sum_{i=1}^{i=N}(\mathbf{0}_i-\boldsymbol{S_i})^2}{\sum_{i=1}^{i=N}(\mathbf{0}_i-\bar{\mathbf{0}})^2} \text{---} 9$$

$$\boldsymbol{P_e} = \frac{(\boldsymbol{S_i}-\boldsymbol{o_i})}{\boldsymbol{o_i}} \times \mathbf{100} \text{---} 10$$

where S_i and O_i are synthetic and actual (observed) production $\overline{O_i}$ is the mean value of O_i and N is the number of observations.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(O_i - S_i)2}{N}} \text{ --11}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |s_i - o_i| \text{ ---12}$$

The model is said to perform better when values of N_s and R^2 approaches one and when values of *Pe, MAE*, and *RMSE* approaches zero (Moriasi et al., 2007).

3. Results and Discussions

3.1. Evaluation of LARS-WG

Based on the Q test function result of LARS-WG the performance of the model to generate future synthetic time series is calibrated and validated. Accordingly, the output statistical test function such as X^2(chi-square), t-test, and K-S Kolmogorov-Smirnov) with its respective p-value is used (**Table 2**). Furthermore, the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Nash–Sutcliffe efficiency (NSE) are calculated based on the mean monthly generated and simulated climate variables (**Table 3).** The significance level of 5% (0.05) which is common in statistical tests is used. The results indicate that *p*-values in all months except in December and January for the Chi-square test in rainfall are higher than the selected significance level of 0.05. However, the p-value for maximum and minimum temperature is higher than 0.05 for both statistical tests. This value indicates that LARS-WG is better to generate future temperatures (Max. and Min.) than rainfall (K.N.Disasa et al., 2019; Amhadi, M. et al., 2021). Moreover, Semenov, M.A, and Barrow, E.M., (2002) suggest that a significant difference may exist between observed and generated data if the mean climate variables do not follow the expected trend of increasing/decreasing. Therefore the model is still satisfactory to simulate future climate data.

Table 2. Q test function statistical results

Month	Precipitation						Max temp.				Min temp.			
	K-S	P-value	t	p-value	X^2	p-value	K-S	p-value	t	p-value	K-S	p-value	t	p-value
J	0.24	0.46	1.84	0.07	2.25	0.02	0.05	1.00	0.11	0.91	0.01	1.00	-0.70	0.49
F	0.05	1.00	0.09	0.93	1.92	0.06	0.11	1.00	1.39	0.17	0.05	1.00	-0.41	0.68
M	0.10	1.00	0.34	0.73	1.17	0.64	0.05	1.00	0.36	0.72	0.05	1.00	-0.96	0.34
A	0.05	1.00	-0.66	0.51	1.07	0.83	0.05	1.00	-0.31	0.76	0.05	1.00	-0.22	0.82
M	0.06	1.00	0.08	0.94	1.44	0.28	0.05	1.00	1.32	0.19	0.05	1.00	-0.71	0.48
J	0.04	1.00	-1.17	0.25	1.24	0.52	0.05	1.00	-0.49	0.63	0.05	1.00	-1.31	0.20
J	0.11	1.00	0.01	0.99	1.56	0.22	0.05	1.00	0.26	0.80	0.05	1.00	-1.06	0.29
A	0.05	1.00	0.49	0.63	1.01	0.96	0.05	1.00	-0.57	0.57	0.05	1.00	0.38	0.70
S	0.05	1.00	0.53	0.60	1.24	0.55	0.05	1.00	0.12	0.91	0.05	1.00	-0.10	0.92
O	0.08	1.00	-1.31	0.20	1.34	0.39	0.11	1.00	0.14	0.89	0.05	1.00	-0.48	0.64
N	0.06	1.00	-0.70	0.49	1.04	0.90	0.05	1.00	0.74	0.47	0.05	1.00	-0.84	0.40
D	0.24	0.47	1.43	0.16	2.92	0.00	0.05	1.00	-0.68	0.50	0.05	1.00	-0.13	0.90

Table 3. Lars-Wg Evaluation Statistical Parameters

Climate variables	Statistical performance		
	R^2	RMSE	NSE
Precipitation	0.988	8.604	0.952
Max temp.	0.949	0.121	0.997
Min temp.	0.967	0.128	0.993

3.2. Distribution of Weather Variables

Figure 2-3 shows the monthly mean distribution and daily maxima of climate variables (Precipitation, Maximum and Minimum temperature) in the study area respectively. The monthly mean baseline distribution of rainfall in the study area indicates that there is a bimodal rainy season with a low rainy season in March and April and a high rainy season in June to August that depicts the sowing season could be two times a year.

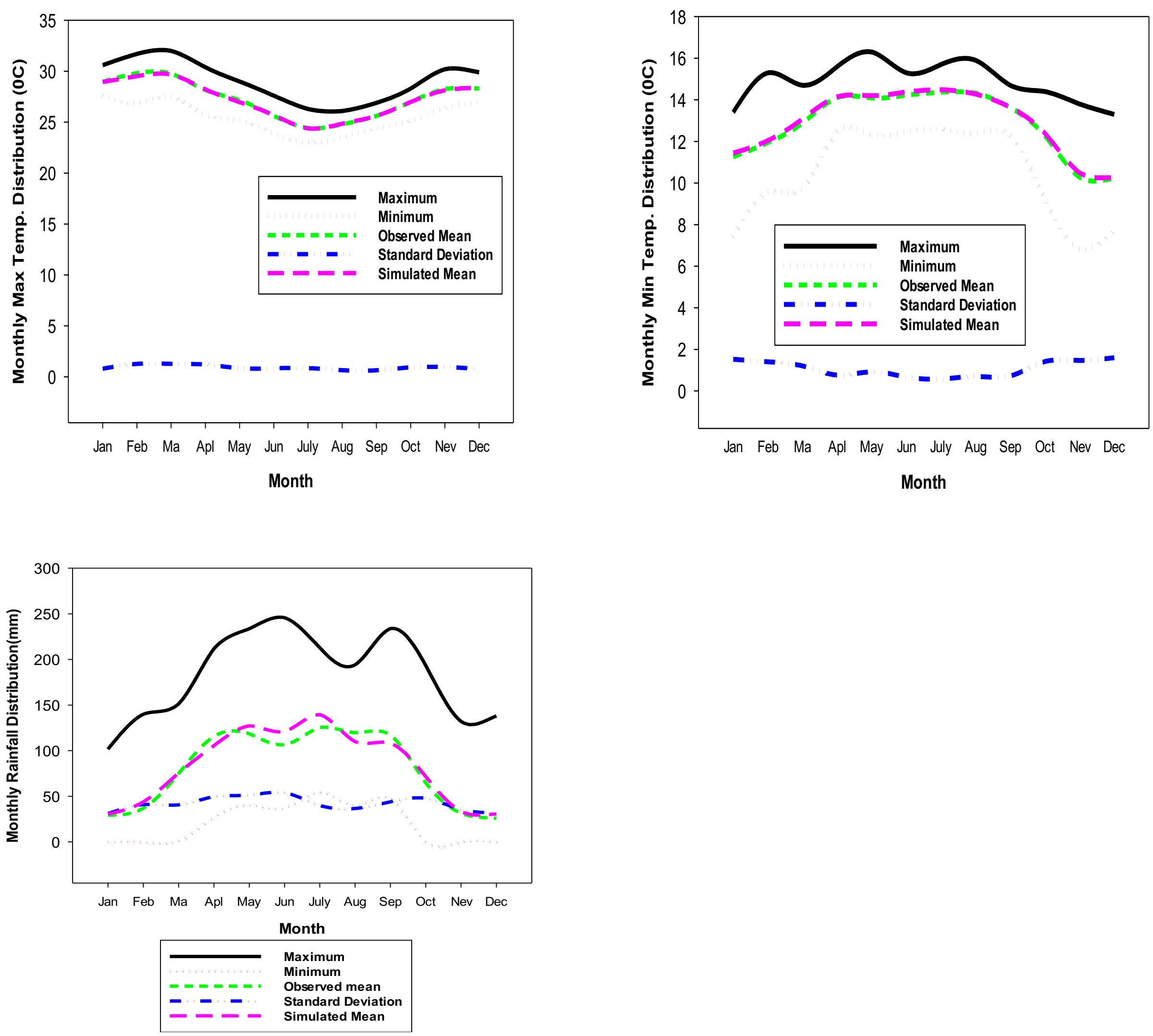


Figure 2. Monthly Distribution of Precipitation, Maximum and Minimum temperature of Hawassa District

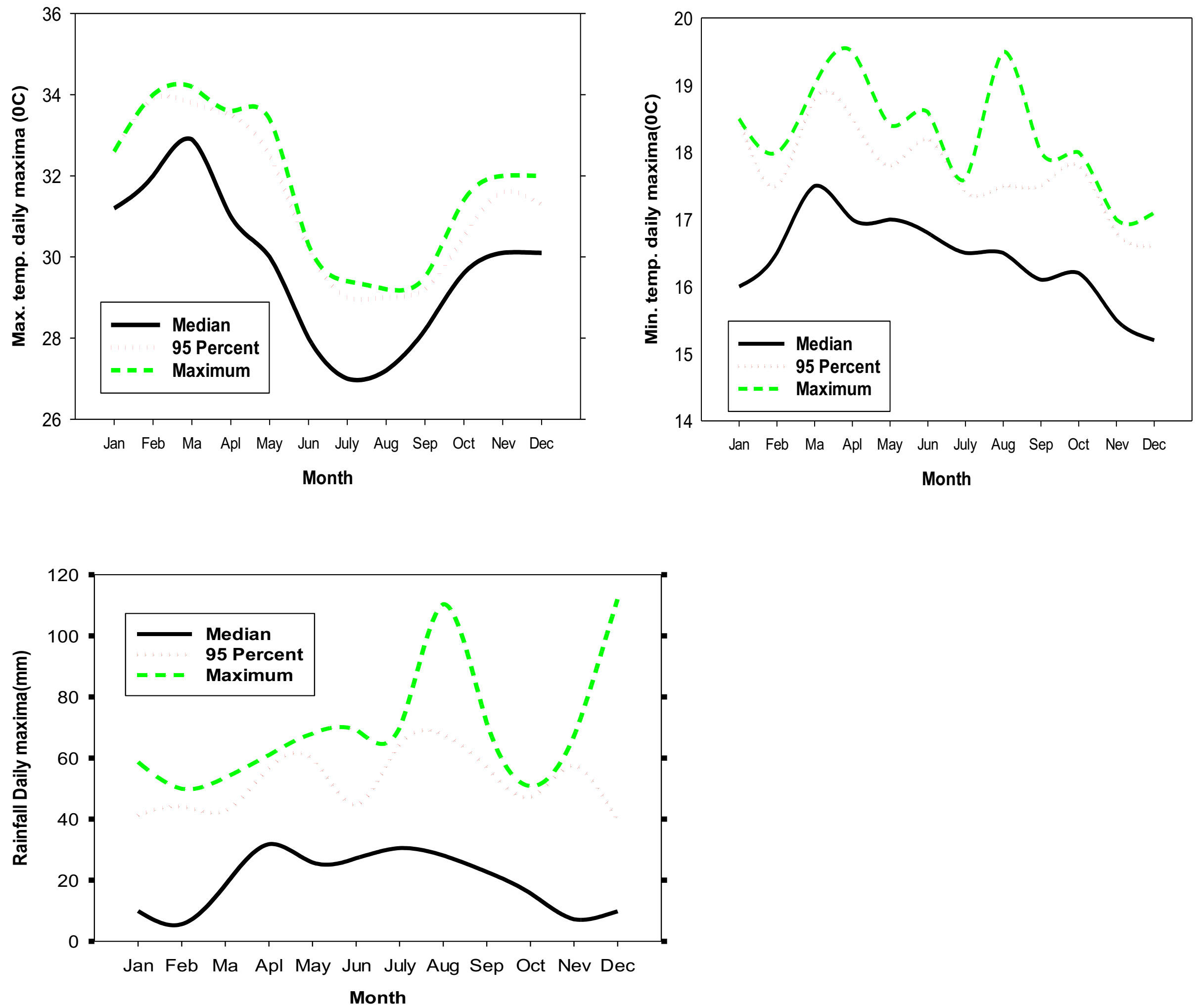


Figure 3. Daily Maxima Distribution of Precipitation, Maximum and Minimum Temperature.

3.3. Generation of Future Climate variables

Once LARS WG is calibrated and validated future climate variables of Precipitation, Maximum and minimum temperature for two time periods (2031-2050) and (2051-2070) under two RCPs are generated. The monthly mean average of change of the climate variables for the respective RCPs and time periods is indicated in **Figure 4**. The seasonal climate change results indicate that the precipitation is expected to increase in September, October, and November (SON) under both RCPs in the two future time horizons relative to baseline. However, precipitation is expected to increase in 2031-2050 under both RCPs but it would tend to decrease from 2051 to 2070 for the winter (DJF) season called 'bega'. For Autumn (MAM) and winter (JJA) seasons, the precipitation is estimated to decrease for both RCPs in the two coming time horizons **(Table 4).** The maximum and minimum temperature is estimated to increase monthly and seasonally throughout the coming two time periods under both RCPs. The percentage of monthly precipitation tends to change in the range of -14.84% to 20.23% in 2031-2050 and -23.18% to 20.04% in 2051-2070 under the RCP 4.5 scenario. Similarly, it is predicted to change in the range of -14.8% to 26.98% in 2031-2050 and -12.83% to 36.66% in 2051-2070 under the RCP 8.5 scenario. In general, the monthly precipitation is expected to increase by 0.52% and 0.22% under the RCP4.5 in 2031-2050 and 2051-2070 respectively (**Table 5**). Moreover, it is estimated to increase by 0.38% and 6.50% under the RCP 8.5 in the respective future time period. However, the future predicted precipitation indicates that there are high intermodal variabilities and the increasing trend among GCMs is non-consistence.

Table 4. Seasonal Mean average change of Tmax, Tmin, and Precipitation relative to baseline (1980-2010)

Season	Prec. change		Min temp change		Max temp change		Prec. change		Min temp change		Max temp. change	
	RCP 4.5						RCP8.5					
	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070
DJF	1.5	-0.7	1.7	2.2	1.2	1.8	-0.4	7.0	1.8	3.0	1.5	2.5
MAM	-6.4	-1.8	1.4	2.1	1.3	1.8	-7.9	-2.4	1.8	3.0	1.6	2.6
JJA	-7.9	-6.2	1.5	2.1	1.7	2.2	-6.6	-10.3	1.7	2.9	1.8	3.1
SON	2.5	4.0	1.7	2.3	1.2	1.8	6.7	3.9	1.9	3.1	1.4	2.5

On the other hand, the minimum temperature is predicted to increase in the range of 1.296 ^{0}C to 2.044 ^{0}C and 1.862 ^{0}C to 2.604 ^{0}C in 2031-2050 and 2051-2070 respectively, under the RCP 4.5 scenario whereas it would appear to increase in the range of 1.492 ^{0}C to 2.192 ^{0}C and 2.648 ^{0}C to 3.432 ^{0}C in the respective coming two time period under RCP 8.5 scenario. At the same time maximum temperature is evaluated to increase in the range of 0.984 ^{0}C to 1.684 ^{0}C and 1.564 ^{0}C to 2.286 ^{0}C in 2031-2050 and 2051-2070 respectively, under the RCP 4.5 scenario. Moreover, it would be expected to increase in the range of 1.17 ^{0}C to 1.844 ^{0}C and 2.18 ^{0}C to 3.184 ^{0}C under the RCP8.5 scenario the specified future two time periods (**Table 5**). In general **Table 6** indicate the monthly average percentage change of precipitation and absolute relative change of maximum and minimum temperature under the two RCPs scenario for future two time periods. Additionally, the mean monthly climate change variables indicate that maximum and minimum temperature increase throughout the year for both RCPs in the coming two time periods but there is a seasonal shift for precipitation that depicts it would decrease in the summer ("Kiremt") and Autumn ("Belg") season of the country whereas it would likely increase the other two seasons **(Figure 4).**

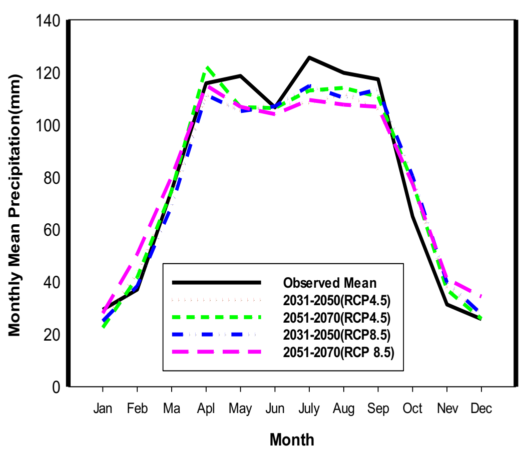
Table 5. Monthly Mean average change of Tmax, Tmin, and Precipitation relative to baseline (1980-2010)

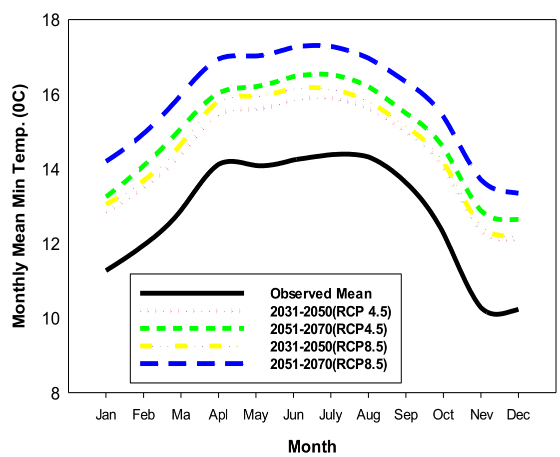
Month	Precipitation change		Min temp change		Max temp change		Precipitation change		Min temp change		Max temp.change	
	RCP 4.5						RCP8.5					
	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070
J	-4.358	-6.806	1.568	1.98	1.372	1.922	-4.344	-1.308	1.78	2.93	1.626	2.568
F	6.262	4.712	1.548	2.134	1.08	1.626	1.364	13.58	1.736	2.998	1.32	2.386
M	-1.464	-0.088	1.496	2.196	1.3	1.876	-5.93	5.294	1.774	3.09	1.608	2.672
A	-4.294	6.504	1.34	1.916	1.34	1.858	-4.338	-0.75	1.694	2.828	1.65	2.648
M	-13.418	-11.926	1.508	2.12	1.16	1.674	-13.44	-11.802	1.86	2.938	1.394	2.546
J	1.368	-0.198	1.61	2.236	1.592	2.182	0.5	-2.558	1.918	3.022	1.818	3.074
J	-17.246	-12.53	1.518	2.144	1.68	2.286	-10.75	-16.116	1.76	2.902	1.834	3.184
A	-7.962	-5.736	1.296	1.886	1.684	2.28	-9.514	-12.11	1.492	2.648	1.844	3.168
S	-11.434	-6.636	1.358	1.862	1.402	2	-3.886	-10.502	1.504	2.702	1.6	2.876
O	12.498	13.026	1.756	2.304	1.212	1.818	15.398	12.512	1.912	3.132	1.458	2.55
N	6.346	5.584	2.044	2.604	0.984	1.564	8.464	9.738	2.192	3.432	1.17	2.18
D	2.708	0.11	1.872	2.414	1.264	1.782	1.878	8.594	1.956	3.118	1.526	2.422

The climate variables change (Precipitation, max, and min temperature) is almost consistent with K.N. Disasa et al., (2019) conducted in Rift valley basins using SRES emission scenarios for future three-time periods 2020, 2055, and 2090. Nevertheless, the precipitation change is somehow less. Indeed maximum and minimum temperature change is more or less consistent with the study but the future time horizons considered in this study are different from the aforementioned study. This study also used Representative Concentration Pathways (RCPs) instead of SRES under two radiative forcing levels RCP 8.5 and RCP 4.5 which are most likely similar to A1F and B1 respectively. Several studies (Birara, H. et al., 2020; Abera et al., 2018) affirm that climate variables (temperatures and precipitation) are increasing in different parts of the country but there is high uncertainty in the projection of rainfall as compared to temperatures. Kassie et al., (2013) study on Climate variability and change in the Central Rift Valley of Ethiopia suggests that rainfall will increase during November–December (outside the growing season), but will decline during the growing seasons (April-September) which is consistent with this study. Moreover, the study result exhibited that the length of the growing season is expected to be reduced by 12–35%. However, the result of this study suggests that it is possible to shift planting dating from the mid-autumn season to the beginning of summer(June) to attain the required growing season since the predicted spring (September- November) season is expected to increase.

Figure 6. Monthly average percentage change range of precipitation and absolute change of Maximum and minimum temperature relative to baseline (1980-2010).

Climate variables	**Rainfall change (%)**		**Min temp change**		**Max temp change**		**Rainfall change (%)**		**Min temp change**		**Max temp change**	
RCP	RCP 4.5						RCP8.5					
Year	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070	2031-2050	2051-2070
Range of change	-14.84 to 20.23	-23.18 to 20.04	1.30 to 2.04	1.86 to 2.60	0.98 to 1.68	1.56 to 2.29	-14.80 to 26.98	-12.83 to 36.66	1.49 to 2.19	2.65 to 3.43	1.17 to 1.84	2.18 to 3.18
Absolute change	0.52	0.22	1.58	2.15	1.34	1.91	0.38	6.50	1.80	2.98	1.57	2.69





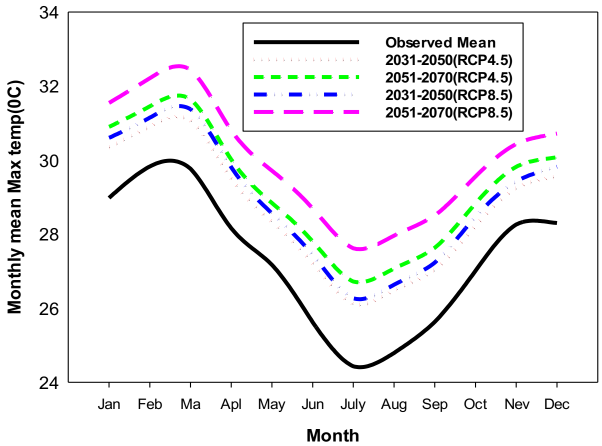


Figure 4. Monthly mean observed and generated precipitation, maximum and minimum temperature

3.4. AquaCrop Calibration

The future climate change measuring standard of the model simulation capacity is set by inputting the 2018 weather data to predict future climate effect on maize production under two RCPs (RCP4.5 and RCP8.5) and two-time periods (2040and 2060). The model grossly overestimated maize yields when compared with recorded data in the study area for the year 2018. It was therefore essential that adjustment of important and sensitive parameters in the model be carried out (Msowoya et al., 2016). By adjusting crop, management, and soil properties in the main menu of AquaCrop, an output yield close in value to the recorded yield in 2018 was derived. Before calibrating the model, first, the potential evapotranspiration (ETo) was estimated using the FAO ETo Calculator which uses the Penman-Monteith equation. Recorded data for maize production in the year 2018 for Hawassa district was averagely 7.5 tons per hectare. After varying the model parameters, the closest simulated production was 7.496 tons per hectare.

3.5. Model Validation

Once model calibration was complete, the model was then validated to determine its potential to simulate maize yields. Accordingly historically recorded maize yields for the area from 2012-2017 were used to compare with those simulated by AquaCrop to determine its potential to simulate future maize yields at two RCPS and two-time periods. **Table 7** presents observed versus estimated maize yield production with their respective statistical indicators used for the validation of the AquaCrop model. The minimum and maximum prediction error (Pe) for maize yields for six growing seasons (2012-2017) range from 0.07 to 2.5% whereas RMSE and MAE are 0.11 and 0.12 respectively. The three statistical parameters are close to zero (Msowoya et al.,2016), which indicates the suitability of the model to simulate future maize yields for two time periods. Estimated values of Nash and Sutcliffe (Ns) and coefficient of determination (R^2) of 0.906 and 0.908 respectively are both close to 1, which further increases confidence in the model's potential to simulate future maize yields. The validation results indicate that the model can be used to simulate future maize yields within acceptable deviations from the true values

Table 7: AquaCrop validation statistical analysis results for maize yields.

Year	**Yields(ton/ha)**		**Pe(±%)**	**Ns**	**R^2**	**RMSE**	**MAE(ton/ha)**
	observed	simulated					
2012	6.5	6.39	1.69	0.906	0.908	0.11	0.12
2013	6.4	6.56	2.5				
2014	6.7	6.746	0.69				
2015	6.8	6.852	0.76				
2016	7.25	7.245	0.07				
2017	7.2	7.06	1.67				

3.6. Simulating Future Maize Yields with Climate Change

This study only considers daily precipitation and temperature change for two-time horizons (2040 and 2060) under two representative concentration pathways (RCPs). Climate data (rainfall, minimum and maximum temperature, sunshine hours, relative humidity) for the 30 years baseline period (1980-2010) were broken down into monthly averages in each of the 12 months. By keeping all parameters the same including the impact of enhanced CO2 and changing only climate parameters (daily rainfall, maximum and minimum temperature) used during model calibration and validation the results from the model run indicated an average baseline period maize production of 7.2 ton/ha. This value is considered maize production without climate change. Accordingly, the average values of future potential maize yields at two-time horizons under two RCPs were calculated similarly. **Table 8** summarizes the simulated maize yields as a percentage, relative to the baseline period both RCPs and two-time periods.

Table 8: Estimated Maize yield production (tons/hectare) at under two RCPs and two future periods.

Period	Production Change (%)		Range (%)
	RCP4.5	RCP8.5	
2031-2050 (2040)	7	4.13	4.13 to 7
2051-2070(2060)	9.32	6.36	6.36 to 9.32

In general, the results suggest an increase in maize yields for both RCPs scenarios and future two time periods. Accordingly, the expected percentage changes in maize yields for 2031-2050(2040), and 2051-2070(2060) are 4.13% to 7% and 6.36% to 9.32% respectively. This result indicates that in the future two time periods maize production is estimated to increase with climate change, whereby all crop parameters, soil fertility, and field management were kept the same or improved relative to the baseline of (1980-2010). The study result is somehow consistent with Abera et al., (2018) that suggest maize yields would increase by 51% with climate change in Hawassa area. B.T. Kassie et al.,(2014) study revealed that there is scope for significantly increasing maize yield in the central rift valley and other, similar agro-ecological zones in Africa under future climate change. A. Y. Kassaye et al., (2021) study also exhibited maize yield will be expected to increase by 17.9% at the end of the twenty-first century with increasing temperature and rainfall decline.

Ironically Study results in Mount Makulu of Zambia (Chisanga et al .,2020) showed that biomass and grain yield of maize is expected to decline by (2040-2069) relative to baseline under both RCP4.5 and RCP8.5 scenarios with temperature rise and rainfall decrease in the study area. Moreover, the research in Malawi's Lilongwe on Climate Change Impacts on Rainfed Corn Production suggests that maize yield can decrease up to 14% in mid-century whereby precipitation decrease and temperature increase by 26% and 2.20 ^{0}C respectively (Msowoya et al.,2014). Furthermore, Chen et al.,(2018) researched the impact of climate change and climate extremes on major crops (wheat, rice, and maize) growth and yield during 2106- 2115 relative to 2006–2015 in china under global warming of 1.5 ^{0}C and 2.0 ^{0}C. The research finding showed that climate change would have major negative impacts on crop production, particularly for wheat in north China, rice in south China, and maize across the major cultivation areas, due to a decrease in crop growth duration and an increase in extreme events. Moreover, Ahmadi M.et al., (2021) study on the effects of climate change on maize water footprint under RCPs scenarios in Qazvin plain, Iran suggests that maize yield decreased in future periods. In contrast to these studies research in Ethiopia indicates that maize yield responds positively to change in climate variables (precipitation and temperature). However, the planting date schedule should be taken to account because there is a seasonal precipitation shift in the study area. As it could be observed from the predicted result the autumn season precipitation is increasing, therefore it is recommended to shift the planting month from April which is common in Ethiopia to May.

4. Conclusions

Climate change is the headline of the global agenda that attracts scientific communities to deal with. It has a direct and indirect impact on the agricultural sector in general, particularly on crop yield. Therefore this study presents the effect of future climate variable changes on rainfed maize production in the southern part of Ethiopia. The study result shows that maize yield production responds positively to climate variables (precipitation, max. temp, and min. temp) change under both RCPs and two future time horizons. Nevertheless, since there is seasonal precipitation variation for both RCPs and time horizons planting dates should be considered under the future climate change scenario. Accordingly, maize yield is predicted to increase from 4.13% to 7% and 6.36% to 9.32% for 2040 and 2060 respectively, provided that all other parameters (crop, management, and soil properties) kept the same.

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