Agric Res J **59** (6) : 1059-1069, *December* 2022
DOI No. 10.5958/2395-146X.2022.00148.X

ESTIMATION OF CLIMATE CHANGE EFFECTS ON RAINFED MAIZE PRODUCTION IN SOUTHERN ETHIOPIA

Kinde Negessa Disasa[1*] and Haofang Yan[1, 2]

[1]*Research Center of Fluid Machinery Engineering and Technology, Jiangsu University, Zhenjiang 212013, China.*
[2]*State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Nanjing Hydraulic Research Institute, Nanjing, 210029, China*

ABSTRACT

A developing country like Ethiopia suffers immensely from the effects of climate change due to its limited economic capability to build irrigation projects to combat climate change impacts on crop production. This study evaluated the impact of climate change on rainfed maize production in the southern part of Ethiopia. The AquaCrop model was employed to assess potential rainfed maize production in the study area with and without climate change. The latest version of the stochastic weather generator model LARS-WG was used to simulate local-scale level climate variables based on low-resolution GCM outputs. The expected monthly percentage change of rainfall during two-time horizons (2040 and 2060) ranged from -23.18 to 20.23 % (2031-2050) and -14.8 to 36.66% (2051-2070). Moreover, the monthly mean of the minimum and maximum temperature were estimated to increase in the range of 1.296 to 2.192 ^{o}C and 0.98 to 1.84 ^{o}C for the first time horizon (2031–2050) and from 1.86 to 3.4 ^{o}C and 1.56 to 3.18 ^{o}C in the second time horizon (2051–2070), respectively. Maize yields were expected to increase with a range of 4.13 to 7 % and 6.36 to 9.32% for the respective time horizons in the study area provided that all other parameters were kept the same.

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

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, 2007). Today, the most important concern on the environmental and socioeconomic agendas across the globe is climate change (Crossman *et al*., 2013). It is the main factor affecting both the hydrological balance and agricultural production (Adams *et al*., 1998). There is evidence from the global scientific community that climate change is occurring now, and 97% of climate scientists concur that human activity is the primary cause of it (IPCC 2001b; Wang *et al*., 2019). Climate change, however, is expected to make agricultural development in Africa more challenging in many places (Blanc, 2012). Ethiopia is one of the most vulnerable countries in Sub-Saharan Africa to climate events (drought and flooding) caused by climate variability and change, which would have a significant impact on the agricultural sector (Gezie, 2019). The study in five regions, namely Amhara, Tigray, Benishangul Gumuz, Oromia, and the Southern Nation Nationality and People (SNNP) of Ethiopia, indicated that all the regions are negatively affected by climate change at varying levels (Baylie and Fogarassy, 2021).

According to the Federal Democratic Republic of Ethiopia's (2011) Ministry of Agriculture report on the agriculture sector program plan adaptation to climate change, Ethiopia's agriculture would be subject to several negative effects brought on by the unfavorable emergence of climate variability. The report demonstrated that these impacts would likely continue to influence the socioeconomic activities of the community on a larger scale. Deressa *et al*.'s (2008) study used biophysical and social vulnerability indices of the Ricardian and suggested that a decline in rainfall and an increase in temperature are more likely to damage Ethiopian agriculture. IPPC (2014) predicted that the tropical and sub-tropical regions would experience higher losses in crop production, while temperate climates might gain 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, which happens nowadays in Ethiopia once again. It is therefore apparent that tropical and sub-tropical parts of the nation wholly rely on rainfed farming.

Maize is the second-largest and most widely produced cereal crop in Ethiopia next to teff in terms of area coverage and is 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 over time. The future prediction

*Corresponding author : nagkindee@gmail.com
Date of receipt: 21.01.2022, Date of acceptance: 31.12.2022

of the study indicates that the production of teff, maize, and sorghum will decline by 25.4, 21.8, and 25.2%, respectively, by 2050. Timothy *et al*. (2019) researched the climate change impacts on crop yields in Ethiopia and suggested that climate change will likely have only relatively small effects on the average yields of maize. However, Kassaye *et al*. (2021) studied the impact of climate change on the staple food crop yield in Ethiopia and suggested that the yield of teff and maize will be expected to increase by 20.2 and 17.9%, respectively, at the end of the 21st century with increasing temperature and rainfall decline. Ironically, Abera *et al*. (2018) revealed that maize yields will decrease by up to 43 and 24% by the end of the century at Bako and Melkassa stations, respectively, while the 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 would decrease on average by 20% under climate change by 2050 (Kassie et al., 2015). The study in the Gambella region also suggested that rainfed maize production would decrease under three RCPs (2.6, 4.5, and 8.5) in the future, but only under RCP8.5 after 2040–2069 (Degife *et al*., 2021).

Crop simulation models have been used in several studies to assess the effects of climate change on crop yield. In this study, the AquaCrop model of the 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 in Ethiopia, in particular, and has a user-friendly interface and is openly accessible. In Africa, it is widely used and validated for various crops (Msowoya *et al*., 2016; Gebremedhin, 2015; Feleke *et al*., 2021; Tsegaye *et al*., 2011). Feleke *et al*. (2021) suggested 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 mid-term 2060(2051-2070) on maize yield production in the southern part of Ethiopia using the AquaCrop model in combination with Global circulation models.

MATERIALS AND METHODS

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°40'0"N to 7° 20'0"N and the longitudinal area 38° 20'0''E to 38° 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. There are many types of soils in the 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 status of the area is characterized by a wilting point of 18.5% and a field capacity of 34.8% with no restrictive soil layer and soil salinity stress (Disasa *et al*., 2019). Sidama region is technically falling into the borderline area between the *kolla* and *Woina Dega* agroecological 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 °C. The main rainy season generally extends from June to October.

Description of LARS-WG

The Long Ashton Research Station Weather Generator (LARS-WG) is a simple tool for generating synthetic weather time series that are statistically identical to observations but are neither predictive nor forecasting (Semenov, M. A. *et al*., 2002). Its latest version (LARS-WG Version 6.0) was used for this study to simulate future weather data (maximum and minimum temperatures, precipitations, and solar radiation) for the near- and mid-term in the study area. 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). Only five CMIP5 GCMs (Table 1) were used in this study under two RCPs (Ahmadi *et al*., 2021).

The model simulates weather data at a single site under current and future conditions (Racsko *et al.,* 1991). It generates synthetic data in daily time series using inputs of minimum temperature (°C), maximum temperature (°C), precipitation (rainfall in mm), and solar radiation (MJ/m2/day). In the absence of solar radiation, the model accommodates the use of sunshine hours. The LARS-WG automatically converts the sunshine hours to solar radiation using an algorithm that was described by Rietveld (1978).

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 one year of observed weather data. Semenov and Barrow (2002) recommended the use of daily weather data spanning at least 20 to 30 years for better results.

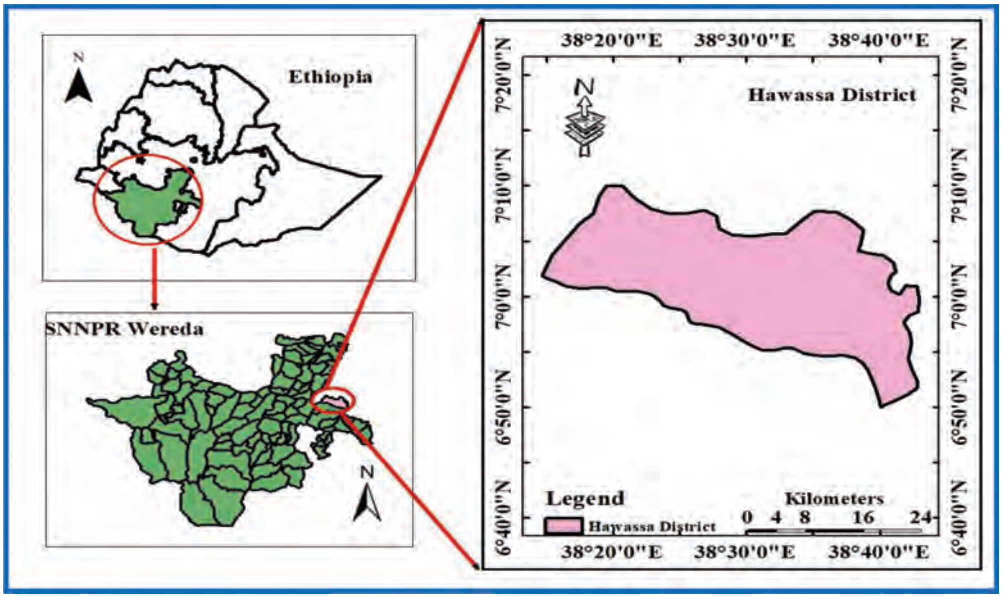

Fig. 1. Map of the study area

Weather data for long periods is significant in the way that it captures some of the less frequent events like droughts and floods. Accordingly, this study used the daily historical observed weather of the past 30 years (1981–2010) as baseline data.

Calibration and validation of LARS-WG

It is likely crucial to calibrate the LARS-WG before developing future scenarios, which are common for the majority of statistical downscaling models. The calibration of LARS-WG was carried out by a function on the main menu called "Site Analysis." The procedure was carried out to identify the statistical traits and location-specifics of the observed meteorological data. After LARS-WG was calibrated, its ability to simulate future weather data at the representative study site was assessed. The capacity of LARS-WG to logically anticipate future climate variables was evaluated using the Q test function. This was achieved using three statistical tests: the chi-square test (X^2), the *t*-test, and the *K-S* (Kolmogorov-Smirnov) test, which were the outputs of the Q test function used to test the performance of the LARS-WG. The chi-square test was used to assess whether there was any statistically significant difference between the simulated and observed frequencies in the meteorological data. A t-test was used to check for 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 is the absolute maximum difference between the observed cumulative probability P (X_m) and the theoretical cumulative probability F (X_m).

$$\Delta = max \mid F(X_m) - P(X_m) \mid \quad (1)$$

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

Moreover, observed and simulated data time series of the monthly *mean precipitation, the maximum*

Table 1. Global Circulation Models used in this study

GCM Name	Name of the research center	Grid Resolution	RCPs	
			4.5	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°	✓	✓

and minimum temperature was checked by using the coefficient of determination (R^2), Root Mean Square Error (*RMSE*), Nash–Sutcliffe efficiency (*NSE*) (Birara *et al*.,2020; Amhadi, *et al*.,2021).

The coefficient of determination (R^2) was 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.

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

RMSE was used to measure the difference between simulated and observed values. When the value is lower, the model is better at projecting future climate variables.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(o_i - s_1)^2}{n}} \quad (3)$$

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.

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

where 0_i is the observed data,is the simulated data.

Climate change in the AquaCrop

In this study, climate change was only addressed by adjusting the precipitation and temperature data files under current and future climate scenarios; the impact of an enhanced CO2 level was not considered. The impact of enhanced CO2 levels was calculated by AquaCrop itself. The AquaCrop used so-called “normalized water productivity” (WP*) for the simulation of aboveground biomass. The WP was 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 the C3 crops. A C4 plant is a plant that cycles carbon dioxide into four-carbon sugar compounds to enter the Calvin cycle.

Calibration of the AquaCrop

Calibration of AquaCrop was achieved by comparing the actual maize production (as provided by the department of agriculture of the Sidama regional state) with the maize yield simulated by the model. The South Region Agricultural Research Institute and the Wondo Genet Agricultural Research Center, Hawassa Maize Research Sub Center of Ethiopia provided input data for crop and soil parameters used in the model. By comparing the actual and simulated maize yields and crop parameters(CC_O, 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) were 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 temperatures) from Hawassa station for the year 2018 has been used to calibrate the model (Msowoya *et al*., 2014).

Validation of the AquaCrop

Loague and Green (1991) indicated that there were numerous statistical indicators for evaluating the performance of AquaCrop; nonetheless, Willmott (1984) argued that each of the statistical indicators had its weaknesses and strengths. It is appropriate to use ensemble statistical indicators to assess the model’s performance (Willmott, 1984). In an analysis of the performance of the 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–Sutcliffe efficiency (*NSE*) (Nash and Sutcliffe, 1970). *NSE* and R^2 indicate the predictive power of the model, while *PE*, *MAE*, and *RMSE* were used to signify the amount of error associated with the model’s prediction (Abedinpour *et al*., 2012). Calibrated crop parameters, management practices, and soil types and conditions remained constant. Maize yields from 2012 to 2017 were used to compare with those simulated by the model within the same period.

$$P_e = \frac{(S_i - O_i)}{O_i} \times 100 \quad (5)$$

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|s_i - o_i| \quad (6)$$

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

RESULTS AND DISCUSSION

Evaluation of the LARS-WG

Based on the Q-test function result of LARS-WG, the performance of the model to generate future synthetic time series was calibrated and validated. Accordingly, the output statistical test function (such as

X^2 (chi-square), *t*-test, and Kolmogorov-Smirnov) with its respective *p*-value was used (Table 2). Furthermore, the coefficient of determination (R^2), root mean square error (*RMSE*), and Nash-Sutcliffe efficiency (*NSE*) were calculated based on the mean monthly generated and simulated climate variables (Table 3). A significance level of 5% was used. The results indicated that the *p*-values in all months except December and January for the chi-square test of rainfall were higher than the selected significance level of 0.05. However, the *p*-value for maximum and minimum temperature was higher than 0.05 for both statistical tests. This value indicated that the LARS-WG was better able to generate future temperatures (max. and min.) than rainfall (Disasa *et al*., 2019; Amhadi *et al*., 2021). Moreover, Semenov, M.A., and Barrow, E.M. (2002) suggested that a significant difference may exist between observed and generated data if the mean climate variables do not follow the expected trend of increasing or decreasing. Therefore, the model was still satisfactory for simulating future climate data.

Distribution of weather variables

Fig. 2 demonstrates the monthly mean distribution of climate variables (rainfall and maximum and minimum temperatures) in the study area. The monthly mean baseline distribution of rainfall in the study area indicated that there is a bimodal rainy season with a low rainy season in March and April and a high rainy season from June to August, which indicated that the sowing season could be two times a year. Fig. 3 displays the daily maxima of climate variables (max., min., and rainfall) at various percentile levels in the Hawassa district (median, 95 percent, and maximum). The daily climate variables revealed that rainfall is at its peak in August, the maximum temperature is at its peak in March, and the minimum temperature is at its peak in both March and September.

Generation of future climate variables

The future climate variables of rainfall and maximum and minimum temperature were generated using calibrated and validated LARS-WG for two time periods (2031-2050) and (2051-2070) under two RCPs. Fig. 5 shows the monthly mean average change of the climate variables for the relevant RCPs and periods. The results for seasonal climate change indicated that the rainfall is expected to increase in September, October, and November (SON) under both RCPs in the two future time horizons relative to the baseline. However, rainfall is expected to increase between 2031 and 2050 under both RCPs, but it is expected to decrease between 2051 and 2070 for the winter (DJF) season known as “bega.” For the autumn (MAM) and winter (JJA) seasons, the

Table 2. The statistical results of the Q test function for the validation of the LARS-WG.

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
JAN	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
FEB	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
MAR	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
APRIL	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
MAY	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
JUNE	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
JULY	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
AUG	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
SEPT	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
OCT	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
NOV	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
DEC	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. The statistical parameters of LARS-WG performance

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

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

Season	Precipitation change (%)		Min. temp. change (ºC)		Max.Temp. change (ºC)		Precipitation change (%)		Min. Temp. change (ºC)		Max. Temp. change (ºC)	
	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
DEC,JAN, FEB	1.5	-0.7	1.7	2.2	1.2	1.8	-0.4	7.0	1.8	3.0	1.5	2.5
MAR,APR,MAY	-6.4	-1.8	1.4	2.1	1.3	1.8	-7.9	-2.4	1.8	3.0	1.6	2.6
JUN,JULY,AUG	-7.9	-6.2	1.5	2.1	1.7	2.2	-6.6	-10.3	1.7	2.9	1.8	3.1
SEPT,OCT,NOV	2.5	4.0	1.7	2.3	1.2	1.8	6.7	3.9	1.9	3.1	1.4	2.5

rainfall was estimated to decrease for both RCPs in the two coming time horizons (Table 4**).**

The maximum and minimum temperatures were 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 -14.84–20.23% in 2031–2050 and -23.18–20.04% in 2051–2070 under the RCP 4.5 scenario. Similarly, it was predicted to change in the range of -14.8% to 26.08% 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 6). Moreover, it was estimated to increase by 0.38% and 6.50% under the RCP 8.5 in the respective future periods. However, the future predicted precipitation indicated that there were high intermodal variabilities

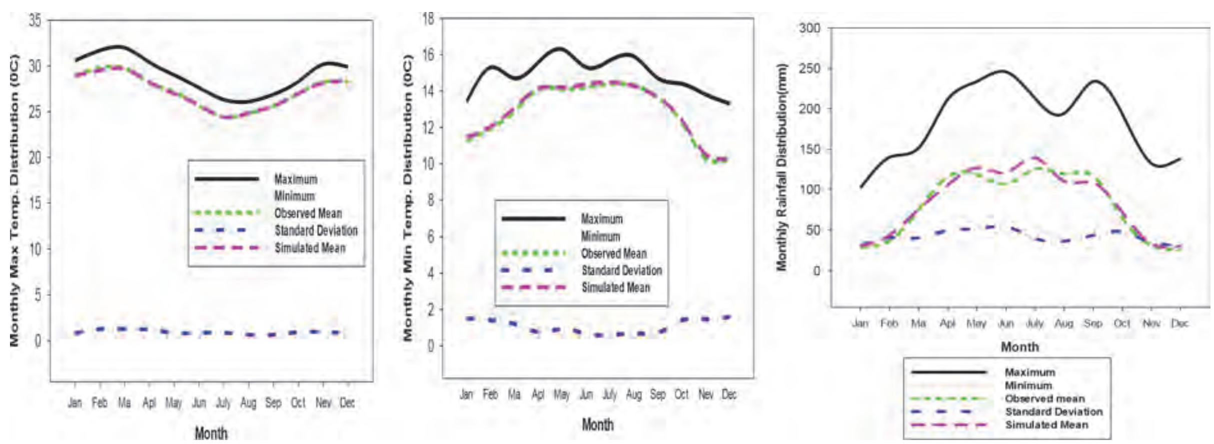

Fig. 2. Monthly distribution of precipitation, maximum and minimum temperature of Hawassa district

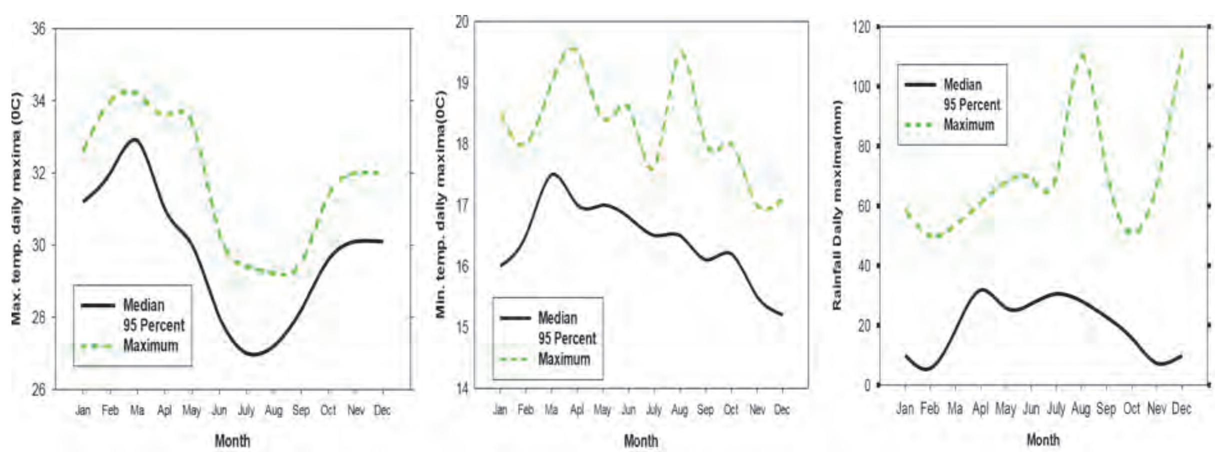

Fig. 3. Daily maxima distribution of precipitation, maximum and minimum temperature.

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

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

and that the increasing trend among GCMs was non-consistence.

On the other hand, the minimum temperature was predicted to increase in the range of 1.296-2.044 °C and 1.862-2.604 °C in 2031-2050 and 2051-2070, respectively, under the RCP 4.5 scenario, whereas it would appear to increase in the range of 1.492-2.192 °C and 2.648-3.432 °C in the respective coming two time periods under the RCP 8.5 scenario. Similarly, the maximum temperature was evaluated to increase in the range of 0.984–1.684 °C and 1.564–2.286 °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 1.17–1.844 °C and 2.18–3.184 °C under the RCP8.5 scenario in the specified future two time periods (Table 5). In general, Table 6 indicates the monthly average percentage change of precipitation and the absolute relative change of maximum and minimum temperature under the two RCP scenarios for the next two time periods. Furthermore, the mean monthly climate change variables show that maximum and minimum temperatures increase throughout the year for both RCPs in the next two time periods, but there are a seasonal shift for precipitation that shows it would decrease in the country's summer ("Kiremt") and autumn ("Belg") seasons while increasing in the other two (Fig. 4).

Precipitation, maximum temperature, and minimum temperature changes are nearly in line with studies were done by Disasa *et al*. (2019) in Rift Valley basins using SRES emission scenarios for the years 2020, 2055, and 2090. Nonetheless, the precipitation change is less pronounced. Indeed, the maximum and minimum temperature changes are roughly consistent with the study, but the future time horizons considered in this study differ from those in the previous study. This study also used Representative Concentration Pathways (RCPs) instead of SRES under two radiative forcing

Table 6. Variability in monthly average precipitation and temperature relative to the baseline (1980–2010)

Climate variables	Rainfall change (%)		Min. Temp. change (°C)		Max. Temp. change (°C)		Rainfall change (%)		Min. Temp. change (°C)		Max. Temp change (°C)	
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

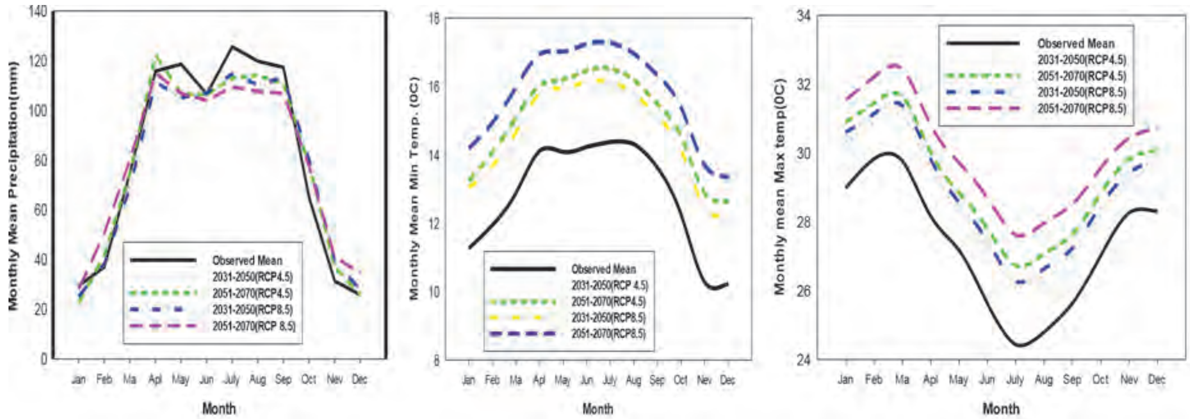

Fig. 4. Monthly mean observed and generated precipitation, maximum and minimum temperatures

levels, RCP 8.5 and RCP 4.5, which are most likely similar to A1F and B1, respectively. Several studies (Birara *et al*., 2020; Abera *et al*., 2018) affirm that temperatures and precipitation are increasing in different parts of the country, but there is higher uncertainty in the projection of rainfall as compared to temperatures. Kassie *et al.*'s (2013) study on climate variability and change in the Central Rift Valley of Ethiopia suggested that rainfall would increase during November and December (outside the growing season) but decline during the growing season (April-September), which is consistent with this study. Moreover, the study results indicated that the length of the growing season is expected to be reduced by 12–35%. However, the result of this study suggested that it is possible to shift planting dates 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.

AquaCrop calibration

The future climate change measuring standard of the model simulation capacity was set by inputting the 2018 weather data to predict the future climate effect on maize production under two RCPs (RCP 4.5 and RCP 8.5) and two time periods (2040 and 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 adjustments be made to important and sensitive parameters in the model (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 the Hawassa district was an average of 7.5 tons per hectare. After varying the model parameters, the closest simulated production was 7.496 tons per hectare.

Model validation

The AquaCrop model was 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 compares actual and anticipated maize yield production together with the corresponding statistical markers that were utilized to verify the AquaCrop model. The minimum and maximum prediction error (*Pe*) for maize yields for six growing seasons (2012–2017) range from 0.07–2.5%, whereas *RMSE* and *MAE* are 0.11 and 0.12, respectively. The model can simulate future maize yields for two time periods because all three statistical parameters are near zero (Msowoya *et al*., 2016). It is more likely that the model will be able to predict future maize yields because the estimated values of Nash and Sutcliffe (*NSE*) and the coefficient of determination (R^2) of 0.906 and 0.908, respectively, are both close to 1.

Simulating future maize yields with Climate Change

Table 8 summarizes the simulated maize yields as a percentage, relative to the baseline period, for both RCPs and two-time periods. In general, the results suggested an increase in maize yields for both RCP scenarios and future periods. Accordingly, the expected percentage changes in maize yields for 2031–2050 (2040) and 2051–2070 (2060) were 4.13–7% and 6.36–9.32%, respectively.

This result indicated that in the future two time periods, maize production was estimated to increase with climate change, whereby all crop parameters, soil fertility, and field management were kept the same or

Table 7. AquaCrop validation statistical analysis results for maize yield prediction.

Year	Yields(ton/ha)		Pe(±%)	*NSE*	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				

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

improved relative to the baseline of 1980–2010. The study's findings were somewhat in line with a study by Abera *et al*. (2018) that predicted that climate change in the Hawassa district would result in a 51% increase in maize yields, although the two studies' estimates of the size of the increase are quite different. Furthermore, Kassie *et al*.'s (2014) study revealed that there is scope for significantly increasing maize yield in the central rift valley and other similar agroecological zones in Africa under future climate change. According to the Kassaye *et al*., 2021 study, when temperatures rise and rainfall decreases, maize production will likely rise by 17.9% by the end of the twenty-first century.

In Mount Makulu, Zambia, the results (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 as temperature rises and rainfall decrease in the study area. Moreover, the research in Malawi's capital, Lilongwe, on climate change impacts on rainfed corn production suggested that maize yield can decrease by up to 14% in mid-century, whereby precipitation decreases and temperatures increase by 26% and 2.20 °C, respectively (Msowoya *et al.,* 2014). Furthermore, Chen *et al*. (2018) studied the impact of climate change and climate extremes on the major crop (wheat, rice, and maize) growth and yield during 2106–2115 relative to 2006–2015 in China under global warming of 1.5°C and 2.0°C.

The results of the study demonstrated that, as a result of a reduction in crop growth duration and an uptick in extreme events, climate change would have significant negative effects on crop production, particularly for wheat in north China, rice in south China, and maize across the major cultivation areas. Moreover, Ahmadi *et al.*'s (2021) study on the effects of climate change on maize water footprint under RCP scenarios in Qazvin Plain, Iran, suggested that maize yield would decrease in future periods. In contrast to these studies, research in Ethiopia indicated that maize yield responds positively to changes in climate variables (precipitation and temperature). However, the planting date schedule should be taken into account because there is a seasonal precipitation shift in the study area. As could be observed from the predicted result, the amount of precipitation during the autumn season is increasing; therefore, it is recommended to shift the planting month from April, which is common in Ethiopia, to May.

In conclusion, climate change is the focus of the global agenda, attracting scientific communities to address it. It affects the agricultural industry generally and crop yields in particular, both directly and indirectly. This study investigates how future climate changes will affect the production of rainfed maize in southern Ethiopia. The results show that maize yield production responds positively to climate variables (precipitation, max. temperature, and min. temperature) 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 from 6.36% to 9.32% for 2040 and 2060, respectively, provided that all other parameters (crop, management, and soil properties) stay the same.

Authors' contribution

Conceptualization of research work and designing of experiments (KD); Execution of field/lab experiments and data collection (KD); Analysis of data and interpretation (YH); Preparation of manuscript (KD)

LITERATURE CITED

Abedinpoura M, Sarangib A, Rajputb T B S, Singh B M, Pathakc H and Ahmad T 2012. Performance evaluation of AquaCrop model for maize crop in a semi-arid environment. *Agric Water Manag* **110**:55– 66

Abera K , Crespo O , Seid J and Mequanent F 2018. Simulating the impact of climate change on maize production in Ethiopia, East Africa. *Environ Syst Res* **7**(1) https://doi:10.1186/s40068-018-0107-z

Adams R , Hurd B , Lenhart S and Leary N 1998. Effects of global climate change on world agriculture: an interpretive review. *Climate Res* **11:** 19–30.

Ahmadi M , Etedali H R and Elbeltagi A 2021. Evaluation of the effect of climate change on maize water footprint under RCPs scenarios in Qazvin plain, Iran. *Agric Water Manag* **254**: 106969.

Baylie, M M and Fogarassy C 2021 Examining the Economic Impacts of Climate Change on Net Crop Income in the Ethiopian Nile Basin: A Ricardian Fixed Effect Approach. *Sustainability* **13:** 7243

Birara H , Pandey R P and Mishra S K 2020 Projections of future rainfall and temperature using statistical downscaling techniques in Tana Basin, Ethiopia. *Sustainable Water Resources Management* **6**(5). doi:10.1007/s40899-020-00436-1

Charles Bwalya Chisanga, Elijah Phiri and Vernon R N Chinene 2020 Reliability of Rainfed Maize Yield Simulation Using LARS-WG Derived CMIP5 Climate Data at Mount Makulu, Zambia. *J Agric Sci* https://doi.org/10.5539/jas.v12n11p275

Chen Y , Zhang Z and Tao F 2018 Impacts of climate change and climate extremes on major crops productivity in China at a global warming of 1.5 and 2.0 °C. *Earth System Dynamics* **9**(2): 543–62.

Crossman J , Futter M N , Oni,S K , Whitehead P G , Jin L , Butterfield D , … and Dillon P J 2013 Impacts of climate change on hydrology and water quality: Future proofing management strategies in the Lake Simcoe watershed, Canada. *Journal of Great Lakes Research* **39**(1): 19–32.

CSA (Central Statistical Authority) 2015 Agricultural sample survey report on area and production for major crops (private peasant holdings Meher season) for 2007/08. The Federal Democratic Republic of Ethiopia. *Statistical Bulletin* **278**, Addis Ababa, Ethiopia

Moriasi, D N, Arnold J G, Van Liew M W, Bingner R L, Harmel R D, Veith T L 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. American Society of Agricultural and Biological Engineers. *ASABE* **50**(3): 885-900.

Degife A W , Zabel F and Mauser W 2021. Climate change impacts on potential maize yields in Gambella Region, Ethiopia. *Regional Environ Change* **21**(2). https://doi:10.1007/s10113-021-01773-3

Deressa T T , Hassen R M and Ringler C 2008 Measuring Ethiopian farmers' vulnerability to climate change across regional states IFPRI Discussion Paper 00806 Washington, DC: International Food Policy Research Institute

Disasa K N , Tura F S and Fereda M E 2019 Climate change downscaling using Stochastic Weather Generator Model in Rift Valley Basins of Ethiopia *American Journal of Climate Change* **8**: 561-90

Blanc E 2012. The impact of climate change on crop yields in Sub-Saharan Africa," *American Journal of Climate Change* **1**: 1-13.

F D R E MoA 2011 *Agriculture Sector Programme of Plan on Adaptation to Climate Change* Ayana Salehu, Beyene Sebeko, Nebil Shekur,Sertse Sebuh, Tefera Tadese. Addis Abeba 101p.

Feleke H G , Savage M and Tesfaye K 2021 Calibration and validation of APSIM–Maize, DSSAT CERES–Maize and AquaCrop models for Ethiopian tropical environments. *South African Journal of Plant and Soil* **38**: 36–51.

Gebremedhin Y 2015. Performance of AquaCrop Model in simulating tuber yield of potato (Solanum tuberosum l.) under various water availability conditions in Mekelle Area, Northern Ethiopia *Journal of Natural Sciences Research* **5:** 123-30.

Gezie M 2019 Farmer's response to climate change and variability in Ethiopia: A review. *Cogent Food Agric* **5**(1).

IPCC 2001 *Climate change 2001: the scientific basis: contribution of Working Group I to the third assessment report of the Intergovernmental Panel on Climate Change*. Houghton J T, Ding Y, Griggs D J, Noguer M, van der Linden P J, Xiaosu D (eds.) Cambridge University Press, Cambridge

IPCC 2007 A *report of working group one of the intergovernmental panel on climate change-summary for policy makers.*

IPCC 2014. *Climate Change 2014: Synthesis Report*. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R K Pachauri and L A Meyer (eds.)]. IPCC, Geneva, Switzerland, 151p.

Kassaye A Y , Shao G , Wang X , Shifaw E ,and Wu S 2021 Impact of climate change on the staple food crops yield in Ethiopia: implications for food security *Theoretical and Applied Climatology* **145**(1-2): 327–43

Kassie B T, Van Ittersum M K, Hengsdijk H, Asseng S, Wolf J, Rotter R P 2014 Climate induced yield variability and yield gap of maize (Zea mays L.) in the Central Rift Valley of Ethiopia. *Field Crops Res* https://doi.org/10.1016/j.fcr.2014.02.010

Kassie B T , Asseng S , Rotter R P , Hengsdijk H , Ruane A C and Van Ittersum M K 2015 Exploring climate change impacts and adaptation options for maize production in the Central Rift Valley of Ethiopia using different climate change scenarios and crop models. *Climatic Change* **129**(1-2): 145–58.

Loague K and Green R E 1991 Statistical and graphical methods for evaluating solute transport models: Overview and application *Journal of Contaminant Hydrology* **7**(1-2), 51–73.

Msowoya K , Davtalab R and Madani K 2014 Climate change impacts on rainfed corn production in Malawi's Lilongwe District. World Environmental and Water Resources Congress 2014 https://doi:10.1061/9780784413548.156

Msowoya K , Madani K , Davtalab R , Mirchi A and Lund J R 2016 Climate change impacts on maize production in the warm heart of Africa. *Water Resources Management* **30**: 5299–5312.

Nash J E and Sutcliffe J V 1970 River flow forecasting through conceptual models part I — A discussion of principles *Journal of Hydrology* **10**(3): 282–90.

Racsko P, Szeidl L and Semenov M A 1991 A serial approach to local stochastic weather models, *Ecol Model* **57**: 27–41.

Rietveld M 1978. A new method for estimating the regression coefficients in the formula relating solar radiation to sunshine. *Agricultural Meteorology* **19**: 243-52.

Semenov M A, Stratonovitch P 2015 Adapting wheat ideotypes for climate change: accounting for uncertainties in CMIP5 climate projections. *Clim Res* 65:123-39.

Semenov M A, Barrow E M 2002. LARS-WG: *A Stochastic Weather Generator for Use in Climate Impact Studies*; Rothamsted Research: Hertfordshire, UK, 2002

Solomon R , Simane B and Zaitchik B F 2021 The impact of climate change on agriculture production in Ethiopia: Application of a Dynamic Computable General Equilibrium Model. *American Journal of Climate Change* **10**: 32-50.

Steduto P, Raes D, Hsiao T C, Fereres E, Heng L K, Howell T A, Geerts S 2009. Concepts and Applications of AquaCrop: The FAO Crop Water Productivity Model. *Crop Modeling and Decision Support,* pp.175–91. https://doi:10.1007/978-3-642-01132-0_19

Thomas T S. Dorosh P A and Robertson R D 2019 Climate change impacts on crop yields in Ethiopia. *ESSP Working Paper* **130**. Washington, DC and Addis Ababa, Ethiopia: International Food Policy Research Institute (IFPRI) and Ethiopian Development Research Institute (EDRI). https://doi.org/10.2499/p15738coll2.133104

Tsegay A , Raes D , Geerts S , Vanuytrecht E , Abraha B , Deckers J , … and Gebrehiwot K 2011. Unravelling crop water productivity of Tef (Eragrostis Tef (Zucc.) Trotter) through Aquacrop in northern Ethiopia. *Experimental Agriculture* **48**(02): 222–37.

Wang X , Zhang, P , Liu, L , Li, D , & Wang, Y (2019) Effects of human activities on hydrological components in the Yiluo River Basin in Middle Yellow River. *Water* **11**(4): 689.

Willmott C J 1984 On the Evaluation of Model Performance in Physical Geography. In *Spatial Statistics and Models*, Springer, Berlin, pp. 443-460.