

Modeling Climate Change Impacts on Bread Wheat (*Triticum aestivum* L.) Production in Central Highlands of Ethiopia

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ABSTRACT

In countries like Ethiopia where vulnerability is high and adaptive capacity is low, studying impacts of climate change and adaptation measures at local scale is critical. In view of this, this study was conducted in Arsi Robe, Asasa, Debre Zeit and Kulumsa areas of central highlands of Ethiopia to model impacts of the changing climate on wheat production by 2050s under RCP 4.5 and RCP 8.5 scenarios. Historical climate data (1981-2015), future climate data downscaled using the ensemble of seventeen climate models, crop and soil data were analyzed using crop simulation model to assess impacts of climate change on wheat yield. The crop model simulation indicated a negative impact on wheat yield in all study sites under both RCPs. There will be high yield reduction under RCP 4.5 than under RCP 8.5 at Arsi Robe and Asasa while the reverse is true at Debre Zeit and Kulumsa sites for Dandaa and Kakaba cultivars. Comparing the two cultivars, Kakaba showed high yield potential than Dandaa in all study sites. Besides, the yield of both cultivars showed declined median from the baseline yield under both RCPs and the yield variability is higher under the baseline conditions than for the future climate conditions.

Keywords: Central Highland of Ethiopia, Climate change, Impact Modeling, Scenario, Wheat

INTRODUCTION

Climate change is an important environmental, social and economic issue. It threatens the achievement of Millennium Development Goals aimed at poverty and hunger reduction, health improvement and environmental sustainability [1]. Such issues are particularly important for Sub-Saharan Africa (SSA).

Agriculture is one of the most vulnerable sectors to changes in climates, due to its reliance on adequate environmental conditions for achieving high productivity [2]. Agricultural systems are inherently vulnerable to climate variability [3,4] and climate change is expected to increase this vulnerability [5,6]. Various global and regional studies warn that progressive climate change is expected to negatively affect crop productivity in most parts of the world [7] and particularly in SSA [5], [8-10].

Ethiopia is among the most vulnerable countries in SSA due to its great reliance on climate vulnerable economy [11]. For the IPCC mid-range (A1B) emission scenario, the mean annual temperature will increase in the range of 0.9 -1.1°C by 2030, in the range of 1.7 -2.1°C by 2050 and in the range of 2.7-3.4°C by 2080 over Ethiopia

compared to the 1961-1990 normal [12]. A small increase in annual precipitation is also expected over the country.

Ethiopian economy is an agrarian economy as agriculture comprises about 41.3% of GDP, generates 90% of foreign exchange earnings, and employs more than 80 % of the population [13]. Currently, however, the performance of this sector is seriously eroded due to climate change induced problems. It is estimated that in Ethiopia, one drought event in 12 years lowers GDP by 7 to 10% and increases poverty by 12 to 14% [14]. The projected reduction in the Ethiopian agricultural productivity due to climate change can reduce average income by 30 percent over the next 50 years [15]. The potential impacts of climate change in Ethiopia are superimposed on stressors such as population pressure, poverty and land degradation [16]. Population growth has contributed to the severe environmental degradation Ethiopia has experienced, especially in the densely populated highlands, and hence to the widespread rural poverty [17]. Land degradation due to population pressure is a serious problem of the highlands of Ethiopia.

Climate change is projected to further reduce food security [18-20]. For instance, the fourth Intergovernmental Panel on Climate Change (IPCC) suggests that at lower latitudes, in tropical

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dry areas, crop productivity is expected to decrease for even small local temperature increases (1-2°C) [21].

Although the figures are varied, recent literature indicates that negative impacts are expected to affect the basic food basket (i.e. wheat, rice, maize, and grain legumes), as well as major cash crops (i.e. sugarcane, coffee, cocoa) at moderate or low ($\leq +3$ °C) levels of warming if no adaptation actions put in place [19, 22, 23].

Wheat is one of the major staple and strategic food security crops in Ethiopia. It covers 1,696,082.59 hectares of land and has the production of 4,537,852.34 tones with the average productivity of 2.7 t/ha in Ethiopia [24]. Currently, about 60% of the total wheat area from a 15% in 1967 and a 40% in 1991 is covered by bread wheat, while durum wheat covers about 40% from an 85% in 1967 and a 60% in 1991 [25]. According to USAID country report, wheat is mainly grown in the central and southeastern highlands (Arsi, Bale and parts of Showa are considered the wheat growing belt). Next to corn, wheat is the second most consumed cereal in Ethiopia. It accounts for approximately 11 percent of the national calorie intake in the country 200 kcal/day in urban areas, 310 kcal/day in rural areas [26].

Therefore, this study aimed at modeling impacts of climate change on bread wheat production using crop simulation modeling approach for possible climate change scenarios in the central highlands of Ethiopia.

MATERIALS AND METHODS

Description of the study area

Location: The study was conducted in selected wheat belt areas of the central highlands of Ethiopia including Arsi, West Arsi and East Shewa zones located between 6 and 15° N latitude and 35 and 42° E long at altitudes ranging from 1500 to 3000 m.a.s.l. (Figure 1).

Four representative study sites (Kulumsa, Asasa, Arsi Robe and Debre Zeit) were selected to represent different production conditions like mid-altitude (Kulumsa and Debre Zeit), terminal drought prone (Asasa) and waterlogged vertisol (Arsi Robe). Arsi Robe and Debre Zeit research centers are located at about 40 and 182 km east of Addis Ababa, respectively, whereas Kulumsa and Asasa are located at about 165 and 282 km South of Addis respectively.

Climate: The rainfall regime over much of the central highland area is typically bimodal, with the main rains, known as the Meher, occurring from June through to September, and the short rains, known as the Belg, occurring during February to May. The Belg rains are not sufficiently reliable to permit crop planting each year, and when they do occur they can merge into the Meher. The mean annual rainfall in the central highlands range from 500 to 1500 mm depending on altitude. However, because of excessive runoff; water shortage is a common problem for 5 to 6 months per year in many parts of the highlands. The mean minimum and maximum

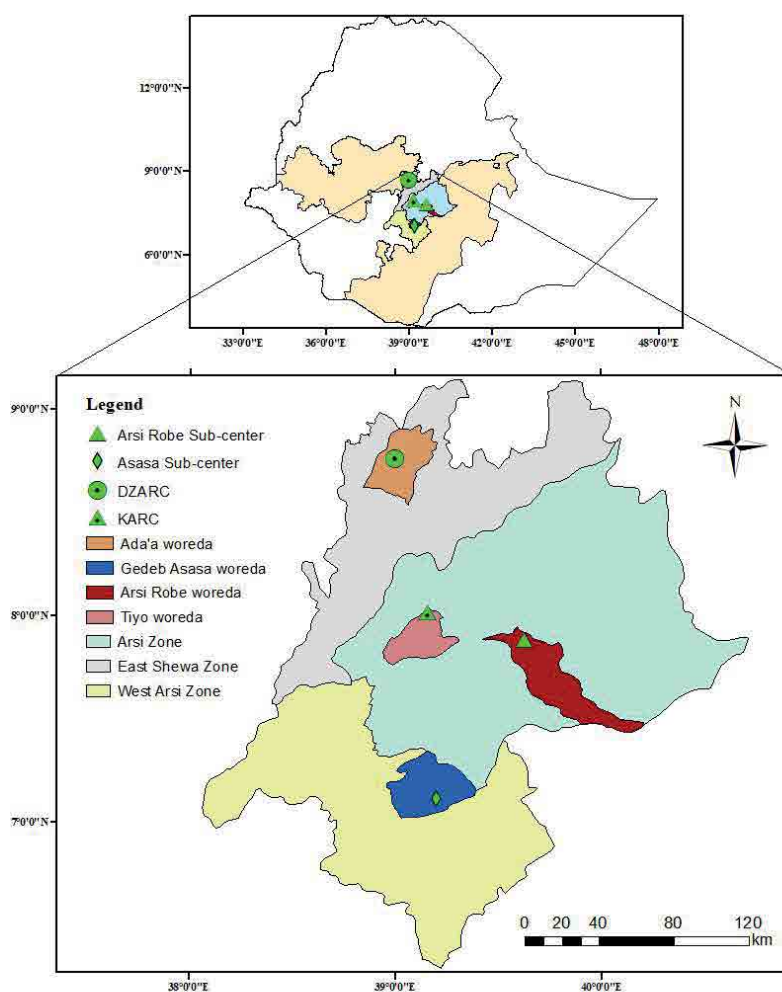


Figure 1: Location map of the study Area.

temperature of study sites (1981-2015) are range from 6.4 to 11.6°C and from 22.4 to 26.6°C respectively whereas mean annual rainfall ranged from 642 to 1020 mm (Table 1).

All study sites have received the highest rainfall amount in the month of August whereas the lowest rainfall amount is received in the month of December (Figure 2). The graph also showed that, greater than 50 mm mean monthly rainfall was received during March to September at all locations except Asasa. Moreover, the mean maximum temperature gets its peak in the month of February at Asasa and Arsi Robe and in May at Debre Zeit and Kulumsa areas while the mean minimum temperature reaches its peak in the month of July at Asasa and Debre Zeit, and in April at Arsi Robe and Kulumsa areas. The lowest mean minimum temperature is recorded in the month of December at all areas. The mean average temperature and mean rainfall of study areas during the wheat growing season (June, July, August, September and October) are 15.6°C and 123.6 mm, 15.6°C and 75.9 mm, 19°C and 124.9 mm and 16.3°C and 98.7 mm at Arsi Robe, Asasa, Debre Zeit and Kulumsa areas, respectively.

Soils: The soils of central highlands in general, are dominated by Alfisols, Vertisols and inceptisols. Eutric Vertisols with high water retention capacity are dominant soils at Arsi Robe and Debre Zeit while Vertic Luvisols at Kulumsa and Mollic Gleysols at Asasa sites. Ethiopia ranks third in Vertisols abundance in Africa after Sudan and Chad [27]. More than half (8.6 Mha) of the Vertisols are found in the central highlands with altitude of more than 1500 meters above sea level [28]. About 25% (1.9 Mha) of the Vertisols occurring in the highlands are cultivated [29]. In addition to the high fixing characteristics of Vertisols [30], lack of response to P application on central highland Vertisols of Ethiopia may be due to deficiency of nutrients other than P.

DESCRIPTION OF EXPERIMENTAL MATERIALS

Kakaba and Dandaa are improved wheat cultivars used in this study for their merits of resistant to rust, high yielding and well known by local farmers. Kakaba is early maturing cultivar which is suited at an altitude ranged from 1500- 2200 m with a rainfall amount ranges from 500-800 mm. It requires 90-120 days to mature with yield potential of 3300-5200 kg/ha under experimental field and 2500-4700 kg/ha at farmers management.

Dandaa is late maturing cultivar and suited at an altitude ranges from 2000-2600 m with rainfall amount >600 mm. It requires 110-145 days and yields about 3500-5500 kg/ha under experimental field and 2500-5000 kg/ha at farmers management.

The detail agronomic information of the two cultivars was obtained from the National Variety Trial (NVT) experiments conducted at Kulumsa and Debre Zeit Research Centers.

The data used for model calibration and validation include crop

Table 1: Mean annual minimum and maximum temperature and rainfall of study sites.

Sites	Minimum T (°C)	Maximum T (°C)	Rainfall (mm)
Arsi Robe	8.13	22.51	1020
Asasa	6.4	22.4	642
Debre Zeit	11.6	26.6	786
Kulumsa	10	23.2	823

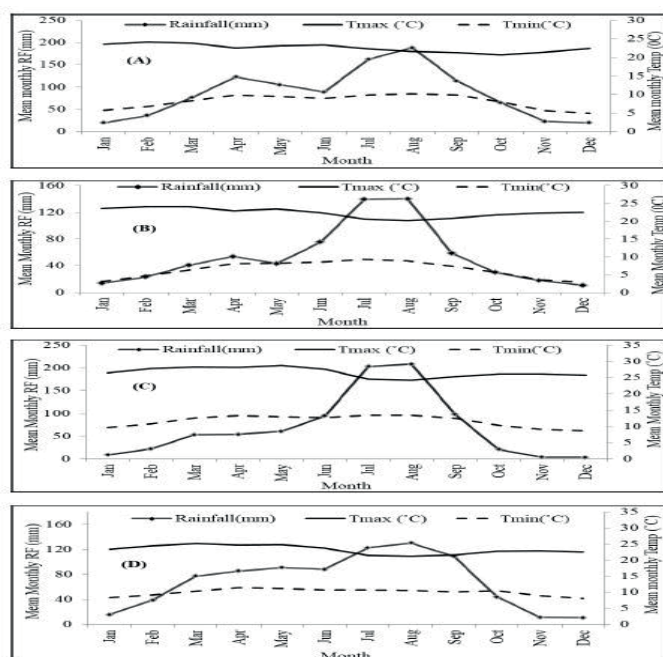


Figure 2: Mean monthly rainfall and temperature distribution of the study sites (A: Arsi Robe; B: Asasa; C: Debre Zeit and D: Kulumsa).

management and phenological information such as planting date, emergence date, anthesis date, maturity date, planting method, plant height, plant population, row spacing and planting depth.

Model calibration

Model calibration was conducted by comparing the simulated values of development and growth characteristics of the crop with the corresponding observed values, and by calculating statistical parameters of an agreement between simulated and observed values.

The CERES-Wheat model was calibrated using data from three experimental years (2012-2014). The data include days to anthesis, days to maturity and grain yield collected from the national variety trial experiments conducted in the study sites under the optimal rates of inputs.

The GenCalc program of DSSAT version 4.6 was used to estimate the cultivar coefficients. The GenCalc is software used for the calculation of cultivar coefficients for use in many crop models [31] including the CERES wheat model, which has 7 cultivar coefficients that describe growth and development of a wheat cultivar (Table 2). In the calibration stage of this study, the typical genetic coefficients of the cultivar IB1015 MARIS FUNDIN and IB0488 NEWTON found in the model by default were used to initialize simulation for Dandaa and Kakaba cultivars respectively. Thus, changes were made to the seven cultivar coefficients to reduce the gap between model simulation and the corresponding observed field data.

Model evaluation

After calibrating the genetic coefficients of the cultivars, the model was run using an independent crop data of two years (2015-2016) obtained from field experiment for model validation. The performance indicators such as Root Mean Square Error (RMSE), Coefficient of Determination (R^2) and the index of agreement (d) were computed for each cultivar to evaluate the model prediction capability. A widely used measure of agreement between measured

and simulated values is the root mean squared error [32,33] and calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (1)$$

Where n is the number of observations, P_i and O_i are predicted and observed values respectively. Similarly, the index of agreement (d) provides a single index of model performance. The index was computed as:

$$d = 1 - \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (|P'_i| + |O'_i|)^2} \right] \rightarrow (2), 0 < d < 1 \quad (2)$$

Where n is the number of observations, P_i the predicted value for the i^{th} measurement, O_i is the observation for i^{th} measurement, M is the mean of the observed variable, $P'_i = P_i - M$ and $O'_i = O_i - M$. The d-statistic value is closer to unity, indicates a good agreement between the observed and simulated results [34]. Coefficient of determination (R^2) was also computed from the linear regression of simulations verses observations graph.

$$R^2 = \frac{S(\text{regression})}{S(\text{residual})} \quad (3)$$

Where, SS (regression) is sum square regression and SS (residual) is sum squared residual.

Climate data source and quality control

Historical climate data: the long-term (1981-2015) weather data for present climate, hereafter referred to as baseline, of study sites was obtained from the National Meteorology Agency (NMA) and agricultural research centers (Kulumsa and Debrezeit). The missing values were interpolated from neighbor stations using the normal ratio method [35].

Future climate data: Future climate data was downscaled from ensemble of 17 GCMs namely BCC-CSM1.1, BCC-CSM 1.1 (m), CSIRO_MK3.6, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-H, GISS-E2-R, HadGEM2-ES, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC-ESM, MIROC-ESM-CHEM, MIROC5, MRI-CGCM3, Nor ESM1-M under RCP 4.5 and RCP 8.5 using MarkSim weather generator [36] which have been statistically bias-corrected [37]. The CO₂ concentration equivalents of RCP 4.5 is 650 ppm [38-40] while it is 1370 ppm for RCP 8.5 [41,42] for 2050s.

Data Quality Control: Data homogeneity was assessed with the RHTestV4 software which uses a two-phase regression model to check for multiple step change points that could exit in a time series [43-45]. Non homogeneity of the time sequence can occur due to change in location of the weather station, instruments, formula used to calculate the statistical parameters, observing practices and station environments [46]. In this case, the temperature data was checked for gross errors and outliers that exceeded 4 standard deviations from the mean for each day, using the quality control procedures of the Microsoft Excel-based RCLimDex software [47].

Modeling climate change impacts

The climate change impact on wheat was simulated using Decision Support System for Agro technology Transfer (DSSAT) dynamic crop model. CERES-Wheat crop model in the DSSAT 4.6 was used

to simulate growth, development and yield of wheat in response to environmental and management factors. This model has the ability to simulate crop growth, development and yield at either plot field or regional scale [48].

The CERES-Wheat model requires input data of crop management such as sowing depth and dates, cultivar, row spacing, emergence date, plant population, fertilizer application dates and amount. The minimum required daily weather data include maximum and minimum temperature, rainfall and solar radiation. Soil data such as soil type, slope and drainage characteristics, and physico-chemical parameters for each soil layer, such as saturated soil water content, lower limit, upper drained limit, initial soil water content, soil pH, bulk density and soil organic matter were also required. The soil data of study sites were collected from Kulumsa and Debre Zeit Research centers and the legacy soil profile data of sub-Saharan Africa fixed-grid at 250 by 250 m [49]. In this study both observed and projected daily climate data were used to simulate the yield and phenological stages of the crop both for baseline period and future time slice under ensemble climate models and RCP scenarios.

Therefore, yield change analysis involves quantifying the differences between simulated yield of 2050s and baseline period. Baseline yields were used as the references for calculating yield difference in the upcoming period (2050) using ensemble climate models under the considered RCP scenarios. The yield percentage change was calculated using the formula [50]:

$$\Delta Y = \frac{Y_s - Y_b}{Y_b} \times 100 \quad (4)$$

Where, ΔY is change in yield; Y_s and Y_b simulated yields of 2050s and baseline period respectively.

RESULTS AND DISCUSSION

Model calibration (Estimating cultivar coefficient)

The model was calibrated and validated with independent field data sets (that included yield and phenology). The phenology coefficients among the list in Table 2 were calibrated so the observed and simulated phenological dates were as close as possible for each study site. The simulated dates of the phenological stages, and therefore the number of days available for accumulation of grain dry matter, are most sensitive to the photoperiod coefficient (P1D). The grain filling duration coefficient (P5) does not have any effect on the anthesis date, but as values of P5 increase there is an increase in the number of days to physiological maturity.

Table 2: Genetic coefficients used in CSM-CERES-model to characterize the growth and development of wheat variety.

Coefficients	Definition
P1V	Days, optimum vernalizing temperature, required for verbalization
P1D	Photoperiod response (% reduction in rate/10 h drop in pp)
P5	Grain filling (excluding lag) phase duration (degree day)
G1	Kernel number per unit canopy weight at anthesis (#/g)
G2	Standard kernel size under optimum conditions (mg)
G3	Standard, non-stressed dry weight (total, including grain) of a single tiller at maturity (g)
PHINT	Thermal time between the appearance of leaf tips (degree days)

The values of grain filling duration (P5) for this study were ranged from 355 to 585 GDD across locations (Table 3). The literature values of this parameter ranged from 332 to 690 GDD [51- 55]. For a particular combination of G1, G2 and G3, the grain yield shows high sensitivity to changes in PHINT value in this study. The genetic coefficients determined in CSM_CERES-model to characterize the growth and development of the wheat cultivars used in this study are presented in Table 3.

Model validation for dandaa cultivar

The CSM-CERES-Wheat model was evaluated with independent data collected from experimental sites. The model was able to simulate crop parameters with reasonable accuracy. The model predicted the dates from planting to anthesis and from planting to maturity with small difference between the observed and simulated dates for cultivar Dandaa. The agreement between observed and simulated days to anthesis and physiological maturity was explained by 83.9 and 75.2%, 91.8 and 86.5%, 78.9 and 85.5% and 82.5 and 86.5% at Asasa, Arsi Robe, Debre Zeit and Kulumsa, respectively (Figure 3-5). The values of d-stat for days to anthesis ranged from 0.79 to 0.95 while the RMSE ranged from 1.09 to 2.32 days across the study sites whereas the values of d-stat and RMSE for days to physiological maturity ranged from 0.87-0.96 and 1.1-2.3,

respectively (Table 4). High values of d-stat and R^2 with low RMSE values indicate good performance of the model in simulating these parameters. Moreover, the model predicted grain yield with good agreement between observed and simulated in all study sites. The values of R^2 and d-stat ranged from 0.80-0.95 and 0.88-0.99, respectively, while the values of RMSE ranged from 86.76 to 283.14 kg/ha across the study sites.

It could be clearly seen from, simulated *vs.* observed plots; there is little deviation from the trend line for days to anthesis, days to maturity and grain yield. This indicated that the model predicted well the actual days to anthesis, days to physiological maturity and grain yield with good precision values of R^2 , RMSE and d-stat for this cultivar in all sites (Table 4).

Model validation for kakaba cultivar

Similarly the model was able to simulate the crop parameters with reasonable accuracy for cultivar Kakaba in the study area. The coefficient of determination (R^2) for the agreement between model simulation and observed for days to anthesis, days to physiological maturity and grain yield were ranged from 80.1-91.7%, 83.7-87.1% and 73.3-94.3%, respectively, across study sites (Figure 6-8). Moreover, the values of d-stat and RMSE were ranged from 0.85-

Table 3: Values of genetic coefficients used in CERES-Wheat model to characterize wheat cultivars in different locations after model calibration and validation.

Parameter	Asasa		Arsi Robe		Debre Zeit		Kulumsa	
	Dandaa	Kakaba	Dandaa	Kakaba	Dandaa	Kakaba	Dandaa	Kakaba
PIV	1	1	1	2	25	1	1	1
PID	31	10	10	2	2	20	2	1
P5	365	450	520	355	480	558	585	525
G1	28	20	15	50	26	45	14	50
G2	74	83	44	82	62	20	55	26
G3	1.5	0.4	3.2	6.8	3	0.8	0.5	2.6
PHINT	140	100	92	110	80	150	90	144

Table 4: Comparison of observed and simulated days to anthesis, days to maturity and grain yield for wheat cultivars after model validation.

Site	Days to anthesis									
	Danda'a					Kakaba				
	Obs	Simu	R2	RMSE	d-stat	Obs	Simu	R2	RMSE	d-stat
Arsi Robe	86.4	87.8	0.92	1.41	0.82	76.5	75	0.812	1.09	0.849
Asasa	77.25	77.5	0.84	1.09	0.95	66.2	67.25	0.917	1.18	0.907
Debre Zeit	72.25	73.75	0.79	2.32	0.79	64.5	65	0.801	0.77	0.875
Kulumsa	79.6	81	0.83	1.95	0.89	68	69.5	0.855	2.1	0.846
Days to Maturity										
Arsi Robe	141.3	142.4	0.87	1.1	0.87	116	115	0.812	0.77	0.849
Asasa	127.3	126.5	0.75	1.26	0.92	123	121.7	0.871	1.18	0.947
Debre Zeit	112.8	113.7	0.86	1.89	0.87	111	110	0.801	1.73	0.875
Kulumsa	127.4	128.4	0.87	2.3	0.96	114	116	0.871	2.14	0.952
Grain Yield										
Arsi Robe	2890	2843	0.94	94.79	0.97	3870	3776	0.812	209.5	0.849
Asasa	3498.75	3513.75	0.96	130.12	0.98	4482.75	4458.25	0.825	110.8	0.936
Debre Zeit	1771	1727	0.8	86.76	0.88	3134	3166	0.801	215	0.875
Kulumsa	5182	5076	0.93	283.14	0.98	4913	4993	0.943	119.8	0.982

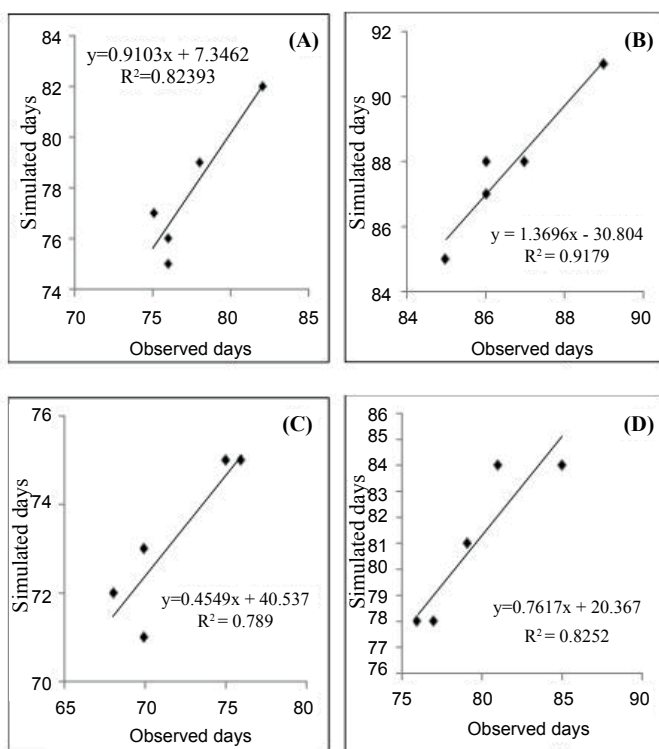


Figure 3: Comparison of measured and simulated days to anthesis at (A) Asasa, (B) Arsi Robe, (C) Debre Zeit and (D) Kulumsa areas for Dandaa.

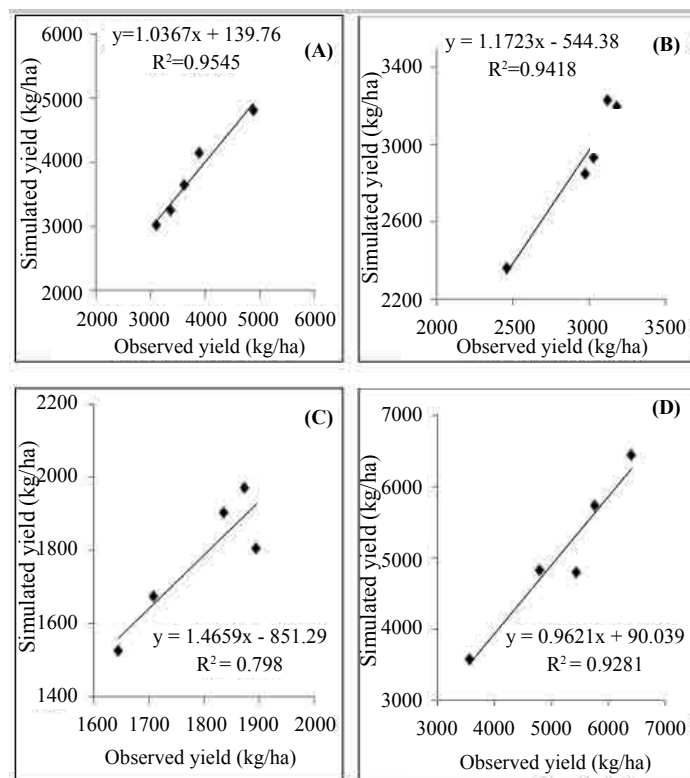


Figure 5: Comparison of observed and simulated grain yields at (A) Asasa, (B) Arsi Robe, (C) Debre Zeit and (D) Kulumsa areas for Dandaa.

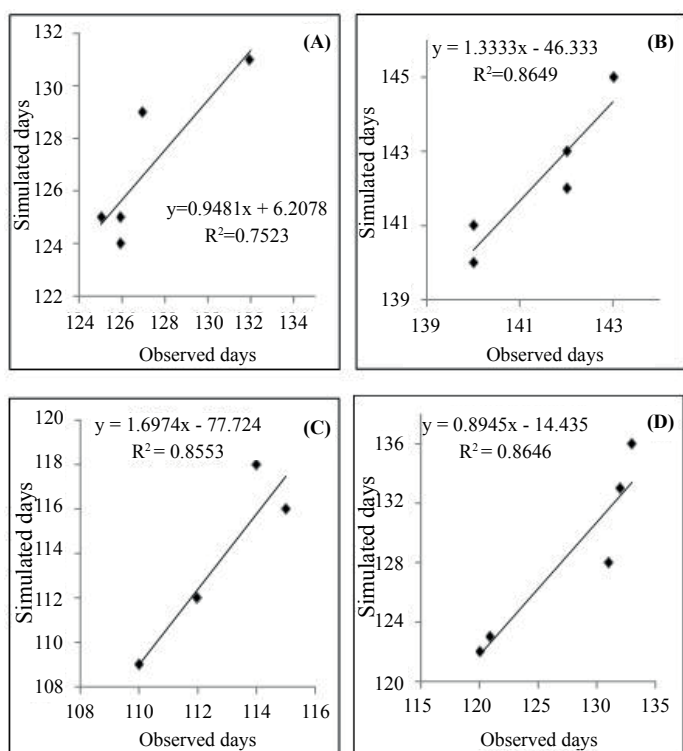


Figure 4: Comparison of measured and simulated days to physiological maturity at (A) Asasa, (B) Arsi Robe, (C) Debre Zeit and (D) Kulumsa areas for Dandaa.

0.91 and 0.77-2.1, 0.81-0.95 and 0.77-2.14 for days to anthesis and days to maturity, respectively. The d-stat values for grain yield ranged from 0.89-0.98 while RMSE ranged from 110.79 to 215 kg/ha in the study area (Table 4). This indicated that there is good agreement between model prediction and observed values of grain yield for this cultivar in all locations.

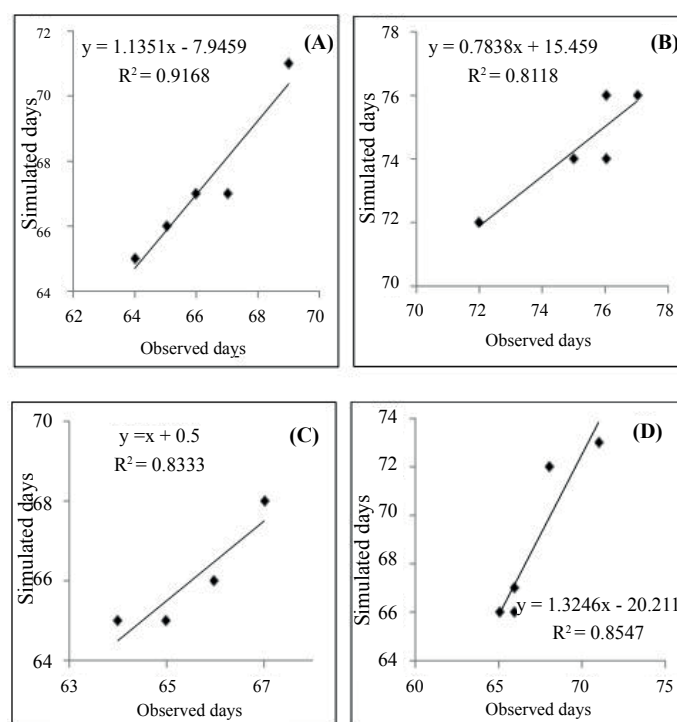


Figure 6: Comparison of measured and simulated days to anthesis at (A) Asasa, (B) Arsi Robe, (C) Debre Zeit and (D) Kulumsa areas for Kakaba.

Therefore, the test statistics and Figure 6-8 show a good ability of the model to predict days to maturity, days to anthesis and grain yield of cultivar Kakaba. Therefore, the calibrated and validated model can be used to simulate climate change impacts on Dandaa and Kakaba cultivars.

Impacts of climate change on bread wheat yield

The projected future climate change has a negative impact on grain

yields of both cultivars in all study sites. There will be higher yield reduction under RCP 4.5 than RCP 8.5 at Arsi Robe and Asasa and the reverse is true at Debre Zeit and Kulumsa areas for Dandaa cultivar (Figure 9). There will be favorable condition under the RCP 8.5 than RCP 4.5 at Arsi Robe and Asasa whereas favored under RCP 4.5 than RCP 8.5 at Debre Zeit and Kulumsa sites. This might be due to the reason that, relatively high rainfall increment will be expected under RCP 8.5 than under RCP 4.5 at Arsi Robe and Asasa whereas increased more under RCP4.5 than RCP 8.5 at

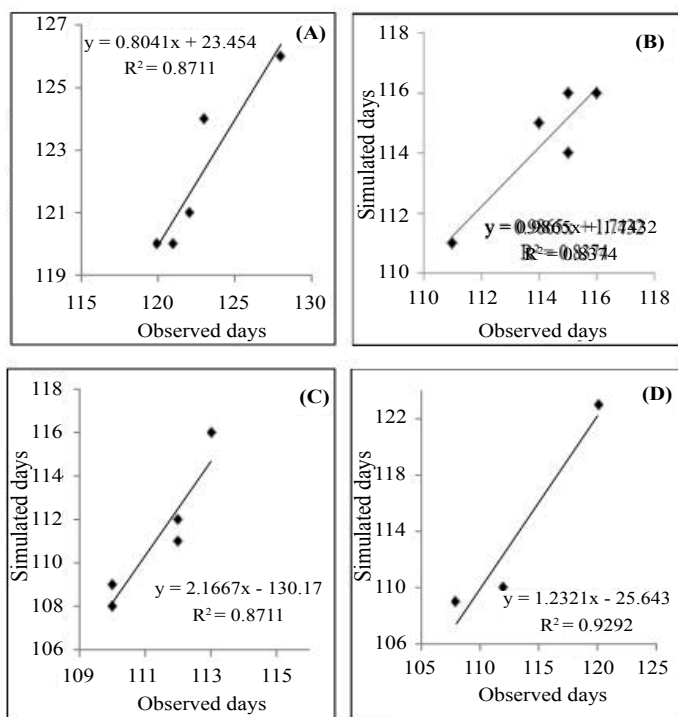


Figure 7: Comparison of measured and simulated days to physiological maturity (A) Asasa, (B) Arsi Robe, (C) Debre Zeit and (D) Kulumsa areas for Kakaba.

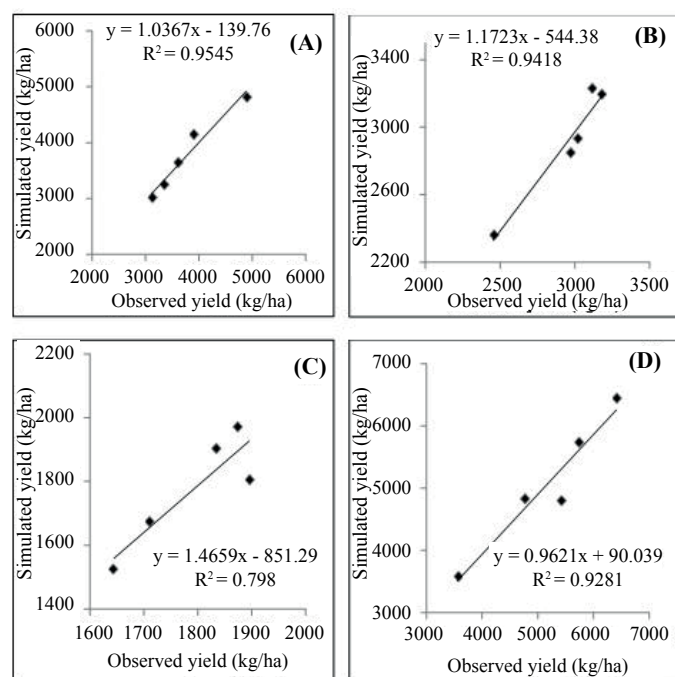


Figure 8: Comparison of measured and simulated results of grain yield at (A) Asasa, (B) Arsi Robe, (C) Debre Zeit and (D) Kulumsa areas for Kakaba.

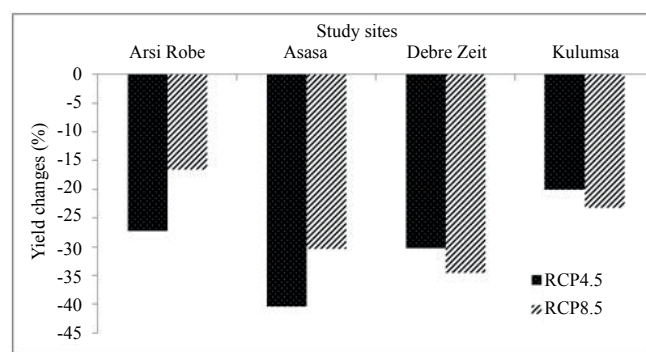


Figure 9: Percentage yield change from baseline period for Dandaa cultivar.

the remaining two sites. In addition to this, the current mean air temperature of Arsi Robe (22.5°C) and Asasa (22.4°C) are lower compared to that of Debre Zeit (26.6°C) and Kulumsa (23.2°C) and increasing in all sites by the midcentury under both RCPs. The temperature change is also relatively higher for these locations accompanied by a projected increase in rainfall. Relatively higher rate of increase in temperature from RCP 8.5 combined with higher water availability could have resulted in a relatively less impact in these locations compared with warmer locations of Debre Zeit and Kulumsa. The yield will be reduced by 27.2, 40.3, 30.3 and 20% at Arsi Robe, Asasa, Debre Zeit and Kulumsa, respectively under RCP4.5 while the corresponding yield reductions under RCP8.5 are 16.5, 30.3, 34.6 and 23.2%.

For Kakaba, the decreasing of grain yield from the baseline condition has been observed by 2050s under both scenarios. The grain yield reduced by 24.7, 39.1, 32.5 and 13.7% under RCP 4.5 scenario while it will be reduced by 18.3, 27.4, 37.9 and 15% under RCP8.5 scenario in Arsi Robe, Asasa, Debre Zeit and Kulumsa areas, respectively (Figure 10). The yield loss is higher for Dandaa than that of Kakaba under both RCPs on average. This might be due to the fact that, Dandaa is highland cultivar and less heat tolerant compared to Kakaba, which is lowland cultivar and more tolerant to temperature induced heat stress over the study area.

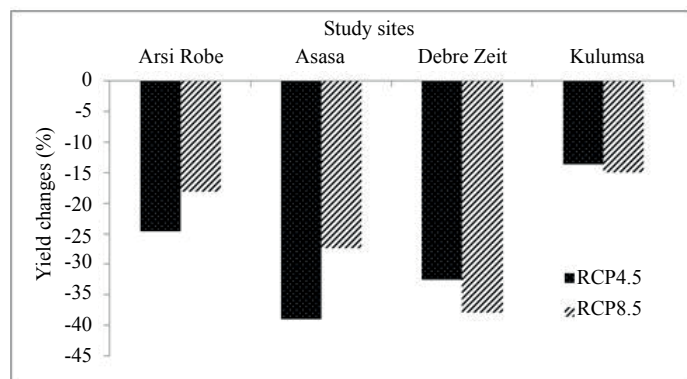
In general, there will be significant yield reduction of both wheat cultivars in all study sites under both scenarios compared to the baseline period. This might be due to the temperature induced heat stress and changes in length of growing season over the study area.

The result in this study is line with other results that have been found from similar studies in Ethiopia. For example, wheat production in Oromia region of Ethiopia may be reduced at 7.26% by 2050s and 9.59% by 2100 due to climate change, while at national level; it may be reduced at 6.21% by 2050s and 11.03% by 2100 [56]. Similarly, reported that there will be substantial reduction in wheat yields in Ethiopia even in the areas where rainfall is expected to increase, presumably owing to heat stress. Thus, the use of best adaptation measures could be needed to offset the problem and increase the productivity of wheat in the study area [57]. Figures 11 and 12 show the observed and projected yield variation for Dandaa and Kakaba due to climate change impacts under both RCP scenarios over the study area.

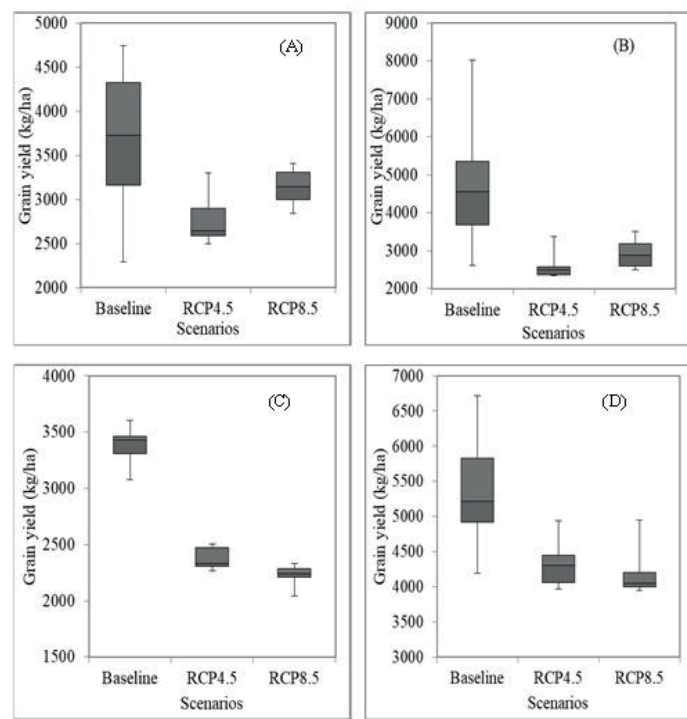
For Dandaa, RCP 4.5 scenario shows a median yield of 2649, 2505, 2329 and 4239 kg/ha was obtained at Arsi Robe, Asasa, Debre Zeit and Kulumsa areas, respectively, while the corresponding yields for RCP 8.5 are 3143, 2868, 2238 and 4037 kg/ha. In the same area,

Table 5: Coefficient of variation of yield variability under baseline and projected climate condition.

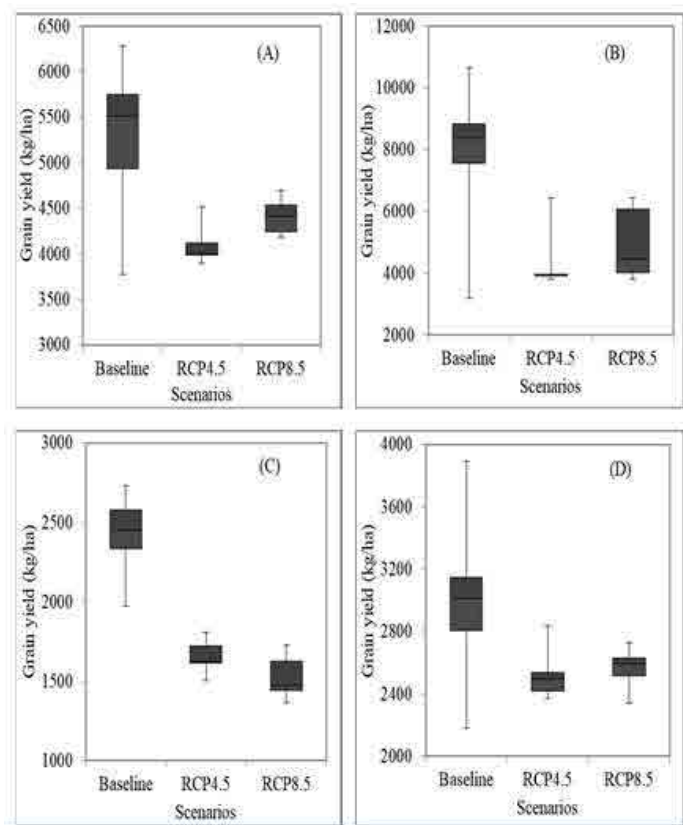
Sites	Dandaa			Kakaba			
	Coefficient of variation	Baseline	RCP 4.5	RCP 8.5	Baseline	RCP 4.5	RCP 8.5
Arsi Robe	CV (%)	19	8	6	19	8	6
Asasa	CV (%)	31	9	12	31	9	12
Debre Zeit	CV (%)	4	4	4	4	4	4
Kulumsa	CV (%)	12	6	3	12	6	3

**Figure 10:** Percentage yield change from baseline period for Kakaba cultivar.

Variability of grain yield from the baseline

**Figure 11:** Box and whisker plots indicating yield variation under the baseline and projected climate conditions for Dandaa in the study sites (A: Arsi Robe; B: Asasa; C: Debre Zeit and D: Kulumsa).

2899, 2568, 2475 and 4374 kg/ha grain yield would be obtained in three out of four years for RCP 4.5 scenario, whereas, 3309, 3186, 2283 and 4088 kg/ha grain yield is expected under RCP 8.5 scenario (Figure 11). Moreover, below 2588, 2357, 2302 and 4023 kg/ha grain yield under RCP 4.5 scenario and 3000, 2599, 2209 and 3995 kg/ha for RCP 8.5 at Arsi Robe, Asasa, Debre Zeit and Kulumsa sites, respectively, are likely in one out of four years for Dandaa. The coefficients of variations are, 8 and 6% at Arsi Robe, 9 and 12% at Asasa and 6 and 3% at Kulumsa for RCP 4.5 and

**Figure 12:** Box and whisker plots indicating yield variation under the baseline and projected climate conditions for Kakaba in the study sites (A: Arsi Robe; B: Asasa; C: Debre Zeit and D: Kulumsa).

RCP 8.5, respectively, and 4% under both RCPs at Debre Zeit area (Table 5). Besides, there is higher yield variation under the baseline condition than under projected climate conditions with coefficient of variation of 19, 31 and 12% at Arsi Robe, Asasa and Kulumsa areas, respectively (Table 5).

Similarly, for Kakaba, both RCP scenarios show declining medians in all study sites. The median will be declining to 4006, 3929, 1619 and 2498 kg/ha under RCP 4.5 and to 4411, 4460, 1471 and 2590 kg/ha under RCP8.5 scenario at Arsi Robe, Asasa, Debre Zeit and Kulumsa, respectively (Figure 12). Similarly, 4116, 3970, 1720 and 2536 kg/ha of grain yield will be likely in three out of four years for RCP4.5 scenario while the corresponding grain yield under RCP 8.5 scenarios is 4534, 6081, 1624 and 2631 kg/ha in the study sites, respectively. Moreover, below 3988, 3911, 1613 and 2419 kg/ha grain yield could be obtained in one out of four years under RCP 4.5 scenario while for RCP 8.5 scenario, 4239, 4001, 1441 and 2515 kg/ha with coefficient of variation of 3, 13, 5 and 5% for RCP 4.5 and 3, 20, 8 and 4% for RCP 8.5 at Arsi Robe, Asasa, Debre Zeit and Kulumsa, respectively.

Overall, it could be concluded that, high yield variability observed under the baseline period than under projected climate conditions

and mean grain yields are declined from the baseline period in all study sites.

CONCLUSION

Climate change is an important environmental, social and economic issue in the world, particularly in SSA. Ethiopia is among the most vulnerable countries in SSA due to its great reliance on climate vulnerable economy. Therefore, urgent and immediate measures that can offset effects of the changing climate are critical. This could be possible through site specific studies like this, which focus on likely future climate change scenarios and their impact on specific enterprises like wheat crop production. In view of this, this study was conducted to model the impacts of projected changing climate in Arsi Robe, Asasa, Debre Zeit and Kulumsa areas of central highlands of Ethiopia.

It is investigated that, how bread wheat production will be affected by the changing climate. The projected future climate change has a negative impact on grain yields of Dandaa and kakaba in all study sites under both RCP scenarios. The two cultivars will respond differently to the future climate change and Dandaa showed high yield reduction at Asasa and Kulumsa areas under both RCPs. The grain yield will be decrease in all study sites for both cultivars by 2050s under RCP 4.5 and RCP 8.5 scenarios compared to the baseline period.

Therefore, climate change will affect bread wheat productivity at different magnitude and fluctuation in the study area. In this study, useful information of the climatic determinants in the study area for wheat growing season has been found.

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