Vol. 14(8), pp. 509-518, 21 February, 2019
DOI: 10.5897/AJAR2018.13801
Article Number: 802E53560335
ISSN: 1991-637X
Copyright ©2019
Author(s) retain the copyright of this article
http://www.academicjournals.org/AJAR

ACADEMIC JOURNALS
expand your knowledge

African Journal of Agricultural Research

Full Length Research Paper

Calibration and validation of CERES-wheat in DSSAT model for yield simulation under future climate in Adet, North Western Ethiopia

Endalew Assefa Abera

Debre Zeit Research Center, Ethiopian Institute of Agriculture Research, Ethiopia.

Received 11 December, 2018; Accepted 16 January, 2019

Crop models are highly useful for simulating crop and soil processes in response to variations in climate and crop management. However, well estimated crop genetic coefficients are required. So the purpose of this study is to calibrate and evaluate the performance of CERES-wheat model and to simulate the climate change impacts on phonological stages and grain yield of bread wheat (Tay and Senkegna varieties) in the study area. Observed climate data from National Meteorological Agency of Ethiopia from 1983 to 2015 and future climate from Climate Research Programme's Fifth Coupled Model Intercomparison Project (CMIP5) database across 20 Global Circulation Models for Representative Concentration Pathway (RCP4.5 and 8.5) emission scenarios in the time horizon of early-term (2010-2039), mid-century (2040-2069) and end-century (2070-2100) were used. Crop and soil data were obtained from Adet Agricultural Research Center. Decision Support System for Agro-technology Transfer (DSSAT) crop model was employed. There was strong agreement between the simulated and observed values with R^2 being 96, 79 and 79% for days to anthesis, grain yield and days to maturity, respectively for Tay wheat variety while 75% for days to anthesis, 92% for grain yield, and 75% for days to maturity of Senkegna bread wheat variety. On the other hand, during model validation, the goodness of fits (R^2) was 86% for anthesis day, 70% for grain yield and 96% for physiological maturity days of Tay wheat variety. Similarly for Senkegna bread wheat variety, R^2 was 89, 82 and 75% for anthesis day, grain yield, and physiological maturity days, respectively. The yield of both bread wheat varieties showed increase except in 2080s under RCP4.5 relative to the baseline. However, days to flowering and to maturity showed decreased in each time slice under both RCPs.

Key words: Calibration, validation, crop model, wheat, Ethiopia, East Africa.

INTRODUCTION

Evidence from the Intergovernmental Panel on Climate Change (IPCC, 2007a, b) is now convincing that climate change is real. Five Coupled Inter-Comparison Project (CMIP5) model predicted global mean surface temperatures for 2046-2065 and 2081-2100 likely to be in the ranges of 1-2 and 1-3.7°C, respectively relative to

E-mail: endalewassefa@yahoo.com. Tel: +251980603020

1986-2005 (IPCC, 2013). In sub-Saharan Africa, Ringler et al. (2010) reported high temperatures and mixed changes in rainfall by the year 2050, and would result in a decrease of wheat yields by -22% in 2050 year. Wheat is an important cereal crop grown in the highlands of Ethiopia (Schulthess et al., 1997). It has been among priority crops on research and development strategies in Amhara Region (ARARI, 2007). However, climate change would adversely affect wheat crop production and cause certain wheat growing areas to be no longer viable, and wheat species will be restricted to higher altitude of Ethiopia (Yumbya et al., 2011). The disrupting of the rainy season in Ethiopia alters national crop production by 90 to 95% (Kidane, 2010). Similarly, Osman and Sauerborn (2002) and Hagos et al. (2009) found the rainfall variability in Ethiopian leads to a 20% production deficit and increase in 25% poverty rate, which costs the economy over one-third of its growth potential. General Circulation Models (GCMs) are capable of simulating global climate and provide reliable representation to local level (Hassan, 2012). Agricultural Model Intercomparison and Improved Project (AgMIP) protocol is a worldwide cooperative effort linking climate, crop and socio-economic modeling to produce improved modeling capacity for integrated assessment of climate change impacts on the agriculture sector at local, regional and global scale (Rosenzwig et al., 2013). Habtamu et al. (2012) identified that the recent modeling studies are urgent to reach all vulnerable populations in Ethiopia under extreme climate condition. Belayneh (2011) reported that most climate models predicted that the temperature will increase over a period of time under future climate scenario in Ethiopia. Crop models are being used to evaluate the impact of climate change on crop production as a result of increased greenhouse gases (Rosenzweig et al., 1992; White et al., 2011). Crop models have also been used in inputs and resource management options for sustained agricultural production (Aggarwal et al., 1994; 2006). CERES-wheat is one of process oriented management level tool that has capacity to simulate the growth, development and yield of wheat under diverse environments in DSSAT model (Ritchie et al., 1998), which helps to enter data from field experiments, evaluate the models, estimate the generic coefficients of crop, conduct sensitivity analysis, analyze economic risk and uncertainty of alternative management options (Hoogenboom et al., 2010; Jones et al., 2003a).

Site specific calibration and validation of CERES-wheat model in specific soil and climate for a particular set of management inputs is needed for further application (Jones et al., 2010; Mavromatis et al., 2001). However, most wheat varieties in the study area are not introduced to the DSSAT model, and it is limited to assess the climate change impact on wheat yield production in Ethiopia in general and in Adet in particular. Most authors, such as Agnew and Chappel (1999), Woldeamlak (2009), and Dereje et al. (2012) assessed the effects of climate variability on yield in the study area. However, these studies correlate rainfall with yields, but not related during different stages of the crop growth to identify the critical effect at each stage of the crop growth, and limited to include more factors for yield production other than rainfall (like, soil properties and CO_2 concentration) (RIDA, 2011). Therefore, the objective of the study was to calibrate and evaluate the performance of CERES-Wheat model and simulating the climate change impact on wheat yield by using DSSAT model v 4.7.

MATERIALS AND METHODS

Description of study area

The study was conducted in Adet, North Western Ethiopia. It is found in Amhara Region and located at 11°16'N and 37°29'E with an altitude of 2216 m above mean sea level (Figure 1). The mean annual rainfall is 1250 mm, and the average annual maximum temperature is 25.5°C and minimum temperature is 9.2°C with the dominant soil types being Nitosol, Vertisols and Luvisols (AARC, 2006, 2012).

Data source

The climate data for the baseline period of 33 years from 1983-2015 were obtained from the National Meteorological Agency of Ethiopian (NMA), Bahir Dar branch for the study area. The data includes daily rainfall, minimum and maximum temperatures, wind speed, relative humidity, and daily solar radiation. Future climate data were generated from Climate Research Programme's Fifth Coupled Model Intercomparison Project (CMIP5) multi-model database systems across 20 GCMs under RCP4.5 and RCP8.5 emission scenarios for the time horizon of early-term (2010-2039), mid-century (2040-2069) and end-century (2070-2100) (AgMIP, 2013a, b). Crop management, phenological observations data were obtained from Adet Agricultural Research Center. Crop data includes maturity date, anthesis date and grain yield, while crop management data includes planting date, planting density and fertilizer application dates and rates. Soil data also obtained from Adet site soil profile (2006) in sample of four layers which are presented in Table 1. The full information was captured from field book and center annual report for 2000 to 2005 cropping season under rain-fed conditions.

Downscaling future climate data

Delta factors methods was employed to generate the daily data of rainfall, minimum and maximum temperatures, and solar radiation by perturbing the daily baseline data (1980-2015) using Agricultural Model Intercomparison and Improved Project (AgMIP) scenario generation scripts with R analytical tool (Diaz-Nieto and Wilby, 2005; Fowler et al., 2007; AgMIP, 2013c; IPCC, 2013). Climate models provide provision of future scenarios to assess the impact of climate change. The adjustment formula for modifying precipitation, maximum and minimum temperatures is stated as shown in Equations 1 and 2, respectively.

$$P_{adj,fur,d} = P_{obs,d} \; X \sum_{1=i}^{k} pi\left(\overline{P}_{GCM,fur,m/}\overline{P}_{GCM,ref,m}\right) \qquad (1)$$

Table 1. Physical and chemical soil properties in Adet experimental site, North Western Ethiopia.

Parameter	Soil depth (cm)			
	0 - 30	30 - 90	90 - 140	140 - 200
Clay	66	69	68	64
Silt	24	15	18	24
Sand	12	16	14	12
Bulk density (g/cm3)	1.13	1.19	1.21	1.29
Organic carbon (%)	1.31	0.98	0.77	0.51
Total N (%)	0.11	0.09	0.06	0.04
pH	5.2	6.3	6.8	7.1
CEC (meq/100 g soil)	50.1	52	55.2	55.8

CEC: Cation exchange.

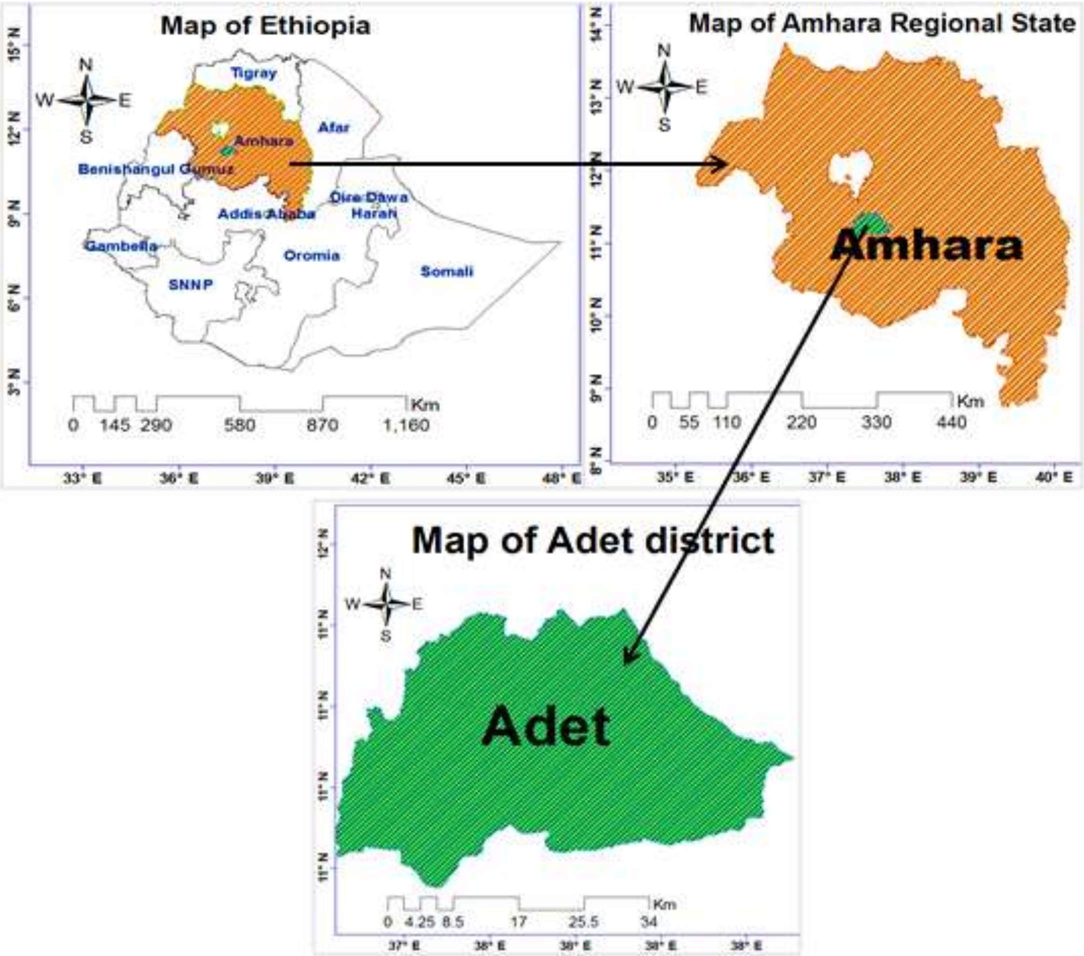

Figure 1. Location map of the study area

where $P_{adj,fur,d}$ was the adjusted daily rainfall for the future years, $P_{obs,d}$ was the observed daily rainfall for the base years, $\overline{P}_{GCM.fur,m}$ was the monthly mean rainfall of GCMs outputs for the future years, $\overline{P}_{GCM.ref,m}$ was the monthly mean rainfall of GCMs outputs for the base years, pi was the weight of each grid cell, and k was the number of grid cells.

Table 2. Genetic coefficients used to calibrate the CERES-Wheat model for Tay and Senkegna wheat variety in Adet, North Western Ethiopia.

Symbol	Definitions
P1V	Days, optimum vernalizing temperature required for vernalization
P1D	Photoperiod response (% reduction in rate/10 h drop in pp)
P5	Grain filling (excluding lag) phase duration (°C.d)
G1	Kernel number per unit canopy weight at anthesis (#/g)
G2	Standard kernel size under optimum conditions (mg)
G3	Standard non-stressed mature tiller wt (incl grain) (g dwt)
PHINT	Interval between successive leaf tip appearances (°C.d)

For temperature:

$$T_{adj,fur,d} = T_{obs,d} \; X \sum_{1=i}^{k} Pi\left(\overline{T}_{GCM.fur,m} - \overline{T}_{GCM.ref,m}\right) \tag{2}$$

where $T_{adj,fur,d}$ was the adjusted daily maximum or minimum temperature for the future years, $T_{obs,d}$ was the observed daily maximum or minimum temperature for the baseline years, $\overline{T}_{GCM.fur,m}$ was the monthly mean maximum or minimum temperature of GCMs data outputs for the future years, $\overline{T}_{GCM.ref,m}$ was the monthly mean temperature of GCMs outputs for the base years, pi was the weight of each grid cell, and k was the number of grid cells.

Crop model calibration

The calibration of CERES-wheat model utilized climate data for the baseline period of 33 years, crop data of 2000, 2001, and 2002 seasons for the most popular wheat varieties of Senkegna and Tay; and soil data on relevant parameters. GENCALC2 is software, which used to determine cultivar trait coefficients from data reported for an array of experiments. The model must use CULTIVAR and ECOTYPE files as specified for the DSSAT models, and must generate an EVALUATE.OUT file which conforms to the standards set up for DSSAT. Although this automatic calculation is a great deal of research to effective and efficient (Madsen et al., 2002), repeated iterations are needed until strong agreements occurred between the simulated and observed values. To initiate calibration, default genetic coefficients were created in WHCER047.CUL of DSSAT-CSM.

The derived genetic coefficients then used for model performance evaluation and finally for yield simulation. The seven genetic coefficients for model calibrations are shown in Table 2.

Crop model validation

In order to evaluate the calibrated model, well-defined criteria and input data are needed. Therefore, the performance of the CERES-wheat model was validated using an independent crop data from years that were not used for model calibration (2003, 2004 and 2005). The ultimate test of a simulation model is the accuracy which is usually involving comparisons between simulated and observed data (Willmott et al., 1985; Jones and Kiniry, 1986; Oreskes et al., 1994). A number of statistical methods for analyzing model performance are available. These are the root mean square error (RMSE) or percent of normalized root mean square error (RMSEn), index of agreement (d) (Willmott et al., 1985), and coefficient of determination (R^2) which is used for evaluating the goodness of fit between the observed and simulated values. Low values of RMSE and RMSEn, as well as d-values and R^2 close to unity is desired to define a good fit. The general formulas are summarized as:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\mathrm{Pi} - \mathrm{Oi})^2}{N}} \tag{3}$$

$$RMSEn = \frac{100}{\bar{\mathrm{O}}} \sqrt{\sum_{i=1}^{n} \frac{(\mathrm{Pi} - \mathrm{Oi})^2}{N}} \tag{4}$$

N was the number of observed values, Oi was observed, Pi was predicted values for the ith data pair, and Ō was the overall mean of observed values. RMSEn (%) gives a measure of relative difference of simulated versus observed data. The index of agreement (d-static) provides a single index of model performance that encompasses bias and variability. The d-statistic was computed as:

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(Pi - Oi)^2}{\sum_{i=1}^{n}(|Pi'| + |Oi'|)^2}\right] \tag{5}$$

where d was 0<d<1, and n number of observations, Pi was predicted value for the ith measurement, and Oi observed value for the ith measurement. Pi'= Pi - Ō and Oi'= Oi - Ō. Finally, the simulations of yield and phenology have been examined by considering the CO_2 concentration (AgMIP, 2012). These carbon dioxide concentrations at baseline and each time period of 2030, 2050 and 2080 under RCP4.5 and RCP8.5 scenarios are shown in Tables 3 and 4. Similarly, the recommended fertilizer level, that is, 1.61 qt ha^{-1} Urea and 1.00 qt ha^{-1} DAP were applied. The calibration, validation as well as the simulation process was done with the nitrogen and water balance routine in model of DSSAT v 4.7.

RESULTS AND DISCUSION

Climate change projection

Future climate were downscaled at local level by using

Table 3. Mean change in projected climate between baseline (1983-2015) and future (2030-2080) under RCP4.5 in Adet, North Western Ethiopia.

Time slice	CO_2 concentration (ppm)	RF (%)	Max. Temp (°C)	Min. Temp (°C)
	RCP4.5	RCP4.5	RCP4.5	RCP4.5
2030	423	1	2.72	2.86
2050	449	2.16	2.11	2.16
2080	532	-0.35	2.69	2.86

Table 4. Mean change in projected climate between baseline (1983-2015) and future (2030-2080) under RCP8.5 in Adet, North Western Ethiopia.

Time slice	CO_2 concentration (ppm)	RF (%)	Max. Temp (°C)	Min. Temp (°C)
	RCP8.5	RCP8.5	RCP8.5	RCP8.5
2030	432	2.47	1.04	0.93
2050	571	2.92	2.76	2.51
2080	801	5.36	4.69	4.73

Table 5. Genetic coefficients for wheat in model and estimation results for both varieties in Adet, North Western Ethiopia.

Symbol	Minima in model	Maxima in model	Tay variety (ET-12D4/HAR-604)	Senkegna variety (HAR-3646)
P1V	0	60	9	10
P1D	0	200	25	31
P5	100	999	727	745
G1	10	50	42	41
G2	10	80	45	52
G3	0.5	8	2.8	2.3
PHINT	30	150	139	135

Equations 1 and 2 and then further analyzed by using R analytical tool. The relative changes of future rainfall and temperatures comparing to the baseline period (1983-2015), and the corresponding CO_2 concentration at each time period are shown in Tables 3 and 4 for RCP4.5 and 8.5, respectively. The temperatures for 2030-2080 is expected to rise in the ranges of 2.11-2.72 and 2.16-2.86°C in maximum and in minimum temperature, respectively, while the rainfall increase by 1 to 2.16% in 2030 to 2050, but decrease by 0.35% in 2080s under RCP4.5 (Table 3). Similarly, for RCP8.5, maximum and minimum temperatures showed increase in the range of 1 to 4.6°C and 0.93 to 4.73°C, respectively, and the rainfall showed increase by 2 to 5% in 2030 to 2080 time periods (Table 4). The positive change in temperature indicates it will be warmer than today. IPCC (2014a) indicated that large scale increase in average temperature in the mid and late 21st century. If the increasing temperature is not offset by adequate moisture, the intensity and duration of drought might increase, and results in failure of bread wheat production. For instance, wheat yield has been predicted to decrease approximately 3 to 4% for each 1°C rise in temperature above 15°C during the grain filling period (Wardlaw and Wrigley, 1994). You et al. (2009) carried out research in China and found out that an increase in temperature of 1°C during the growing period may lead to yield reduction by 3 to 10%. Flato et al. (2013) noted, future climate projection is quite uncertain and the output depends on the number and type of climate models used.

Model calibration

The parameters for the specific crop are shown in Table 5. During the model calibration, the crop developments or phenologies were more sensitive to the genetic coefficients of P1V, P1D, and P5; crop growth or yield attributes were more sensitive to G1, G2, and G3 coefficients.

The calibration results are satisfactory as depicted in Table 6. Strong agreement is shown between the

Table 6. Statistical indicators during model calibration for both bread wheat varieties in Adet, North Western Ethiopia.

Statistical parameter	Senkegna variety			Tay variety		
	Anthesis day	Yield (qt ha^{-1})	Maturity day	Anthesis day	Yield (qt ha^{-1})	Maturity day
Observed	66	36.7	120	69	36.5	119
Simulated	70	29.1	120	73	28.7	122
R^2 (%)	75	92	75	96	79	79
d-stat (%)	51	62	76	57	60	52
RMSE	4	7.3	1.3	4	8.2	3
RMSEn (%)	6.8	19.8	1	6.1	22.5	2.6

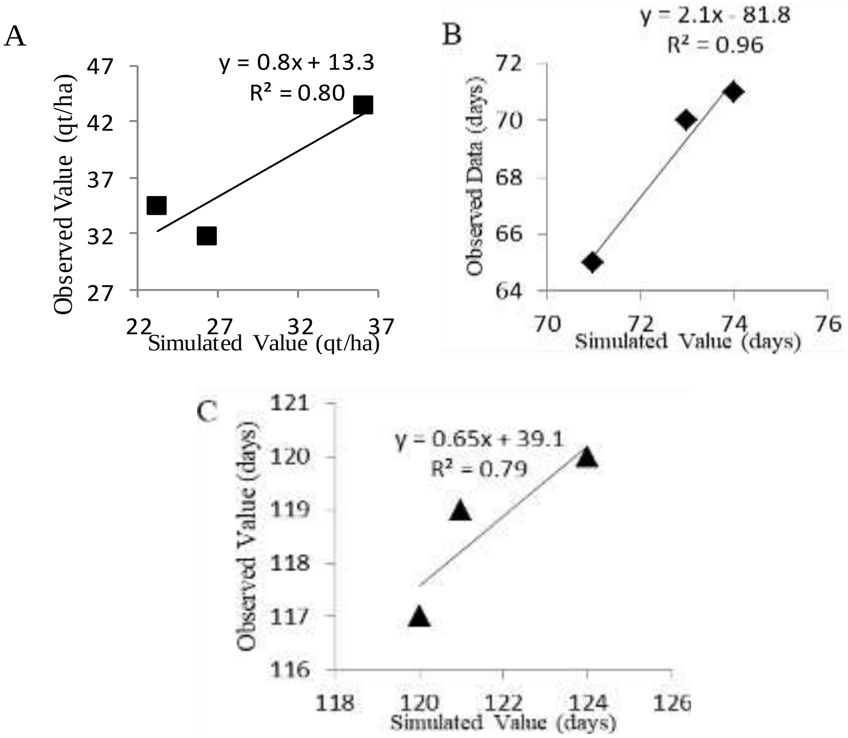

Figure 2. Relationship between simulated and observed value of grain yield (A), days to anthesis (B), and days to maturity (C) in calibration for Tay bread wheat variety.

simulated and observed values with R^2 of 96, 79 and 79% for days to anthesis, days to maturity, and maturity yield, respectively for Tay wheat variety, 75% for days to anthesis, 75% for days to maturity, and 92% for maturity yield for Senkegna wheat variety. The overall performance for Tay wheat, the simulation of days to anthesis, was found to be good as compared to the yield and maturity days, and there was good agreement.

The regression coefficients, that is, 0.8 for grain yield, 2.1 for days to anthesis and 0.65 for days to maturity indicated a good association between observed and simulated values for Tay wheat variety (Figure 2). Similarly, for Senkegna wheat, the regression coefficients of 0.67, 1.5 and 0.37 for grain yield, days to anthesis and days to maturity, respectively showed strong association between the observed and simulated values (Figure 3). The 1:1 line graph showed observed yield in Y-axis and simulated yield in X-axis. The amount of R^2 resulted from analysis of linear regression of the functions closer to 1, which indicates the model description for yield simulation is better (Reza et al., 2005).

Model validation

As depicted in Table 7, the validation results are also satisfactory. The model had strong performance for Tay wheat during model evaluation with the goodness of fits

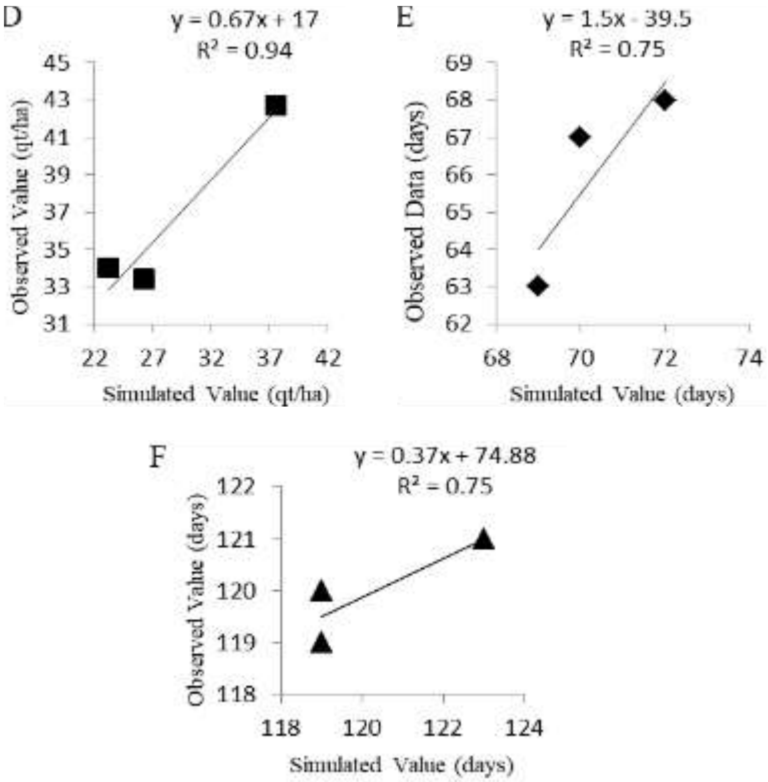

Figure 3. Relationship between simulated and observed value of grain yield (D), days to anthesis (E), and days to maturity (F) in calibration for Senkegna bread wheat variety.

(R^2) as 86, 70 and 96% for anthesis day, grain yield and maturity days, respectively, while 89, 82 and 75% for anthesis day, grain yield, and maturity days, respectively for Senkegna wheat. The corresponding observed index agreement statistics (in Equation 5) also supports the same results for days to anthesis and days to maturity (d>51%), but lower for grain yield (d=42%) for Tay wheat, and good agreement for all parameters ranged between 52 and 76% for Senkegna wheat. Table 7 also shows the RMSEn (in Equation 4) indicated the excellent agreement between simulated and observed value by 4.1% for anthesis days, fair agreement by 20.2% for grain yield, and good agreement by 12.5% for physiological maturity for Tay wheat (Valizadeh et al., 2013). Similarly, the RMSEn for Senkegna wheat showed excellent agreement by 6.2 1.4% for days to anthesis and grain yield, respectively while good agreement for days to maturity by 17.8% (Valizadeh et al., 2013). The study showed high RMSEn for grain yield as compared to other parameters, and revealed low in model performance (Table 7). Rezzoug et al. (2008) used DSSAT model to calibrate and validate 9 wheat cultivars in Algeria, and predicted final yield with RMSE of 7.6 qt ha^{-1} and R^2 of 0.71.

Therefore, well calibrated and validated CERES-wheat model can be ready for applications such as prediction of crop growth, phenology, water management, potential and actual yields, and generating agronomical adaption options.

Simulation of yield and phenology under future climate

The yields of both wheat varieties in response to future climate are expected to increase from 2030 to 2050, except in 2080s under RCP4.5 for Tay wheat (Table 8). However, the days to anthesis and days to maturity of both wheat varieties become decline. Wheat yield and growth are influenced by CO_2. For instance, doubling of ambient CO_2 has been reported to cause an approximate 40% decrease in stomatal space, which may reduce transpiration by 23 to 46% (Cure and Acock, 1986; Morison, 1987), and might cause a 10 to 50% increase in growth and yield of C_3 crops. Similarly, doubling of CO_2 concentration enhances photosynthetic rate of leaves by 25 to 50% and adds up to the increase in photosynthetic yielding and plant productivity up to 30 to 60% (Mulholland et al., 1997). On the contrary, for each temperature increase in mean air temperature during grain filling in wheat, the duration of grain filling was shortened by 3.1 days and final kernel weight was

Table 7. Statistical indicators of model performance of wheat in Adet, North Western Ethiopia.

Statistical parameter	Senkegna variety			Tay variety		
	Anthesis days	Yield (qt ha^{-1})	Maturity day	Anthesis days	Yield (qt ha^{-1})	Maturity days
Observed	67	32.4	119	65	34.1	116
Simulated	70	27.1	120	72	28	121
R^2 (%)	0.89	0.82	0.75	0.86	0.7	0.96
d-stat (%)	0.47	0.51	0.84	0.51	0.42	0.52
RMSE	4.2	5.7	1.5	8	6.9	5
RMSEn (%)	6.2	17.8	1.4	12.5	20.2	4.1

Table 8. Days to anthesis (DTA), maturity (DTM) and grain yield of Tay and Senkegna bread wheat varieties under baseline and future climate in Adet, North Western Ethiopia.

Scenario	Tay variety			Senkegna variety		
	DTA	DTM	Yield (qt ha^{-1})	DTA	DTM	Yield (qt ha^{-1})
Baseline	70	119	38.20	71	121	38.79
RCP4.5_2030	66	112	39.05	67	114	39.43
RCP4.5_2050	62	106	38.25	63	108	39.23
RCP4.5_2080	60	102	38.48	61	104	39.78
RCP8.5_2030	66	112	38.81	67	114	39.18
RCP8.5_2050	61	103	38.47	62	105	39.68
RCP8.5_2080	55	94	36.10	56	95	39.11

DAT: Days to anthesies, DAM: days to maturity.

reduced by 2.8 mg (Wiegand and Cuellar, 1981). These results suggest that an increase in temperature may offset the benefits of increasing CO_2 on crop yield. Wolf et al. (2005) reported that temperature increase would result in yield reduction whereas increase in the level of precipitation and CO_2 fertilization would have positive impact on the production of wheat in Europe. As shown in Table 3, the CO_2 concentration is increasing. Thus, the elevated CO_2 increases carbohydrate pools of leaves and stems, and finally to grain yield (Attri and Rathore, 2003). Evidence wheat production will increase by 25% in Mexico region (Lobell et al., 2005), and increase by 3.1 and 4% at low high altitude, respectively up to 2030s (Xiao et al., 2005).

Grain yield variability under the baseline and future climate

For Tay wheat variety, 25% of the yield results ranged between 32 and 34 qt ha^{-1} and 75% of the yield results ranged between 41 and 44 qt ha^{-1} in time horizon of 2030 to 2080 under both RCPs (Table 9). For Senkegna wheat variety, 25% of the yield results ranged between 34 and 39 qt ha^{-1}, and 75% of the yield results ranged between 42 and 45 qt ha^{-1} in time horizon of 2030 to 2080 under both RCPs (Table 10). The variability of yield (coefficients of variations ranged between 14 and 17%) under baseline and future climate showed less varied thought, the time period for both bread wheat varieties (Hare, 1983).

Conclusion

The study involved through calibrating and validating of the model and simulating of wheat yield and phenology under baseline and future climate. The overall calibration and validation of CERES-wheat model has good agreement between the observed and simulated value of days to anthesis, days to maturity and yield and for both wheat varieties and revealed suitable further applications, such as in prediction of crop growth, phenology, potential and actual yields. Although future climate changes have positive and negative impact on Tay wheat, the grain yield will increase relative to the baseline for both wheat varieties. On the other hand, the simulation days from planting to flowering and to maturity of the two wheat varieties were reduced.

LIMITATIONS

The general aim of the CERES- wheat model calibration and validation study was to bring the model performance in approach to 100% agreement and applicable for further agricultural decision making for the particular crop varieties in the specific environment including this study.

Table 9. Variability grain yield (qt ha^{-1}) for Tay wheat at different time slice under RCP4.5 and RCP8.5 scenarios in Adet, North Western Ethiopia.

Statistical parameter	Baseline	RCP4.5			RCP8.5		
		2030	2050	2080	2030	2050	2080
Minimum	30.57	31.02	31.21	26.11	30.21	27.80	18.03
1st quadrant	32.89	32.97	33.84	33.68	32.66	33.26	33.48
Median	36.82	37.86	36.61	37.48	37.63	37.97	35.39
3rd quadrant	42.81	43.60	41.67	43.75	43.59	43.12	40.08
Maximum	49.13	49.19	50.14	49.48	49.77	49.05	45.42
Mean	38.20	39.05	38.25	38.48	38.81	38.47	36.10
SD	59.7	6.11	5.70	5.95	6.49	5.98	5.37
CV (%)	15.6	15.6	14.9	15.5	16.7	15.5	14.9

Table 10. Variability of grain yield (qt ha^{-1}) for Senkegna whea at different time slice under RCP4.5 and RCP8.5 scenarios in Adet, North Western Ethiopia.

Statistical parameter	Baseline	RCP4.5			RCP8.5		
		2030	2050	2080	2030	2050	2080
Minimum	29.37	31.03	31.10	29.08	30.12	28.70	22.89
1st quadrant	33.26	34.81	33.49	39.43	32.96	33.47	34.75
Median	36.73	39.30	38.21	38.24	37.97	38.41	38.80
3rd quadrant	43.85	44.57	42.08	42.20	44.68	44.85	43.34
Maximum	51.15	49.94	51.41	51.28	50.26	50.36	49.57
Mean	38.79	39.43	39.22	39.78	39.18	39.68	39.11
SD	6.47	6.14	6.6	6.55	6.72	6.63	5.86
CV (%)	16.7	15.6	16.8	16.5	17.2	16.7	15.0

However, this might be achieved as a result of high quality data, which was obtained from well managed fields and well calibrated model used.

RECOMMENDATION

Crop models need reliable data inputs and able to generate more relevant climate information for decision making and adaptations measurements in agriculture. Therefore, building of data archive capacity, such as network of weather stations, soil database, and crop phenological observation should be established in order to promote soil-crop-climate research.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

ACKNOWLEDGMENT

The author hereby express hissincere gratitude to Dr. Mezgebu Getnet, Dr. Lisanework Nigatu and Mr. Fasil Mekuanent for their valuable advice and self dedication to the excellence and quality of this work.

REFERENCES

Adet Agricultural Research Center (AARC) (2006). Soil of Adet Agricultural Research Center and its testing sites. National Soil Research Center, Soil Survey and Land Evaluation Section. P. 85.

Aggarwal PK, Kalra N, Singh AK, Sinha SK (1994). Analyzing the limitations set by climatic factors, genotype, water and nitrogen availability on productivity of wheat I. The model description, parametrization and validation. Field Crops Research. 38(2):73-91.

Aggarwal PK, Banerjee B, Daryaei MG, Bhatia A, Bala A, Rani S, Chander S, Pathak H, Kalra N (2006). Infocrop: A Dynamic Simulation Model for the Assessment of Crop Yields, Losses Due to Pests and Environmental Impact of Agro-Ecosystems in Tropical Environments. II. Performance of the Model. Agricultural Systems 89:47-67.

AgMIP (2013a). Guide for running AgMIP climate scenarios generation tools with R in windows. AgMIP, New York.

AgMIP (2013b). The coordinated climate crop modeling project C3MP: an initiative of the agricultural model itercopmarison and improvement project C3MP protocols and procedures. AgMIP, New York.

AgMIP (2012). Guide for Regional Integrated Assessments: Handbook of Methods and Procedures. Version 4.

AgMIP (2013c). Guide for regional integrated assessments; handbook of methods and procedures, version 5. Center for Climate Systems Research, Earth Institute, Columbia University, AgMIP, New York.

Agnew CT, Chappel A (1999). Drought in the Sahel. GeoJournal 48:299-311.

Attri SD Rathore LS (2003). Simulation of impact of projected climate change on wheat in India. International Journal of Climatology 23:693-705.

Belayneh A (2011). Economic implications of climate change in Ethiopia: a computable general equilibrium analysis. Dissertation for Award of MSc Degree at Addis Ababa University, Addis Ababa, Ethiopia P. 84.

Cure JD, Acock B (1986). Crop responses to carbon dioxide doubling a literature survey on Agricultural and Forest Meteorology 38:127-145.

Dereje A, Kindie T, Girma M, Birru Y, Wondimu B (2012). Variability of rainfall and its current trend in Amhara Region, Ethiopia. African Journal of Agricultural Research 7(10):1475-1486.

Flato G, Marotzke J, Abiodun B, Braconnot P, Chou SC, Collins W, Cox P, Driouech F, Emori S, Eyring V, Forest C, Gleckler P, Guilyardi E, Jakob C, Kattsov V, Reason C, Rummukainen M (2013). Evaluation of climate models. In climate change. The physical science basis. Contribution of working group I to the fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, P. 866.

Fowler HJ, Blenkispo S, Tebaldi C (2007). Link in climate change modeling to impacts studies: recent advances in downscaling technology for hydrological modeling. Review International Journal of Climatology 27:1547-1578.

Habtamu A, Mezgebu G, Timothy ST, Michael W Miriam K (2012). East African agriculture and climate change: A comprehensive analysis-Ethiopia. International Food Policy Research Institute (IFPRI), ASARECA, CGIAR P. 25.

Hare FK (1983). Climate and Desertification. Revised analysis (WMO-UNDP) WCP, Geneva, Switzerland 44:520.

Hassan ZB (2012). Climate Change Impact on Precipitation and Streamflow in a Humid Tropical Watershed. .https://core.ac.uk/display

Hoogenboom G, Jones JW, Wilkens PW, Porter CH, Boote KJ, Hunt LA (2010). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5, Honolulu, University of Hawai, CD ROM.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens P, Singh UK, Gijsman AJ, Ritchie JT (2003a). The DSSAT cropping system model. European Journal of Agronomy 18(3-4):235-265

Jones JW, Naab JB, Fatondji D, Dzotsi K, Adiku S, He J (2010). Uncertainties in simulating crop performance in degraded soils and low input production systems. In Fatondji D, C. Martius, C. Bielders, P. Vlek, A. Bationo, B. Ge´rard. (2006), eds, Water Productivity in African Cropping Systems. https://link.springer.com

Kidane G (2010). Agricultural based livelihood systems in drylands in the context of climate change. Inventory of adaptation practices and technologies of Ethiopia, Ethiopian Institute of Agricultural Research in collaboration with Environmental Sustainability P. 112.

Lobell David B, Ortiz-Monasterio JI, Asner PG, Matson PA, Naylo RL, Falcon, WP (2005). Analyses of wheat yield and climate trends in Mexico. Field Crops Research 94: 250-256.

Madsen H, Wilson G, Ammentorp HC (2002). Comparison of different automated strategies for calibration of rainfall-runoff models. Journal of Hydrology 261:48-99.

Mavromatis T, Boote KJ, Jones JW, Irmak A, Shinde D, Hoogenboom G (2001). Developing genetic coefficients for crop simulation models with data from crop performance trials. Crop Science 41:40-51.

Morison JIL (1987). Intercellular concentration and stomatal response to CO_2. In Stomatal Function, Zeiger E, Cowan IR, Farquhar GD (eds). Standford University Press pp. 229-251.

Mulholland BJ, Craigon J, Black CR, Colls JJ, Atherton J, Landon G (1997). Effects of elevated carbon dioxide and ozone on the growth and yield of spring wheat (*Triticum aestivum* L). Journal of Experimental Botany 48(306):113-122.

Osman M, Sauerborn P.2002. A Preliminary Assessment of Characteristics and Long Term Variability of Rainfall in Ethiopia Basis for Sustainable Land Use and Resource Management. In Challenges to Organic Farming and Sustainable Land Use in the Tropics and Subtropics, Deutscher Tropentag 2002: Witzenhausen.

Reza ESA, Gholipour M, Azad HH (2005). SBEET: A simple model for simulating sugar beet yield. Journal of Agricultural Science and Technology 19:11-12.

Rezzoug W, Gabrielle B, Suleiman A, Benabdeli K (2008). Application and evaluation of the DSSAT-wheat in the Tiaret region of Algeria. African Journal of Agriculture Research 3:284-296.

Research Instituite for Dryland Agriculture (RIDA) (2011). Crop Weather Modeling Lecture Note, Subrahmanyanagar Saidabad colony, HYDERABAD-500059, e-mail: psnsastry36@gmail.com. /P.S.N. Sastry, 17-1-391/17.

Ringler C, Zhu T, Cai X, Koo J, Wang D (2010). Climate Change Impacts on Food Security in Sub -Saharan Africa. IPFPRI.

Ritchie J, Singh U, Godwin D, Bowen W (1998). Cereal growth, development and yield. In understanding options for agricultural production. Academic publishers: Dordrecht P 98.

Rosenzweig C, Liverman D (1992). Predicted Effects of Climate Change on Agriculture: A Comparison of Temperate and Tropical Regions. In: Majumdar, S.K., Ed., Global Climate Change: Implications, Challenges, and Mitigation Measures, the Pennsylvania Academy of Sciences, PA, pp. 342-361.

Rosenzwig C, Ruane AC, Winter JM, Boote KJ, Porter C, Jones J, Wasseng S, Hatfield L, Tharburn P, Antle LM, Nelson GC, Janssen S, Basso B, Ewert F, Wallach D, Baigorria G (2013). The agricultural model intercoparsison and improvement project (AgMIP): protocols and pilot studies. Agriculture for Meteorology 170:166-182.

Schulthess U, Feil B, Jutzi SC (1997). Yield independent variation in grain nitrogen and phoshororus concentration among Ethiopian wheat. Agronomy Journal 89(3):497-506.

Valizadeh J, Ziaei SM, Mazloumzadeh SM (2013). Assessing climate change impacts on wheat production (a case study). Journal of the Saudi Society of Agricultural Sciences 13(2):107-115.

Wardlaw IF, Wrigley CW (1994). Heat tolerance in temperate cereals: an overview. Australia Plant Physiology 21:695-703.

White JW, Hoogenboom G, Kimball BA, Wall GW (2011). Methodologies for Simulating Impacts of Climate Change on Crop Production. Field Crops Research 124:357-368.

Wiegand CL, Cuellar JA (1981). Duration of grain filling and kernel weight of wheat as affected by temperature. Crop Science 21:95-101.

Willmott CJ, Akleson GS, RE, Davis JJ, Feddema KM, Klink DR (1985). Legates, J. Odonnell, and C. M. Rowe, 1985: Statistics for the evaluation and comparison of models. Journal of Geophysical Research 90:8995–9005.

Woldeamlak B (2009). Rainfall variability and crop production in Ethiopia; Case study in the Amhara region; proceeding of the 16th International conference of Ethiopian Studies, Addis Ababa.

Wolf J, Even J, Evans LG, Semenov MA, Eckersten H, Iglesias A (1996). Comparison of wheat simulation models under climate change. I. Model caliberation and sensitivity analyses. Climate Research 7:253-270.

Xiao Guojo, Zhang Qiang, Yao Yubi, Zhao Hong, Wang Runyuan. 2008. Impacts of recent climatic change on yield of winter wheat at low and high altitude in semiarid northwestern China. Agriculture, Ecosystems and Environment 127:37-42.

You L, Rosegrant MW, Wood S, Sun D (2009). Impact of growing season temperature on wheat productivity in China. Agriculture for Meteorology 149:1009-1014.

Yumbya J, Kiambi D, Kebebew F, Rao KPC (2011). Climate Change Effects on Teff Geographic Ranges and Its Impacts on Yield. Poster, African Biodiversity Conservation and Innovations Centre (ABCIC), Kenya 1 p.