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Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia

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ABSTRACT

Maize yield productivity in Ethiopia has been below the genetic potential—constrained, among other factors, by frequent moisture stress due to local weather variability. Changes in climate may exacerbate these limitations to productivity, but current research on projecting responses of maize yields to climate change in Ethiopia is inadequate. The research objectives of this project were to (1) calibrate and evaluate the performance of the APSIM-maize and DSSAT CSM-CERES-Maize models, and (2) assess the impact of climate change on future maize yield. The climate periods considered were near future (2010–2039), middle (2040–2069) and end of the 21st century (2070–2099). Climate simulations were conducted using 20 General Circulation Models (GCMs) and two Representative Concentration Pathways (RCPs; RCP4.5 and RCP8.5). Both crop models reasonably reproduced observations for time to anthesis, time to physiological maturity and crop yields, with values for the index of agreement of 0.86, 0.80 and 0.77 for DSSAT, and 0.50, 0.89 and 0.60 for APSIM. Similarly root mean square errors were moderate for days to anthesis (1.3 and 3.7 days, for DSSAT and APSIM, respectively), maturity (4.5 and 3.1 days), and yield (1.1 and 1.2 tons). Deviations of simulated from observed values were low for days to anthesis (DSSAT: −2.4–2.3%; APSIM: 0–6%) and days to maturity (DSSAT: −0.6–4.4%; APSIM: −1.9–3.3%) but relatively high for yield (DSSAT: −18.5–21.2%; APSIM: −19.1–37.1%). Overall the goodness-of-fit measures indicated that models were useful for assessing maize yield at the study site.

Simulations for future climate scenarios projected slight increases in the median yield for the near future (1.7%–2.9% across models and RCPs), with uncertainty increasing toward mid-century (0.6–4.2%). By the end of the 21st century, projections ranged between yield decreases by 6.3% and increases by 4%. Differences between the RCPs were small, probably due to factor interactions, such as higher temperatures reducing the CO_2-induced yield gains for the higher RCP. Uncertainties in studies on the impact of climate change on maize might arise mostly from the choice of crop model and GCM. Therefore, the use of multiple crop models along with multiple GCMs would be advisable in order to adequately consider uncertainties about future climate and crop responses and to provide comprehensive information to policy makers and planners. Overall, results of this study (based on two different crop simulation models across 20 GCMs, and two RCPs under similar crop management) consistently indicated a slight increase in yield.

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1. Introduction

Anthropogenic emissions of greenhouse gases are changing the earth's climate. This is expected to lead to increasing temperatures, changes in rainfall regimes and increased frequencies of extreme weather events (IPCC, 2007a, 2009; Jon, 2009). Besides, ecological

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systems will also be directly affected by higher atmospheric carbon dioxide levels (IPCC, 2007a,b).

Projected climate change is expected to have a severe impact on agriculture (IPCC, 2007a, 2009). Farmers in Sub-Saharan Africa (SSA) are at risk because of the rainfed nature of most farming systems and the general fragility of many rural societies that already struggle to produce sufficient food even under the current climate. Crop productivity in SSA is expected to decline under future climate in most places (Jones and Thornton, 2009). Ethiopia, in particular, has experienced frequent droughts and other climate extremes over the past decades, and these conditions are often accompanied by serious shortfalls in food supply (Araya and Stroosnijder, 2011; Conway and Schipper, 2011; Demeke et al., 2011; Araya et al., 2012). It is likely that Ethiopian farmers, many of whom are currently food insecure, will suffer from changes in rainfall patterns and increasing temperature (Deresa, 2006).

Maize (*Zea mays* L.) is one of the major food crops in Ethiopia, both in terms of the area it covers and the overall amount of production (CSA, 2011). Maize can grow at higher temperatures compared to many other cereals and may therefore be a suitable crop for warmer conditions. Maize is well adapted to well-drained soils (Landon, 1991) but sensitive to water stress (Doorenbos and Kassam, 1979), making its likely success under future climates depend to a large extent on the future rainfall conditions.

The variety 'BH-660' is one of the dominant improved late maturing maize varieties grown in southern and southwestern Ethiopia, at low to mid altitude (1500 to 1800 m above sea level). In order to attain its maximum yield, the cultivar requires adequate rainfall over its growth duration of at least 800 mm. As the crop is highly dependent on rainfall, small changes in rainfall distribution or amount could potentially affect maize productivity under future climate. Yield gap assessments are needed to supply policy makers with information to develop appropriate plans in order to reduce the negative impacts of climate change and improve the ability of agricultural systems to meet future food demand (Lv et al., 2015).

One source of uncertainty regarding climate change impact is uncertainty about the most appropriate choice of climate model and greenhouse gas emissions scenario. It is assumed that actual climate change will fall within the range of future conditions predicted by different climate models (Meehl et al., 2007; Wilby et al., 2009; HLPE, 2012; Asseng et al., 2013; Challinor et al., 2013). Impact assessments should, therefore, be based on multi-model climate projections, which are assumed to provide a more representative range of climate change impacts than single-model approaches (Diekkrüger et al., 1995; Meehl et al., 2007; Hanson et al., 2004; Kersebaum et al., 2007; Tao et al., 2009; Taylor et al., 2009).

Crop models are useful tools for translating weather scenarios into agricultural responses such as crop yield (Challinor et al., 2013). Various process-based dynamic crop models are available across the world. After careful calibration and evaluation, they allow exploration of crop performance under a range of soil, climate and management scenarios, and to predict the likely impacts of climate change on food production (AgMIP, 2012; Rosenzweig et al., 2013; Ruane et al., 2013). Crop yield projections with multiple climate scenarios and multiple crop models at a site where all other major parameters of the cropping system are known provides an opportunity to compare how the choice of crop model and climate scenario impacts expected crop yield (White and Hoogenboom, 2010; Asseng et al., 2013; Rosenzweig et al., 2013; Ruane et al., 2013). It also allows to explore and quantify the range of yield uncertainty as well as to understand our present capabilities or failures in predicting the impacts of climate change (White et al., 2011; AgMIP, 2012; Challinor et al., 2013).

Detailed maize climate change impact assessment studies that address major maize growing areas of the southwestern midlands of the sub-humid agro-ecologies of Ethiopia are limited. Studies exist at the scale of sub-Saharan Africa (e.g. Cairns et al., 2013) and some are focused on the Central Rift Valley of Ethiopia whose climate is very different from southwestern Ethiopia (e.g. Kassie et al., 2015). Other studies have mostly focused on economic aspects rather than crop responses (e.g. Mideksa, 2010). One reason why climate impact projections are difficult for Ethiopia is that future rainfall patterns in Ethiopia are not clear, and projections differ even in the direction of change (Conway and Schipper, 2011). Thus, unlike previous studies, we present an analysis of climate change impacts on maize yield based on 20 General Circulation Models (GCM), two Representative Concentration Pathways (RCPs) and two crop models for three time scenarios (near future, mid and end century), considering farm survey information from 200 maize growing farmers in the sub-humid areas of southwestern Ethiopia.

The objectives of this study were to (1) calibrate and evaluate the APSIM and DSSAT-CSM crop models; and (2) assess the impact of climate change on maize yield using climate simulation outputs from 20 different GCMs under high and moderate RCP scenarios for southwestern Ethiopia.

2. Materials and methods

2.1. Study site

The study site was the Bako National Maize Research Center (BNMRC) located in the sub-humid agro-climatic zone of southwestern Ethiopia. BNMRC is located at lat. 09° 06′N and long. 37°09′E. The altitude of the study site ranges between 1550 and 1750 meters above sea level with undulating topography in which many agroforestry tree species are grown scattered on farmlands. This region features some of the major maize growing areas in Ethiopia. Most farmers practice traditional maize—livestock mixed farming, with both maize and livestock production critical for their livelihoods. Rainfall follows a unimodal pattern, which allows production of a 150-day maize crop. Long-term mean annual rainfall and reference evapotranspiration were approximately 1246 mm and 1790 mm, respectively, while the annual mean daily maximum and minimum temperature were 28.0 °C and 13.7 °C, respectively.

2.2. Data collection

2.2.1. Climatic data and scenarios

Long-term (1980–2009) daily records of rainfall, maximum temperature ($T_{\max}$), minimum temperature ($T_{\min}$) and solar radiation were obtained from Ethiopia's National Meteorological Agency (NMA). Daily reference evapotranspiration (ET_o) (1980–2009) was computed based on Hargreave's equation, since a full climate data set was unavailable (Allen et al., 1998). Fig. 1 shows the long-term (1980–2009) daily mean rainfall versus daily reference evapotranspiration, daily mean maximum and minimum temperature of the study area.

Future climate scenario analysis was based on thirty years (1980–2009) of weather data from Bako's weather station that included daily rainfall, minimum temperature, maximum temperature and solar radiation. Less than 5% of the rainfall and temperature values were missing. To fill the gaps in the daily weather data, background daily weather time series were obtained from the global bias shifted Modern Era Retrospective—Analysis for Research and Application (MERRA) dataset which was provided by AgMIP (2013a,b), Ruanea et al. (2015) climate team. Simple interpolations were also used to fill short data gaps (less than 4 days) from neighboring good values. Site-specific climatic scenarios were generated using the CMIP5 GCM delta scenario technique with climate

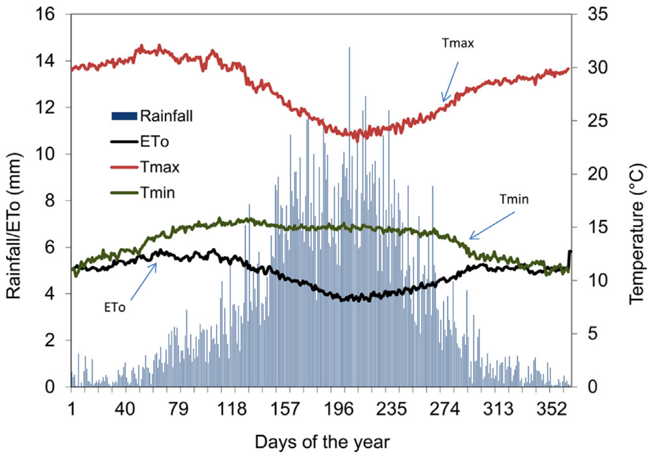

Fig. 1. Long-term (1980–2009) daily mean rainfall versus daily mean reference evapotranspiration, maximum and minimum temperature for Bako area, south-western Ethiopia.

scenario generation tools ("R" scripts were used to prepare delta based climate scenarios of the study area in formats required by APSIM and DSSAT) as presented in the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Wilby et al., 2004; AgMIP, 2013a,b; Ruane et al., 2013). The technique produces climate scenarios by adjusting historically observed weather records at a given site according to changes in precipitation, minimum temperature and maximum temperature predicted by climate model runs. This adjustment is based on predicted absolute changes in temperatures and relative changes in precipitation (Wilby et al., 2004; Ruane et al., 2013). Future climate projections for Bako were obtained from 20 General Circulation Models (GCMs) for near future (2010–2039), mid (2040–2069) and end of the 21st century (2070–2099) scenarios under two RCPs (4.5 and 8.5) using the methodology developed by AgMIP (AgMIP, 2013a,b).

Detailed descriptions of RCPs and their equivalent representation for atmospheric CO_2 concentrations are available in Moss et al. (2010) and Wayne (2013). In our case, the corresponding carbon dioxide concentration under RCP4.5 and 8.5 for each AgMIP middle year of the three future period scenarios were adopted (AgMIP, 2012). The fixed AgMIP central year CO_2 assumptions were then entered into the AgMIP seasonal strategy template, which was used to set up conditions for multi-year scenarios (along with other files that include information such as cultivar, management, climate, soil and other assumptions). They were then converted into model input formats as required by APSIM and DSSAT with the help of AgMIP tools (ADA and QuadUI). This allowed crop models to use similar and consistent inputs for climate change impact assessment.

2.2.2. Soils

Soil survey results showed that the soil was a deep and moderately well drained Nitosol. The soil physical and chemical characteristics are presented in Table 1. The soils in the study area were reddish brown clay soils with a topsoil (0–0.25 m) bulk density of 1.06–1.15 g/cm^3 with organic carbon and total nitrogen contents (in the top 0. 25 m) of 1.6% and 1.8%, respectively.

2.2.3. Crop data

2.2.3.1. On-station data collection. Seasonal maize yield (12 years, 2000–2009 and 2010–2011), days to anthesis (7 years, 2002–2004; 2006–2009) and maturity (7 years, 2000, 2002–2004; 2007–2009) data were obtained from Bako National Maize Research Center (BNMRC). Multi-site BH-660 seasonal trials were carried out in some of the years. In such cases, average seasonal values of yield and phenological observations were taken. The experimental season in 2007 had multiple trials with marked yield differences. These trials were grouped into two data sets based on our assumption that difference in crop management during the growing season might result in yield difference. Trials that had higher yield levels were assumed to have received optimal management (for external yield reducing factors such as weeds, insect pests etc.) (set-I) whereas trials that had relatively lower yield levels were assumed to have not received optimal management (set-II). Those data sets (2007) that assumed to have received optimal management (set-I) were used for model calibration and those assumed to have not received were used for model evaluation.

2.2.3.2. On-farm survey. Farm survey was carried out in the Bako area during the cropping season of 2012. About 200 farms and farm households were surveyed. During the survey, interviews and focus group discussions were conducted with farmers, and results were disaggregated by age group (old vs. young). Management practices (planting date, planting density, fertilizer type, fertilizer quantity and harvest date), crop data (yield and phenology) and soil information (soil physical characteristics) were gathered. Planting dates often varied between the end of May and early June. Planting densities varied between 3.3 and 5.5 plants/m^2 with an average density of 4.4 plants/m^2. BH-660 was one of the major maize cultivars in the survey region. The majority of farmers applied low to moderate quantities of nitrogen (15 to 64 kg N/ha) while peak fertilizer doses ranged up to 300 kg N/ha. The average surveyed maize yield was about 3900 kg/ha. Weeds and insect pests were among major yield-reducing factors in the study site.

2.3. Crop water requirement

Mean seasonal rainfall, reference evapotranspiration, and temperature (maximum and minimum) for the baseline and future scenarios (for each GCM) were calculated. The Seasonal Rainfall-Evapotranspiration Index (SREI) was calculated for the future scenarios as the ratio of seasonal (May to Oct.) rainfall to seasonal reference evapotranspiration. Maize crop water requirement (ET_c) was estimated as the product of maize crop coefficient and evapotranspiration. Maize crop coefficient was obtained from Doorenbos and Kassam (1979), and the length of growing stages was obtained from field survey (baseline) and from crop model outputs (future scenarios). The estimation of maize crop water requirement for the near future, mid and end century was carried out considering two planting dates (1st of May and 1st of June). Water deficits and surplus were estimated by subtracting crop water requirement from effective rainfall. Effective rainfall (P_{eff}, in mm) was estimated as: $P_{eff} = [0.8 \times P_{tot}] - 24$ (FAO, 1992), based on monthly total rainfall (P_{tot}, in mm).

2.4. Crop models

2.4.1. DSSAT

The Cropping System Model (CSM) of DSSAT consists of a plant module, a soil module (that contains a soil water submodule, a soil organic carbon and a nitrogen sub module), a soil-plant atmosphere interface module, a weather module and an operation and management module. It also includes crop modules (the CERES, CROPGRO, CROPSIM and SUBSTOR modules) for simulating yield, development and growth of many different crops (Hoogenboom et al., 2010). The crop model simulates crop yield, growth and development based on some characteristics of the simulated crop: phenology, photoperiod, biomass accumulation as well as partitioning among its roots, stems and leaves, as defined by cultivar-specific genetic coefficients. For example, the set of genetic coefficients for the CSM-CERES-Maize in DSSAT, the maize module

Table 1
Soil physical and chemical characteristics of Bako area, southwesternEthiopia.

Depth (cm)	Clay (%)	Silt (%)	LL (mm/mm)	DU (mm/mm)	Saturation (mm/mm)	BD (g/cm^3)	OC (%)	TN (%)
0–25	50–60	14–18	0.2–0.26	0.33–0.36	0.35–0.40	1.0–1.15	1.6	0.15
25–50	60–66	10–12	0.2–0.26	0.30–0.33	0.35–0.40	1.0–1.15	0.09–0.2	0.07
50–99	60–66	10–12	0.2–0.26	0.30–0.34	0.35–0.40	1.0–1.15	0.09–0.2	0.07
100–209		–	–	0.18–0.32	0.35–0.41	1.0–1.15	0.09–8.5	–

Source: Birhanu (2011) and from field survey. LL, lower limit; DU, drained upper limit; BD, bulk density; OC, organic carbon; TN, total nitrogen.

used in this study (Hoogenboom et al., 2010), includes: duration in degree days from emergence to juvenile stage (P_1), photoperiod sensitivity coefficient (P_2), duration in growing degree days from silking to physiological maturity (P_5), maximum possible number of grains per head (G_2), potential kernel growth rate during the linear kernel filling phase, maximum kernel growth rate in mg/(kernel/d) and duration in degree days for a leaf tip to emerge (phyllochron interval (PHINT)) (Hoogenboom et al., 1999, 2010). The minimum data (weather, crop, soil and management etc.) needed for model calibration and evaluation, as well as further details on the model simulation process, have been presented by Hoogenboom et al. (2010, 2012).

2.4.2. APSIM

The Agricultural Production Systems Simulator (APSIM) is a farming systems model that consists of several modules integrated to perform farming systems simulation. The APSIM modeling structure includes biophysical modules, management modules, data input and output modules, and a simulation engine module (Keating et al., 2003). In APSIM, any module can be added by the user when needed and removed when no longer needed as described in Kirschbaum et al. (2001). Several modules and sub modules developed by many different researchers have been integrated into the APSIM framework for farm system analysis. APSIM simulates yield in response to inputs of daily weather, crop, soil and management practices (Keating et al., 2003). The minimum climate data requirements are maximum and minimum temperature, rainfall and solar radiation (Kirschbaum et al., 2001). APSIM uses two soil water balance approaches described by either SoilWat (a “cascading bucket” approach) or APSWIM (Richards' equation approach) (Kirschbaum et al., 2001). Further details on the APSIM model are provided by Keating et al. (2003).

2.5. Calibration and evaluation of CSM-CERES-Maize in DSSAT and APSIM-maize in APSIM

Crop models must be calibrated such that model parameters truly represent crop characteristics and crop responses to soil and atmospheric conditions. Calibration of both models was based on datasets of soil characteristics, climate and crop management, including planting density, sowing date, type and amount of fertilizer application (Table 2). Both DSSAT-CSM and APSIM were calibrated based on separate data set-I of the actual experimental phenology and yield data of the cultivar BH-660 obtained in 2007 from BNMRC (Table 3; Section 2.2.2). When calibrating the model, planting density was set to 4.4 plants/m^2; planting date was between 25th and 28th May, nitrogen was set to 110 kg/ha (based on BNMRC practice) and all other management conditions were considered nearly optimal as used by BNMRC, with the exception of water supply, since the maize crop was grown under rainfed conditions. The calibration of the crop characteristics was conducted for phenology first and then for yield. During the process of calibration, we found by trial and error that the cultivar ‘2750–2800 GDD’ in DSSAT best represented the general characteristics (anthesis, maturity and yield) of the experimental maize cultivar in Bako area (BH-660). In APSIM, the Dekalb_X182 cultivar was used as starting point for calibrating the experimental cultivar (BH-660). Calibration was carried out first by adjusting each phenological characteristic (emergence to end of juvenile, flowering to maturity etc.) and then followed by adjusting the growth and yield characteristics (grain growth rate, grain number, etc.) based on available measured or estimated data. After several iterations of adjustments, an APSIM cultivar emerged that satisfactorily reproduced the behavior of BH-660.

Table 2
Management data inputs used for BH-660 maize cultivar (for model calibration and evaluation) at Bako area, southwestern Ethiopia.

S.N	Parameter	Value
1	Lat.	9° 6′
2	Long.	37° 9′
3	Sowing start date	25-May
4	Sowing end date	08-Jun
5	Sowing depth	7 cm
6	Amount of rain for sowing	30 mm over 3 days
7	Minimum allowable soil water	45 mm
8	Initial water	80% field capacity from the top
9	PAW	129 mm
10	Plant density	4.4 plants/m^2
11	Row spacing	0.75 m
12	Starter fertilizer	(non limiting)
13	Fertilizer type	Urea
14	Amount of fertilizer required after sowing	(110 kg/ha)
15	Type of fertilizer	Urea
16	Stover removed	0.95
17	Initial NO_3 (PPM)	Default
18	Initial NH_4 (PPM)	Default
19	Prior crop residue	1000 kg/ha
20	Irrigation	None
21	General Assumption	optimal; no disease

Evaluation of a model is the process of comparing the simulated output by the model with the observed data. This includes evaluation of model performance using various statistical techniques. CSM-CERES-Maize in DSSAT v.4.5 (hereafter DSSAT) and the maize module in APSIM v.7.4 (hereafter APSIM) were used for simulating maize phenology and yield. A well controlled experimental dataset from 2007 was used for model calibration. For model evaluation, we used 10 years of maize yield data (2000–2009) and 7 years (anthesis, 2002–2004; 2006–2009, and maturity, 2000, 2002–2004; 2007–2009) of phenological data obtained from BNMRC. Experimental set-II of 2007 was included for model evaluation. Such use of separate evaluation data sets of the same year other than model calibration is not uncommon although not optimal (e.g. Kassie et al., 2014).

Sowing dates were set to the actual observed sowing dates in both models. The actual sowing dates slightly varied between years (14th of May to 10th of June). The observed grain yield and phenological data (days to anthesis and maturity) were compared with simulated yield and phenological data, respectively, across the observation years. Statistical and graphical tests were used to evaluate the performance of the models.

The following goodness-of-fit statistics were used to compare simulation output with observed data:

Table 3
Experimental observations used as model calibration data sets and their respective simulated values.

Cultivar name	Model	Year	Data set	Days to anthesis		Days to maturity		Yield (t/ha)	
				Observed	Simulated	Observed	Simulated	Observed	Simulated
BH-660	DSSAT (CSM-CERES-Maize)	2007	I	86	87	155	158	9.17	9.3
BH-660	APSIM (APSIM Maize)	2007	I	86	91	155	155	9.17	8.8

Planting date was on 25/05/2007.

Percent of deviation (D%)

$$D\% = \left[\frac{S_i - O_i}{O_i}\right] \times 100\%, \tag{1}$$

where S_i is the simulated yield (t/ha), and O_i is the observed yield (t/ha) in a given year. The percent of deviation indicates the deviation of yields simulated by the model from observed values. Percent of deviation close to zero indicates excellent agreement.

Index of agreement (I)

$$I = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|S_i - S_m\right| + \left|O_i - O_m\right|\right)^2}, \tag{2}$$

where I is the index of agreement; O_m and S_m are the means of observed and simulated values, and O_i and S_i are the corresponding observed and simulated values for a particular data set i. Values of I may vary from negative infinity to 1. Values closer to 1 indicate better agreement between simulated and observed yields. This goodness-of-fit I was proposed by Willmott (1982).

Root mean squared error (RMSE)

$$\text{RSME} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{3}$$

where S_i and O_i are the simulated and observed values in a given year i. The RMSE is a statistical indicator of model uncertainty (Eq. (3)). Values close to zero indicate excellent agreement and hence good performance of the model.

Evaluation of model performance using data from farmers' fields was not done as yields under farmers' conditions could be reduced by many factors such as weeds, pests and agronomic practices that differed from those at the experimental station. In addition, the interest in this study was to simulate impacts of climate change on maize yield considering rainfed agriculture with its low fertilizer levels without looking at the impacts of weeds and pests on yields. Simulations of on-farm conditions for both baseline and future time periods thus represent changes in climate factors under the assumption that crop management (considering weeds and pests are well controlled or are not a problem) and cultivar characteristics remain unchanged.

3. Results and discussion

3.1. Climate change scenarios

The simulated mean seasonal (May to Oct.) minimum temperatures at Bako for near future, mid and end century were 15.4, 16.8 and 18.3 °C, respectively, whereas the mean seasonal maximum temperatures for the corresponding periods were 26.2, 26.7 and 29.2 °C. Simulation results indicated increases for minimum temperature by up to 1.5, 3.5 and 5.9 °C and for maximum temperature by up to 1.5, 3.4 and 6 °C for the near future, mid and end century period, respectively, relative to the baseline (Tables 4–6). The projected temperatures were consistent with projections for sub-Saharan Africa and southwestern Ethiopia (Cairns

Table 4
Simulated seasonal (May to Oct.) climatic changes (precipitation (P_n), evapotranspiration (ET_o), max. and min. temperature) for the near future under RCP4.5 and RCP8.5 relative to the corresponding values for baseline data, and Seasonal Rainfall-Evapotranspiration Index (SREI).

GCM	NF_RCP4.5							NF_RCP8.5						
	P_n		T_{max}	T_{min}	ET_o		SREI	P_n		T_{max}	T_{min}	ET_o		SREI
	(mm)	%	(°C)	(°C)	(mm)	%	()	(mm)	%	(°C)	(°C)	(mm)	%	()
ACCESS1-0	−31.1	−3	1.1	1.0	25.3	3	1.2	−21.3	−2	1.1	1.1	24.0	3	1.2
bcc-csm1-1	10.6	1	0.6	0.6	14.2	2	1.2	87.9	9	0.7	0.7	12.2	2	1.3
BNU-ESM	478.4	48	−0.1	0.4	−15.1	−2	1.9	425.1	43	0.0	0.4	−13.4	−2	1.8
CanESM2	40.7	4	0.7	1.1	5.6	1	1.3	209.5	21	0.6	1.3	−7.5	−1	1.5
CCSM4	−7.2	−1	0.8	0.7	21.6	3	1.2	−55.9	−6	0.8	1.0	13.7	2	1.2
CESM1-BGC	−26.7	−3	0.9	0.7	22.6	3	1.2	−50.4	−5	1.1	0.9	26.8	3	1.2
CSIRO-Mk3-6-0	−61.1	−6	1.2	1.0	30.8	4	1.1	−96.1	−10	1.3	1.0	35.1	4	1.1
GFDL-ESM2G	−42.4	−4	0.6	0.6	12.5	2	1.2	−90.9	−9	0.7	0.8	11.9	2	1.1
GFDL-ESM2M	−58.9	−6	0.7	0.8	14.3	2	1.2	−134.3	−14	0.8	0.9	14.6	2	1.1
HadGEM2-CC	14.0	1	1.2	1.4	21.0	3	1.2	−9.4	−1	1.5	1.5	30.5	4	1.2
HadGEM2-ES	−27.7	−3	1.5	1.4	34.7	4	1.2	−14.0	−1	1.3	1.4	24.5	3	1.2
inmcm4	−17.7	−2	0.4	0.2	13.4	2	1.2	−45.7	−5	0.7	0.4	23.4	3	1.2
IPSL-CM5A-LR	137.9	14	1.1	1.2	20.4	3	1.4	149.5	15	1.0	1.3	11.6	1	1.4
IPSL-CM5A-MR	69.6	7	0.9	1.0	16.3	2	1.3	127.2	13	0.8	1.2	4.8	1	1.4
MIROC5	0.7	0	0.8	0.8	17.3	2	1.2	53.4	5	0.8	0.9	13.9	2	1.3
MIROC-ESM	10.1	1	0.2	0.7	−7.7	−1	1.3	38.3	4	0.3	0.8	−5.4	−1	1.3
MPI-ESM-LR	57.4	6	0.9	0.9	19.0	2	1.3	87.8	9	1.1	1.2	21.2	3	1.3
MPI-ESM-MR	74.3	8	1.0	0.9	24.6	3	1.3	44.1	4	1.3	1.1	30.7	4	1.3
MRI-CGCM3	−41.9	−4	0.6	0.5	14.8	2	1.2	−18.4	−2	0.8	0.7	18.4	2	1.2
NorESM1-M	−61.5	−6	0.5	0.6	10.1	1	1.2	−4.5	0	0.7	0.7	13.7	2	1.2
Maximum	478.4	48.4	1.5	1.4	34.7	4.4	1.9	425.1	43.0	1.5	1.5	35.1	4.5	1.8
Minimum	−62	−6	−0.1	0.2	−15	−2	1	−134	−14	0.0	0.4	−13	−2	1
Median	−3.2	−0.3	0.8	0.8	16.8	2.1	1.2	−7.0	−0.7	0.8	1.0	14.3	1.8	1.2

P_n, precipitation (rainfall), ET_o, reference evapotranspiration; Seasonal Rainfall-Evapotranpiration Index (SREI), T_{max}, maximum temperature; T_{min}, minimum temperature; RCP, Representative Concentration Pathway; NF, near future.

Table 5
Simulated seasonal (May to Oct.) climatic changes (precipitation (P_n), evapotranspiration (ET_o), max. and min. temperature) for the mid century under RCP4.5 and RCP8.5 relative to the corresponding values for baseline data, and Seasonal Rainfall-Evapotranspiration Index (SREI).

GCM	MC_RCP4.5							MC_RCP8.5						
	P_n		T_{max}	T_{min}	ET_o		SREI	P_n		T_{max}	T_{min}	ET_o		SREI
	(mm)	%	(°C)	(°C)	(mm)	%	()	(mm)	%	(°C)	(°C)	(mm)	%	()
ACCESS1-0	−79.6	−8	2.0	1.8	44.9	6	1.1	−66.9	−7	2.8	2.7	60.5	8	1.1
bcc-csm1-1	−49.4	−5	1.4	1.3	30.8	4	1.1	75.1	8	1.6	1.7	30.6	4	1.3
BNU-ESM	1088.2	110	−0.1	0.7	−21.5	−3	2.7	1022.6	103	0.5	1.3	−10.8	−1	2.6
CanESM2	220.4	22	1.1	2.0	−0.5	0	1.5	210.5	21	2.1	2.8	24.3	3	1.5
CCSM4	−25.6	−3	1.5	1.4	34.1	4	1.2	1.6	0	1.9	2.0	39.4	5	1.2
CESM1-BGC	−93.1	−9	1.7	1.4	43.5	6	1.1	−39.9	−4	2.0	1.8	46.2	6	1.1
CSIRO-Mk3-6-0	−203.7	−21	3.0	2.2	81.6	10	0.9	−157.6	−16	3.4	2.7	88.8	11	0.9
GFDL-ESM2G	26.6	3	0.9	1.1	11.7	1	1.3	−154.5	−16	1.9	1.9	40.4	5	1.0
GFDL-ESM2M	−132.1	−13	−6.1	1.4	−36.8	−4.7	2.0	−150.3	−15	1.9	2.1	36.5	5	1.0
HadGEM2-CC	−10.6	−1	2.6	2.8	49.6	6	1.2	−8.7	−1	3.1	3.4	58.6	7	1.2
HadGEM2-ES	−16.1	−2	2.7	2.8	55.9	7	1.2	−73.5	−7	3.3	3.3	68.2	9	1.1
inmcm4	−60.6	−6	1.1	1.0	26.8	3	1.1	43.5	4	1.1	1.9	0.9	0	1.3
IPSL-CM5A-LR	261.4	26	2.1	2.4	35.5	5	1.5	382.1	39	2.5	3.5	23.7	3	1.7
IPSL-CM5A-MR	344.3	35	1.3	2.4	−3.7	0	1.7	413.2	42	1.9	3.3	−0.3	0	1.8
MIROC5	68.3	7	1.4	1.4	29.5	4	1.3	141.0	14	1.8	2.0	30.8	4	1.4
MIROC-ESM	−36.9	−4	1.4	1.6	24.0	3	1.2	70.7	7	1.5	2.2	13.5	2	1.3
MPI-ESM-LR	64.0	6	2.2	2.0	51.4	7	1.3	79.7	8	3.0	2.8	65.5	8	1.3
MPI-ESM-MR	33.7	3	2.3	2.0	57.8	7	1.2	118.3	12	3.1	2.7	73.5	9	1.3
MRI-CGCM3	17.9	2	1.4	1.4	28.6	4	1.2	−19.7	−2	2.0	2.1	37.5	5	1.2
NorESM1-M	−51.1	−5	1.3	1.2	28.3	4	1.1	−65.7	−7	1.7	1.8	32.9	4	1.1
Maximum	1088.2	110.1	3.0	2.8	81.6	10.4	2.7	1022.6	103.5	3.4	3.5	88.8	11.3	2.6
Minimum	−204	−21	−6.1	0.7	−36.8	−4.7	1	−158	−16	0.5	1.3	−11	−1	1
Median	−13.4	−1.4	1.4	1.5	30.2	3.8	1.2	22.6	2.3	2.0	2.2	37.0	4.7	1.2

P_n, precipitation (rainfall), ET_o, reference evapotranspiration; Seasonal Rainfall-Evapotranpiration Index (SREI), T_{max}, maximum temperature; T_{min}, minimum temperature; RCP, Representative Concentration Pathway; MC, Mid century.

Table 6
Simulated seasonal (May to Oct.) climatic changes (precipitation (P_n), evapotranspiration (ET_o), max. and min. temperature) for the end century under RCP4.5 and RCP8.5 relative to the corresponding values for baseline data, and Seasonal Rainfall-Evapotranspiration Index (SREI).

GCM	EC_RCP4.5							EC_RCP8.5						
	P_n		T_{max}	T_{min}	ET_o		SREI	P_n		T_{max}	T_{min}	ET_o		SREI
	(mm)	%	(°C)	(°C)	(mm)	%	()	(mm)	%	(°C)	(°C)	(mm)	%	()
ACCESS1-0	−34.3	−3	2.7	1.5	89.6	11	1.1	−64.9	−7	4.8	3.3	141.4	18	1.0
bcc-csm1-1	−8.4	−1	1.7	0.7	60.2	8	1.2	73.6	7	3.3	2.5	92.7	12	1.2
BNU-ESM	1410.7	143	−0.3	2.4	−83.5	−11	3.4	1553.2	157	1.2	4.5	−77.9	−10	3.6
CanESM2	262.8	27	1.7	1.6	35.8	5	1.5	405.7	41	3.6	3.2	86.3	11	1.6
CCSM4	−7.8	−1	1.7	1.6	40.5	5	1.2	65.9	7	3.5	3.0	88.4	11	1.2
CESM1-BGC	−78.3	−8	1.9	2.9	10.0	1	1.1	86.2	9	3.5	5.1	26.0	3	1.3
CSIRO-Mk3-6-0	−196.1	−20	3.7	1.4	137.1	17	0.9	−262.7	−27	6.0	3.4	196.2	25	0.7
GFDL-ESM2G	−72.2	−7	0.9	1.9	−11.3	−1	1.2	−199.8	−20	3.4	3.5	69.8	9	0.9
GFDL-ESM2M	−119.7	−12	1.4	3.6	−35.2	−4	1.2	−6.0	−1	3.3	5.8	−9.5	−1	1.3
HadGEM2-CC	−21.9	−2	3.5	3.7	66.1	8	1.1	4.4	0	5.3	5.7	100.4	13	1.1
HadGEM2-ES	55.3	6	3.4	1.3	125.0	16	1.1	19.8	2	5.1	3.4	155.4	20	1.1
inmcm4	−84.5	−9	1.7	3.0	−3.7	0	1.2	23.4	2	2.3	5.8	−69.4	−9	1.4
IPSL-CM5A-LR	302.2	31	2.6	2.8	47.1	6	1.5	573.9	58	4.3	5.9	40.5	5	1.9
IPSL-CM5A-MR	30.7	3	2.7	1.7	79.9	10	1.2	733.6	74	3.5	3.2	82.5	10	2.0
MIROC5	79.7	8	1.8	2.2	28.7	4	1.3	251.8	25	2.9	3.9	32.4	4	1.5
MIROC-ESM	−90.2	−9	1.8	2.4	23.2	3	1.1	1.0	0	3.2	4.9	14.8	2	1.2
MPI-ESM-LR	140.7	14	2.6	2.4	60.3	8	1.3	239.5	24	5.3	4.8	123.2	16	1.3
MPI-ESM-MR	116.6	12	2.8	1.8	88.1	11	1.3	105.3	11	5.3	3.7	156.1	20	1.2
MRI-CGCM3	−33.2	−3	1.6	1.6	34.8	4	1.2	−48.9	−5	3.3	2.8	84.6	11	1.1
NorESM1-M	−71.0	−7	1.6	0.0	76.0	10	1.1	−48.9	−5	2.7	0.0	124.0	16	1.0
Maximum	1410.7	142.8	3.7	3.7	137.1	17.4	3.4	1553.2	157.2	6.0	5.9	196.2	24.9	3.6
Minimum	−196	−20	−0.3	0.0	−83	−11	1	−263	−27	1.2	0.0	−78	−10	1
Median	−15.1	−1.5	1.8	1.9	43.8	5.6	1.2	44.6	4.5	3.5	3.6	85.5	10.9	1.2

P_n, precipitation (rainfall), ET_o, reference evapotranspiration; Seasonal Rainfall-Evapotranpiration Index (SREI), T_{max}, maximum temperature; T_{min}, minimum temperature; RCP, Representative Concentration Pathway; EC, end century.

et al., 2013). These temperature ranges in the study site are suitable for growing maize in highland and lowland tropics (Cairns et al., 2013). According to Landon (1991), maize grows well in between mean temperature of 15 and 35 °C. Some other studies showed that maize net photosynthesis might decrease when plants are exposed to temperatures above 38 °C (Crafts-Brandner and Salvucci, 2002). Maize pollen viability could also decrease at temperatures above 36 °C (Decker et al., 1986).

Mean seasonal rainfall (May to Oct.) varied with GCM used, ranging from 854 to 1466, 784 to 2076 and 725 to 2541 mm, for the near future, mid and end century, respectively. The median seasonal rainfall changes across the 20 GCMs varied between −0.7 and

Table 7
Statistical evaluation of the simulated against observed days to anthesis, maturity and yield for BH-660 maize cultivar at Bako area, southwestern Ethiopia.

Year	Anthesis (days)						Maturity (days)						Yield (days)					
	DSSAT			APSIM			DSSAT			APSIM			DSSAT			APSIM		
Year	OBS	SIM	D%	OBS	SIM	D%	OBS	SIM	D%	OBS	SIM	D%	OBS	SIM	D%	OBS	SIM	D%
2000	–	–	–	–	–	–	162	168	3.7	162	165	1.9	8.2	9.9	21.2	8.2	9.1	11.1
2001	–	–	–	–	–	–	–	–	–	–	–	–	8.6	8.1	−6.4	8.6	7.4	−13.9
2002	83	85	−2.4	83	88	6	150	151	0.7	150	150	0	9.2	7.5	−18.5	9.2	8.7	−5.5
2003	88	86	2.3	88	91	3.4	151	155	2.6	151	156	3.3	6.2	6.2	−0.2	6.2	8.5	37.1
2004	84	85	−1.2	84	89	6	150	156	4	150	154	2.7	9.5	9.3	−1.4	9.5	9.2	−2.4
2005	–	–	–	–	–	–	–	–	–	–	–	–	10.7	10.3	−4.1	10.7	9.3	−12.8
2006	87	86	1.1	87	89	2.3	–	–	–	–	–	–	8.7	8.8	1.4	8.7	8.4	−3.4
*2007	86	87	−1.2	86	91	5.8	158	158	0	158	155	−1.9	8.4	9.3	10.3	8.4	8.8	4.7
2008	87	87	0	87	90	3.4	156	155	−0.6	156	154	−1.3	10.3	8.7	−15.6	10.3	8.3	−19.1
2009	90	89	1.1	90	90	0	158	165	4.4	158	160	1.3	8.1	9.7	20.1	8.1	9	10.4
RMSE		1.3			3.7			4.5			3.1			1.1			1.2	
I		0.86			0.5			0.8			0.89			0.77			0.6	

OBS., observed; SIM., simulated; D%, percent deviation; * data set II (from separate experiment); RMSE, root mean square of error; I, index of agreement.

−0.3, −1.4 and 2.3 and −1.5 and 4.5%, for near future, mid and end century period, respectively (Tables 4–6). Overall, most of the GCMs projected a slight increase in rainfall under future scenarios, which is in agreement with IPCC (2007b) and Collier et al. (2008). However, expected rainfall change patterns in Ethiopia are not entirely consistent (Conway and Schipper, 2011).

Mean seasonal reference evapotranspiration varied from 722 to 822, 766 to 876 and 704 to 983 mm for near future, mid and end century, respectively. Models indicated that mean seasonal reference evapotranspiration may increase by up to 4.5, 11.3 and 24.9% for near future, mid and end century period, respectively, but decreases of up to 2, 3 and 11% for the corresponding future periods were also indicated by some models (Tables 4–6). Projected values for the GFDL-ESM2M GCM under RCP4.5 for mid-century, were so far outside the ranges indicated by all other scenarios for changes to minimum temperature (−6.1 °C) and ET_o (−36.8 mm) that they were not considered credible and are therefore not included in this summary. Median change in ET_o for near future, mid and end century ranged between 1.8 and 2.1, 3.8 and 4.7 and 5.6 and 10.9%, respectively. Overall, an increase in ET_o was projected across the century, which is consistent with some studies in sub-Saharan Africa (Cairns et al., 2013). However, crop evapotranspiration is expected to decrease due to increases in CO_2 levels (Žalud and Dubrovsky, 2002; Cairns et al., 2013).

The Seasonal Rainfall-Evapotranspiration Index (SREI) value was 1.2 across the future scenarios (Tables 4–6). This implies seasonal rainfall might be sufficient for meeting the seasonal evaporative demand of the atmosphere.

3.2. Model calibration and evaluation

For the number of days to anthesis, both DSSAT and APSIM showed good simulation performance. The deviation of simulated days to anthesis from observed data was very low (−2.4 to 2.3% for DSSAT and 0 to 6% for APSIM) (Table 7). This was also reflected by the index of agreement (I), which ranged from 0.5 to 0.89. The I index for this variable was lower for APSIM (I = 0.5) than for DSSAT (I = 0.86). Furthermore, RMSE values for days to anthesis simulated by DSSAT (1.3 days) were slightly lower than those for APSIM (3.7 days). These statistical evaluations generally showed that APSIM produced a slight mismatch between simulated and observed days to anthesis (Fig. 2). Despite the slight differences in simulating days to anthesis, there was similarity between some of the cultivar genetic coefficients used for calibrating APSIM and DSSAT.

There was strong agreement between the simulated and observed days to maturity of maize for both models (I = 0.8 to 0.89).

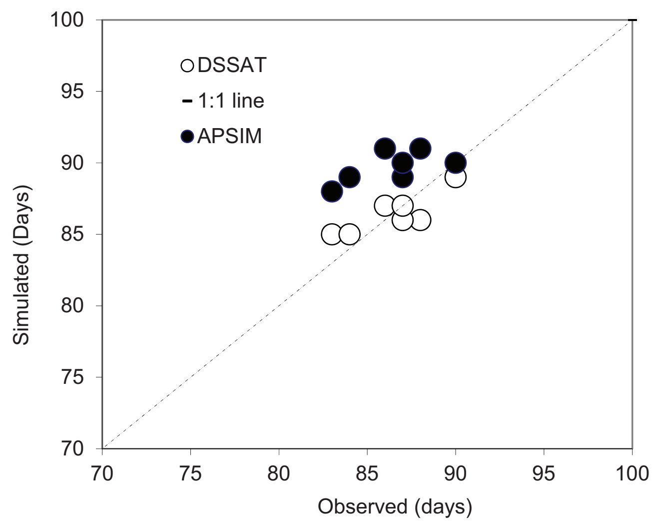

Fig. 2. Observed versus simulated days to anthesis for the BH-660 maize cultivar during the cropping seasons 2002–2004 and 2006–2009 for DSSAT (R^2 = 0.7) and APSIM (R^2 = 0.4).

The RMSE value for days to maturity was as low as 4.5 days for DSSAT and 3.1 days for APSIM. The deviation of the simulated against the observed days to maturity was very low (−0.6 to 4.4% for DSSAT and −1.9 to 3.3% for APSIM) (Table 7). The 'days to maturity' variable was well simulated by both models (Fig. 3).

The simulated grain yield agreed well with the observed data (I = 0.77 for DSSAT and I = 0.6 for APSIM). The RMSE values were also moderate (1.1 t/ha for DSSAT and 1.2 t/ha for APSIM). However, the wide range of deviations of simulated from observed grain yield (−18.5–21.2% for DSSAT and −19.1–37.1% for APSIM) indicated that yields were not simulated well for some of the years. Overall, there was a good match between the long-term observed and simulated yields when plotted as probability of exceedance (Fig. 4). Results showed that both models adequately simulated the yield variability over the observation period. However, yields were substantially overestimated by both models in one of the observation years. Besides slight deficits in model calibration, such effects may also have arisen from variation in unmeasured soil parameters, such as soil organic matter and initial soil nitrogen and management variation at the experimental site (e.g. in fertilization or weed, pest and disease control). The genetic coefficients of the maize cultivar under investigation for both DSSAT and APSIM are presented in Table 8.

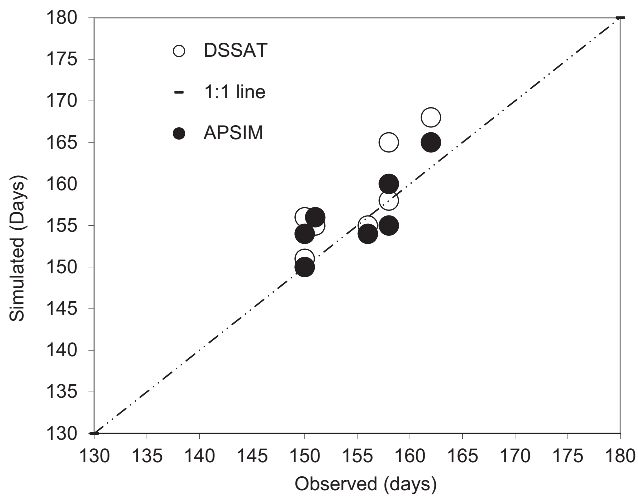

Fig. 3. Observed versus simulated days to maturity for BH-660 maize cultivar during the growing seasons 2000, 2002–2004, 2007–2009 for DSSAT (R^2 = 0.7) and APSIM (R^2 = 0.64).

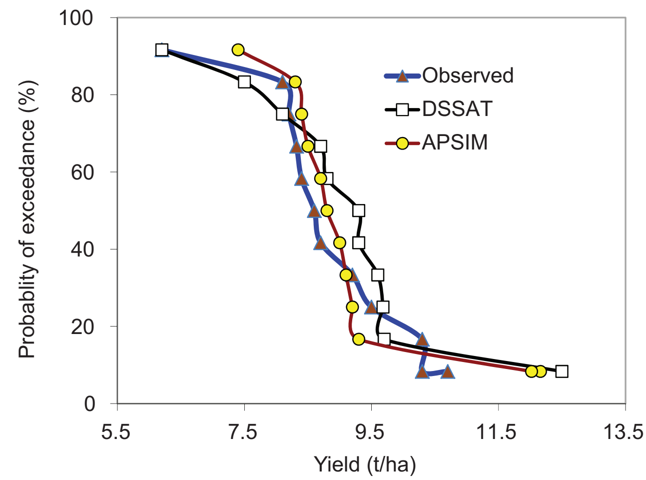

Fig. 4. Probability of exceedance for the observed versus simulated (APSIM and DSSAT) yield over the 12 years experimental period (2000–2011) for the BH-660 maize cultivar in the Bako area.

3.3. Scenario runs and analysis

Table 9 shows yield changes over three future scenarios as simulated using APSIM and DSSAT based on 20 GCMs under RCP4.5 and RCP8.5 scenarios. Overall, future median yields were projected to increase by 1.7% (for both RCPs), 2.9 and 4.2%, and 3.5 and 3.8% for RCP4.5 and 8.5 during the near future, middle and end of the 21st century, respectively, when simulated using DSSAT. Projected yield changes were by 2.9 and 3.6%, 0.6 and 1.4%, and −6 and 4%, when simulated with APSIM for the respective RCPs and future periods (Table 9). There were small differences in simulated maize yield among the three future periods for most of the GCMs. Appreciable differences were found in the quantity of simulated yield between the two crop models contributing to uncertainties of yield

Table 8
Genetic coefficients for BH-660 maize cultivar calibrated in DSSAT and APSIM.

DSSAT	Cultivar name: BH-660	APSIM	Cultivar name: BH-660
Parameter	Value	Parameter	Value
P1	260	tt-emergence to end of juvenile	260
P2	0.75	Grain growth rate	9.17
P5	850	tt_flower to maturity	850
G2	800	Head grain no	800
G3	8.5	tt_flagleaf to flower	101
PHINT	49	tt_flower_to_start of grain	170
		tt_endjuv_to_init	0
		est_days_endjuv_to_init	15

Note: tt, heat units required in degree days (GDD, °C).
P1 Thermal time from seedling emergence to the end of the juvenile phase (degree days).
P2 Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (days).
P5 Thermal time from silking to physiological maturity (degree days).
G2 Maximum possible number of kernels per plant.
G3 Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).
PHINT Phylochron interval; the interval in thermal time between successive leaf tips (degree days).

Table 9
Median yield changes over three future time periods as simulated by APSIM and DSSAT models based on 20 GCMs under RCP4.5 and RCP8.5 scenarios.

Time period	Crop model	RCP	Assumed average CO_2 concentration for the period (ppm)	Median yield change for Bako area based on 20 GCM (%)
2070–2099	DSSAT	RCP4.5	532	3.8
2070–2099	DSSAT	RCP8.5	801	3.5
2070–2099	APSIM	RCP4.5	532	4.0
2070–2099	APSIM	RCP8.5	801	−6.3
2040–2069	DSSAT	RCP4.5	499	2.9
2040–2069	DSSAT	RCP8.5	571	4.2
2040–2069	APSIM	RCP4.5	499	1.4
2040–2069	APSIM	RCP8.5	571	0.6
2010–2039	DSSAT	RCP4.5	423	1.7
2010–2039	DSSAT	RCP8.5	432	1.7
2010–2039	APSIM	RCP4.5	423	2.9
2010–2039	APSIM	RCP8.5	432	3.6

RCP, Representative Concentration Pathway; GCM, Global Climate Model; Baseline [CO2] was assumed 360 ppm.

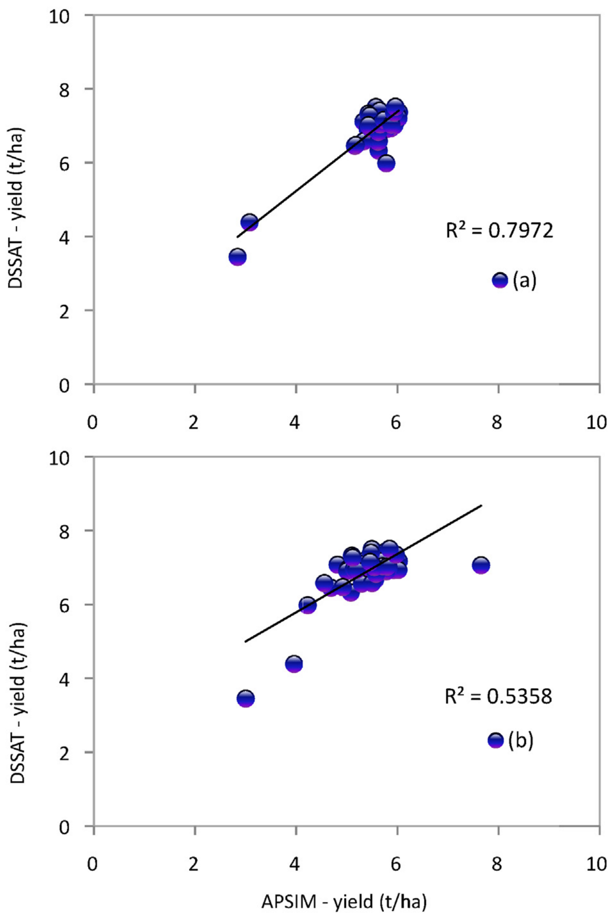

Fig. 5. Regression of simulated yield (t/ha) with APSIM versus DSSAT under RCP4.5 (a) and RCP8.5 (b) across the century (near future, mid and end century period).

projection under future climate. These might be caused by various factors, such as absence of evaluation datasets for elevated CO_2, difference in the internal model structures and use of default parameters and assumptions for unmeasured data inputs (White and Hoogenboom, 2010; Rosenzweig et al., 2013). Differences in data input requirements and absence of 'user interface uniformity' might have also contributed to simulated yield difference (White and Hoogenboom, 2010). However, simulated yield trends by both APSIM and DSSAT across the century showed moderate to strong correlations with R^2 of 0.54 for RCP8.5 and 0.80 for RCP4.5 (Fig. 5 a and b). Results from APSIM and DSSAT were strongly correlated, especially during the middle and end of the century ($R^2 > 0.8$ for RCP4.5 and >0.7 for RCP8.5) (data not shown). The strong agreement between both models in projecting relatively stable future yields instills some confidence that climate change might not decrease future yields compared to simulated baseline yields (Figs. 6 and 7; Table 9).

Several authors have reported the expectation that an increased atmospheric CO_2 concentration will increase crop yields (Woodrow, 1994; Wittwer, 1997; Kimball et al., 2007; US Global Change Research Program, 2009).

The DSSAT and APSIM versions used in this study are capable of simulating the impacts of CO_2, however, we have not observed substantial yield differences between the high and moderate RCPs throughout the 21st century (Table 9, Figs. 6 and 7). Despite claims for yield-raising effect, elevated CO_2 had only a small beneficial effect on maize yield across the future time periods. In a similar climate impact assessment study, Kassie et al. (2015) also reported small positive effects of increased CO_2 (5%). Some other studies

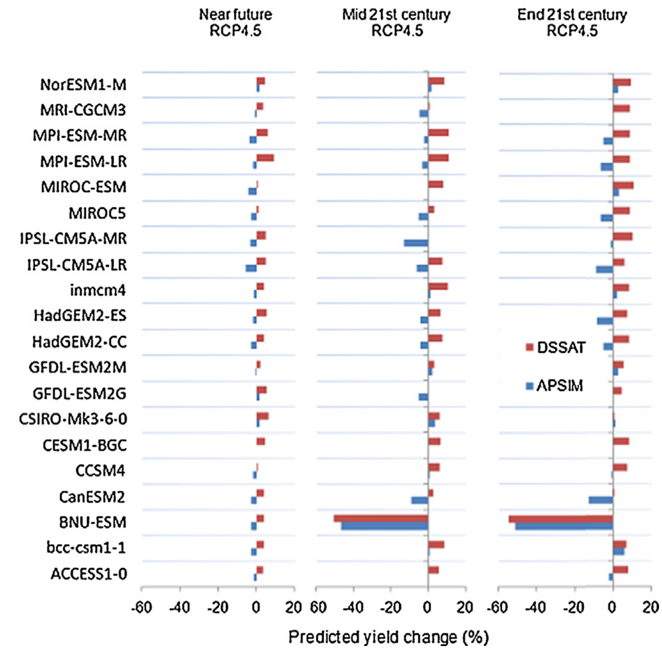

Fig. 6. Yield gained/lost (as compared to the historical) as simulated using APSIM and DSSAT based on 20 GCM under RCP4.5 for near future (2010–2039), middle of the 21st century (2040–2069) and end of 21st century (2070–2099).

indicated that elevated CO_2 might not cause substantial increase in yield (Twine et al., 2013) except for moisture stressed crops (Leakey et al., 2006). Kim et al. (2007) also reported that growth, development and photosynthetic rate of maize were not affected by elevated CO_2. Many uncertainties exist on the response of crops to elevated CO_2 and heat (White and Hoogenboom, 2010), and some independent responses to elevated CO_2 effects might not be adequately modeled (White and Hoogenboom, 2010).

Temperatures above the optimal range have been reported to have several negative effects for many crops (Badu-Apraku et al.,

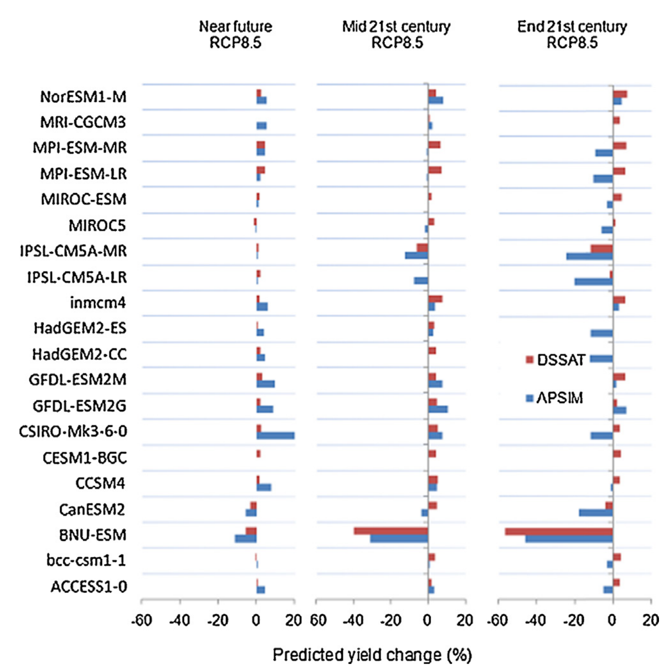

Fig. 7. Yield gained/lost (as compared to the historical) as simulated using APSIM and DSSAT based on 20 GCM under RCP8.5 for near future (2010–2039), middle of the 21st century (2040–2069) and end of 21st century (2070–2099).

Table 10
Estimated change (%) in duration of maize growth period across the 21st century as simulated based on 20 GCMs under RCP4.5 and 8.5 using APSIM and DSSAT for the Bako area of southwestern Ethiopia.

	NC		MC		EC	
Crop model	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
APSIM	0	0	−4	−8	−7	−17
DSSAT	−4	−4	−9	−13	−13	−22

NC, near century, MC, mid century and EC, end century.

1983; Jones et al., 1984; Muchow et al., 1990; Lobell and Field, 2007; Supit et al., 2012; Rosenzweig et al., 2014; Teixeira et al., 2013). However, temperature at the study site at Bako in southwestern Ethiopia was not beyond the upper suitable temperature for maize. Despite the shortening of the maize growing period (due to increased temperatures), future yield was found to be slightly higher than baseline yield. This could be attributed to effects of various interacting factors such as increased temperature, rainfall and CO_2 which appeared to remain favorable for maize yield in this agro-ecological zone. This study was in agreement with Araya et al. (2015), who showed similar results for the Bako site when simulating performance of a different maize cultivar. For the Central Rift Valley in Ethiopia, Kassie et al. (2015) projected maize yield decreases by about 20%. This implies that maize production in the Rift Valley, which is warmer than our study region and subject to greater rainfall variability, may be affected more negatively by climate change. Other reasons for differences in results across these two studies could be uncertainty about future climate changes in Ethiopia (Conway and Schipper, 2011), as well as methodological differences. Our study, for example, used more GCMs, enabling it to expose better the uncertainty in expected future crop performance that stems from the choice and number of climate models (AgMIP, 2012; Rosenzweig et al., 2013). Some other climate change impact studies reported decreases in yield on a regional scale (e.g. Jones and Thornton, 2009; Thornton et al., 2010), though expectations for East African highlands have generally been more favorable. In agreement with our study, AgMIP (2014) reported a slight increase for the mid-century scenario when using DSSAT and considering 20 GCM to simulate yields of other maize cultivars and for three other sites in the Adama region of the Central Rift Valley of Ethiopia. In our study, there was a maximum of 6% decline in maize yield when compared to the baseline as simulated using APSIM, and this was only indicated for the end of the 21st century under the RCP8.5 scenario. This 6% yield decline might be mainly caused by shortening of the maize growth duration (Table 9).

3.4. Crop water requirement and duration of growth period

The maize growing season is expected to shorten with an increase in temperature (Table 10), and this may reduce yield. In agreement with Kassie et al. (2015) we found considerable shortening of the maize growth duration (Table 10). However, the negative effects of the shortening of the growing period observed in our study did not result in substantial yield reduction compared to the baseline. The effects might have been compensated by the interaction effects of increased CO_2, rainfall and temperature at the study site.

Maize water requirement (ET_c) decreased from 578 mm in the baseline to 500 mm in the end century both when May and June planting was used (Table 11). At the same time, effective rainfall increased from 616 mm in the baseline to 723 mm at the end of the 21st century when maize was assumed to be planted in May, whereas it increased from 576 mm in the baseline to 707 mm at the end of the century when planting was done in June. Regardless of planting date, rainfall generally increased relative to the baseline whereas crop water requirement decreased during the main growing season across the century. Shortening of the growing period (due to elevated temperatures) has contributed to reduction of the ET_c across the century. However, assuming the length of the growing period of the present maize cultivar remains unchanged under future climate, maize water requirement could increase from about 578 mm in the baseline to 670 mm in the late-century period. Likewise, mean effective rainfall would increase from about 616 mm in the baseline to about 728 mm at the end of the century. This indicates that the increased crop water requirement at the end of the century would be compensated by increases in effective rainfall (data not shown) implying maize may not suffer from water stress under future climate even if late-maturing cultivars are planted. However, maize crop water demand at the study site is better attuned to simulated future rainfall when crops are planted in May rather than June (Table 11). Many studies showed that planting time adjustment could potentially improve crop performance under changing climate (Laux et al., 2010; Araya et al., 2012; Waongo et al., 2015). This could be one of the less costly strategies which could be implemented easily by resource poor farmers in sub-Saharan Africa.

The water requirement for maize is expected to be fully met, according to simulations for future climate scenarios (Table 11). This may have positive impacts on maize, especially when accompanied by the increase in atmospheric CO_2 concentrations compared to the baseline. Furthermore, simulation results showed that maize yield was substantially affected by seasonal rainfall. There was an overall strong relationship between yield and seasonal rainfall (R^2 = 0.76 to 0.96) with the exception of the near future period (Table 12; Figs. 8 and 9). This shows that rainfall is the most important yield determining factor in the Bako area of southwestern Ethiopia. Reasons for the exceptionally poor relationship between simulated maize yield and seasonal rainfall in the near future was not entirely clear to us. However, significant yield reduction was observed for specific GCMs such as BNU-ESM (Figs. 6 and 7). GCM BNU-ESM projected exceptionally high seasonal rainfall across the century.

Table 11
Estimated effective rainfall and maize water requirement for May and June planting dates across the 21st century period under both RCP4.5 and 8.5 for the Bako area of southwestern Ethiopia.

		N		MC		EC	
Planting date	$E_{Tc}/E_{ff.}$ rainfall	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
1st of May	E_{Tc} (mm)	570	570	550	520	520	500
	$E_{ff.}$ rainfall (mm)	630	634	652	664	658	723
	Surplus/deficit (mm)	60	64	102	144	138	223
1st of June	E_{Tc} (mm)	570	570	550	520	520	500
	$E_{ff.}$ rainfall (mm)	594	602	630	641	636	701
	Surplus/deficit (mm)	24	32	80	121	116	201

N, near future, MC, mid century and EC, end century, RCP, Representative Concentration Pathways.

Table 12
Relationship between seasonal rainfall and simulated yield using DSSAT and APSIM models for the Bako area of southwestern Ethiopia.

	Yield simulated with APSIM versus Seasonal Rainfall	Yield simulated with DSSAT versus Seasonal Rainfall
Scenarios	R^2	R^2
NF_RCP4.5	0.00	0.00
NF_RCP8.5	0.45	0.48
MC_RCP4.5	0.96	0.80
MC_RCP8.5	0.97	0.76
EC_RCP4.5	0.95	0.86
EC_RCP8.5	0.79	0.80

NF, near future; MC, mid century; EC, end century; RCP, Representative Concentration Pathways.

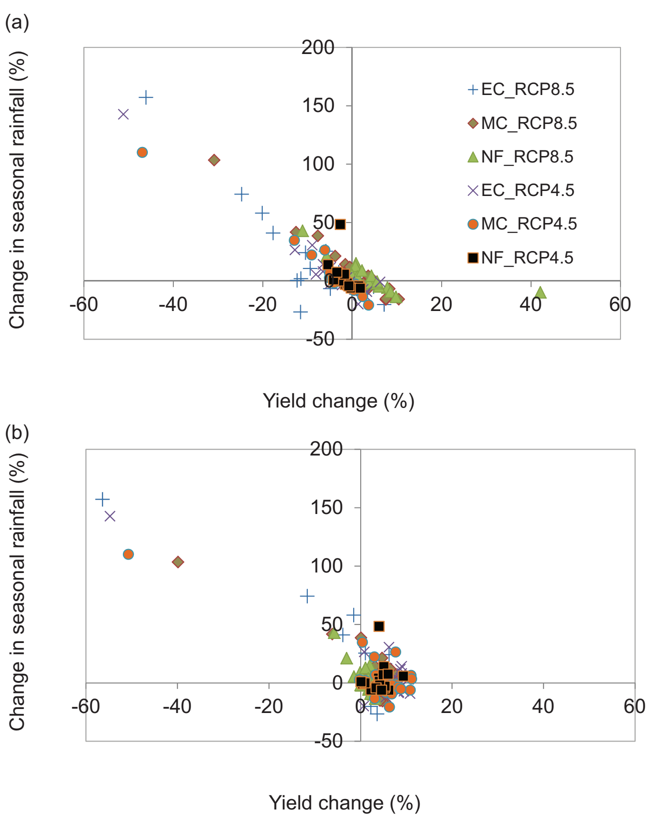

Fig. 8. Change in seasonal rainfall (May to Oct.) simulated based on 20 GCM versus change in yield as simulated using APSIM (a) and DSSAT (b) for (NF) near future, (MC) mid and (EC) end century period under RCP4.5 and RCP8.5 scenario for Bako area, southwestern Ethiopia.

Aeration stress and leaching of nitrogen might interfere with crop growth which could significantly affect growth and yield of maize (Figs. 8 and 9). Ruane et al. (2013) indicated that growth and yield of maize might be negatively affected if the rainfall distribution in a season is highly irregular (e.g. with dry spells or storms that cause surface runoff).

Overall, climate change may not have significant impacts on current maize varieties grown in the semi-arid and sub-humid climate of Ethiopia (Araya et al., 2015). However, changes in management practices such as planting date (e.g. Laux et al., 2010; Araya et al., 2012; Waongo et al., 2015), nitrogen inputs, and possibly choice of variety (AgMIP, 2014; Kassie et al., 2015) may cause positive changes in yield of greater magnitude. Simulations with different levels of nitrogen use under farmers' conditions in this study have

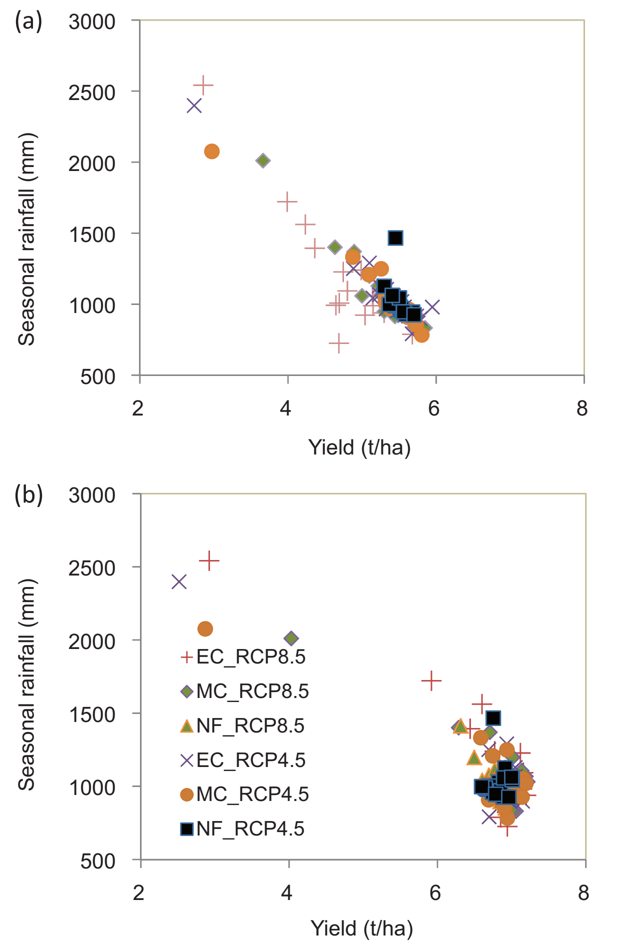

Fig. 9. Mean seasonal rainfall (May to Oct.) simulated based on 20 GCM under RCP4.5 and RCP8.5 versus yield simulated using APSIM (a) and DSSAT (b) for (NF) near future, (MC) mid and (EC) end century period for Bako area, southwestern Ethiopia.

shown stronger yield differences among model runs than were observed in response to climate factors. Therefore, we recommend more in-depth analysis on the impacts of improved management practices on maize yield including their costs and benefits under future climate conditions.

3.5. Model comparison and uncertainties

The BNU-ESM GCM projected the lowest maximum temperatures, whereas HadGEM2-CC and CSIRO-Mk3-6-0 projected the highest minimum and maximum temperatures, respectively. The CSIRO-Mk3-6-0 and BNU-ESM GCMs projected the lowest and highest seasonal rainfall across the future scenarios, respectively (Tables 4–6). Use of few GCMs with highly distinct characteristics might narrow apparent uncertainty but could produce extreme results that may not reflect the true state of scientific uncertainty about the future climate. This stresses the importance of using a wide range of models for climate change projections.

The effect size of the choice of GCM (when averaged by time period, RCPs and crop models) varied between −33 and 10%, which is smaller than the effect of the choice of crop model, which (when averaged by GCM, time period and RCP) ranged between −23 and 30%. Maize yield simulated using DSSAT was generally higher than yield simulated with APSIM (Fig. 9). In agreement with our findings, Asseng et al. (2013) reported that uncertainties from crop models were relatively higher than uncertainties from GCM. In contrast to our result, some other studies indicated that GCMs are a major source of uncertainties (Kassie et al., 2014). Use of multiple GCMs is understood to have significant importance in climate impact studies (Wilby et al., 2004). Since the objective is to predict the likely representation of the future, use of many available crop models and GCMs might improve our understanding (from many climate change drivers) of the future uncertainties and thus could provide better information to policy makers, planners and researchers (Diekkrüger et al., 1995; Meehl et al., 2007; Hanson et al., 2004; Kersebaum et al., 2007; Tao et al., 2009; Taylor et al., 2009).

On the other hand, uncertainties due to RCPs (when averaged by time period, GCM, and crop model) ranged only between 3 and 6%. Our finding was comparable with Kassie et al. (2015), which indicates that changes in CO_2 concentration contribute little to maize yield across the century and thus could be considered as a minor source of uncertainty in maize climate change impact studies in the study area. This finding mirrors results from Panama, where climate change impacts for maize were expected to differ little across high (A2) and low (B1) greenhouse gas emissions scenarios throughout the 21st century (Ruane et al., 2013).

There was no substantial difference in yield across the future scenarios (near future, mid and end century). One possible reason could be that the simulated climatic conditions remained near-optimal for maize throughout the 21st century. For example, rainfall appeared to consistently meet crop water demand and effects of elevated temperatures in shortening the growth duration and in reducing yield might be compensated by effects of increased rainfall and CO_2. Generally, this study showed a strong relationship between yield and seasonal rainfall across the future scenarios with a slight overall tendency of increasing strength when CO_2 concentration level was increased (Table 12).

4. Conclusion

APSIM and DSSAT simulated the yield and phenology of maize for the environmental conditions of the study area in Ethiopia satisfactorily. Results of the climate change projection showed that maize yield under future climate may increase slightly compared to historical conditions by, on average, 1.7% (for both RCPs), 2.9 and 4.2%, and 3.5 and 3.8% for RCP4.5 and 8.5 during the near future (2010–2039), middle (2040–2069) and end of the 21st century (2070–2099), respectively, when simulated using the DSSAT model. Simulations with APSIM resulted in changes between 2.9 and 3.6%, 0.6 and 1.4%, and −6.3 and 4.0%, for the respective RCPs and time periods. Overall, this study indicated that maize yield in southwestern Ethiopia is likely to increase slightly under projected future climates.

In our climate change impact studies we found a strong influence of the choice of crop model and GCM compared to the choice of RCPs, which only caused small differences. Multi-crop model and multi-GCM ensemble projections are recommended for climate change sensitivity studies, especially for this region.

Even though our simulations indicated slight yield increases in the future, this may not be the case under different soil conditions or for different maize cultivars. More in-depth analysis is needed to produce more comprehensive and reliable climate change sensitivity assessments with more crop models under various soil and cultivar conditions. Variation in the use of inputs, such as the amount of nitrogen fertilizer used by farmers, probably caused significant differences in yield and biomass of maize. This implies that yield changes relative to the baseline could be more pronounced or attenuated, if climatic changes are accompanied by changes in farming practices. However, considering the present conditions, climate change impact assessment based on multiple model simulations for southwestern Ethiopia has generally projected positive yield effects with narrow ranges of uncertainty indicating that yield might not significantly decrease compared to the baseline.

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