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RESEARCH

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Future climate change impacts on common bean (*Phaseolus vulgaris* L.) phenology and yield with crop management options in Amhara Region, Ethiopia

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Abstract

Food insecurity is a recurrent feature of the Ethiopian drylands. The risk of food insecurity has been aggravated by climate variability, climate change, population pressure, and subsistence agricultural practices. In Ethiopia, common bean is the main source of protein for people who do not get access to animal protein. The national average yield in Ethiopia is 1600 kg ha^{-1} which is far below yield at research sites (3000 kg ha^{-1}) mainly due to drought, low soil fertility and lack of improved agronomic practices. A simulation study was conducted with the objectives (1) to calibrate and evaluate the CROPGRO-dry bean model of DSSAT for simulating phenology, growth and yield of common bean (2) to assess impacts of future climate on phenology and yield (3) to explore climate adaptive strategies for common bean. Three sowing dates (early, normal and late) and two water regime (rainfed and irrigated) were evaluated as climate adaptive measures. Results of model calibration indicated that the crop genetic coefficients were properly estimated. The RMSE, R^2 and d-index values for days to flowering in the model evaluation phase were 2.42 days, 0.76 and 0.82, respectively. The RMSE, R^2 and d-index values for days to physiological maturity were 3.19 days, 0.70 and 0.87, respectively while the values for grain yield were 113.7 kg ha^{-1}, 0.95 and 0.89 for the respective parameters. The impact analysis showed that both days to flowering and days to maturity may decrease in 2030s and 2050s at both sites and under both RCP4.5 and RCP8.5 scenarios as compared to the simulated values for the baseline period (1981–2010) but the decrease is not statistically significant. On the other hand, grain yield may significantly increase by 11% in 2030s under RCP8.5 scenario and by 9.2% and 21.1% in 2050s under RCP4.5 and RCP8.5 climate scenarios respectively. The highest significant increase in grain yield may be obtained from the early sowing (SSD − 15 days) combined with supplemental irrigation which may increase yield by 89%, 71% and 56% for the baseline period, 2030s and 2050s, respectively. However, the pattern of climate changes and the nature of crop stressors may change overtime. Thus, understanding the cumulative effects of these factors may help to develop climate resilient cropping systems in the study region.

Keywords: Climate change, Common bean, DSSAT, Ethiopia, RCPs, RMSE

Introduction

Common bean (*Phaseolus vulgaris* L.) is one of the most important food legumes in Ethiopia. The crop is mainly grown by farmers mainly for household consumption and for soil fertility improvement (Asfaw et al. 2009, 2012; CSA 2015). Most farmers in Ethiopia prefer to

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grow common beans because the crop matures early and can escape from the effect of terminal moisture deficit. It also serves as an emergency crop during crop failure (Legesse et al. 2006). The white beans are exported (Ferris and Kaganzi 2008) whereas the small red beans are mainly used for local and regional household consumption (Ferris and Kaganzi 2008; Rubyogo et al. 2011; CSA 2015). Due to the rising demand in the international and domestic markets farmers are encouraged to grown common bean in almost all parts of Ethiopia (Katungi et al. 2009; CSA 2015). The actual yield obtained under the smallholder farm remains below 1700 kg ha^{-1}, which is by far lower than the potential yield (3500 kg ha^{-1}) (MoANR 2016; Zerihun 2017; Berhanu et al. 2018). The report of Amanuel and Girma (2018) indicated that the low yield is due to the low adoption of improved production technologies, lack of improved varieties and poor cultural practices. Yitayal and Lema (2019) suggested that diseases, pests, drought are among the major constraints of common bean production in Ethiopia. The Central Statistical Agency (CSA 2014) reported that the production share of common bean has consistently been 19% of all the pulses for the last 2 years in Ethiopia. Common bean production has been increased in Ethiopia by more than twofold between 2005 and 2014 (CSA (2015). Common bean covers the dominant part of pulse exports contributing approximately USD 134 million (ERCA 2015). The bean export accounted about 41% of all the pulse exported in terms of quantity (FAO 2014).

Climate change is negatively affecting the agriculture sector in many developing countries (IPCC 2009). Crop productivity in developing countries is expected to decline under future climate (Jones and Thornton 2009). Ethiopia has been frequently affected by droughts and climate extremes over the last decades with serious shortfalls in food supply (Araya and Stroosnijder 2011; Conway and Schipper 2011; Demeke et al. 2011; Araya et al. 2012). Farmers who currently are food insecure could suffer from the changes in rainfall patterns and increasing temperature (Deresa 2006). Climate change could affect the production of maize, beans, wheat, vegetables, and sugarcane, either negatively or positively depending to the climatic conditions where the crops are growing. African economies are relying heavily on climate therefore, the changes in climatic could affect future agricultural production (Araya et al. 2012).

Food insecurity is a recurrent feature of Ethiopian drylands, particularly in Northeastern Ethiopia, where land degradation has been a primordial challenge. The region is characterized by limited access to markets and weak institutional capacities. The risk of food insecurity has been aggravated by climate variability, high population pressure, and subsistence agricultural practices dominated by rainfed farming with low input–output agriculture. For example, 80% of populations in Ethiopia are depending on rainfed agriculture and they are vulnerable to weather-related shocks. Rainfall varies greatly by region and is particularly unpredictable (World Bank 2010). Projections of mean annual rainfall averaged over the country from different models showed a wide range of changes for Ethiopia, but tend toward increases (USAID 2015). The mean annual rainfall distribution in Northeastern Ethiopia ranges from 200 mm to maximum of 800 mm. The seasonal and annual rainfall has exhibited high variability between 1951 and 2016 (Gummadi et al. 2017). Rainfall has decreased during the *Belg* (February–May) season, which contributed about 30% of the food and feed in the currently food insecure lowlands (Gummadi et al. 2017). The short season (*Belg*) rainfall in the region exhibits the largest percent reductions (Gummadi et al. 2017).

Field studies have challenges because they demand long the time and a lot of logistical facilities. They have also problems to answer questions arising from weather conditions. Currently, most studies are conducted using models. Crop models are alternative tools to predict crop yields as a function of weather, crop and soil management practices. Crop models are computer-based mathematical models representing the interaction of crop growth and the environment (Graves et al. 2002). Crop models have been used as research tools for assessing the relationships between crop productivity and environmental factors (Adejuwon 2005). Models can simulate growth, development and water balance of different crops in compliance with soil, plant and atmospheric characteristics (Hoogenboom et al. 2012). For instance, the Decision Support System for Agrotechnology Transfer (DSSAT) has been widely used to study soil fertility, water and irrigation management, yield gap analysis, genotype by environment interaction in plant breeding, climate change and climate variability, risk insurance and adaptive management (Bhupinde 2018). The application of crop models for assessing the impacts of climate change on crops has received major attention providing a solution to reduce cost and improving knowledge (Li et al. 2015). The DSSAT package has been used to simulate crop biomass and yield, and soil nitrogen dynamics under different management practices and various climatic conditions (Li et al. 2015). The CROPGRO-dry bean model is one of the crop models embedded in the DSSAT that can simulate physiological processes of several crop species. The model is mechanistic and deterministic that can simulate the length of vegetative and reproductive stages, biomass accumulation and grain yield for a given cultivar based on soil type, climatic conditions and management practices adopted. However, there is a continuous need to evaluate crop models under a wide range of environments and cropping practices before using them for further application (López-Cedrón et al. 2008).

Considering the increase in population pressure in future and expected climate changes, crop production must increase to meet the current and future demand for food. This could be possible through improved crop management strategies. Crop models have to be calibrated for a given location under the specific crop and cultivar. The CROPGRO-dry bean model has not been calibrated in the region. There are only limited published works on impacts of climate change on crops and potential management strategies. The majorities of studies in Ethiopia have focused on rainfall and temperature changes and did not address impact of climate on crops. Limited studies are available by Dereje et al. (2012) and Adem et al. (2016) who assessed impact of projected climate change on maize and chickpea crops, respectively. Adem et al (2016) suggested that change in cultivars, change in sowing dates and supplemental irrigation are effective management strategies for sustainable chickpea production under the projected climate change conditions. Common is selected for this study because it is a cash crop in Ethiopia and it is main source of protein for those people who do not get animal protein due high cost. At present, productivity of the crop is decreasing due to biotic and abiotic factors. Thus, this study was initiated with the following objectives (1) to calibrate the CROPGRO-dry bean model of DSSAT for simulating phenology, growth and yield of common bean (2) to assess impacts of future climate change on common bean production (3) to explore crop adaptation strategies that can sustain common bean productivity in the study region.

Materials and methods

Description of the study area

Data for the crop model calibration and evaluation were collected from field experiments conducted at two sites (Sirinka and Chefa) which are located in the semi-arid region of Ethiopia. *Sirinka* is located at an altitude of 1850 m above sea level (masl) with geographic coordinates of 11.45.00 N latitude and 39. 36. 00 E longitude. The mean maximum air temperature is about 25 °C with mean annual rainfall of 741 mm. The soil texture is mainly clay loam. The second site, *Chefa* is located at an altitude of 1450 masl with geographic coordinates of 10. 43. 12 N latitude and 39. 49. 48 E longitudes. The mean maximum air temperature is about 26.4 °C with mean annual rainfall of 793 mm. The study region is generally characterized by rugged topography with undulating mountains, hill sides and valley bottoms. Rainfall follows bimodal pattern with the small rainfall season that extends from February to April/May (locally known as *Belg*) and the main rainfall season that extends from June to September (locally known as *Kiremt*). Seasonal and annual rainfall has exhibited high variability between 1951 and 2016. In particular, rainfall has decreased during February to May, which used to produce about 30% of the food and feed in the currently food insecure lowlands of Ethiopia (Gummadi et al. 2017). Rainfall in the *Belg* season exhibited the largest percent reductions. The cropping system is mainly of monoculture system dominated by cereals such as sorghum, chickpea, haricot bean, teff (*Eragrostis teff*), cowpea, lentil and wheat. Mixed farming (crops and livestock) is the major farming system. Crop rotation mainly of cereals with legume crops is practiced at some extent. Intercropping of cereals with legumes is also practiced in the region. Most of the field crops are grown during the long rainy season (June to September) under rainfed condition while limited crops such as teff and Mung bean are grown in the small rainy season under rainfed condition (February to April/May).

Field experiments

Common bean variety *Awash Melka* was selected as the test crop. The cultivar is categorized as medium maturing group. Cultivars under this maturity group reached maturity in 95 to 104 days. The seed color is white and has a high market value. Thus, the variety is preferred by most farmers in the study areas. For calibrating the crop model, data on days to flowering, days to physiological maturity, pod yield, leaf area index (maximum), grain and above ground biomass yields, were collected from variety trial experiments conducted in 2017, 2018 and 2019 at Sirinka site. However, the model was calibrated using the 2019 season as the crop performed well in all the parameters considered in this study. Whereas, the model was evaluated using data collected from variety trial conducted in 2015, 2016, 2017, 2018, and 2019 at Chefa site.

Model inputs

Field management parameters

Crop management information that include sowing date, sowing depth, plant spacing, simulation start date, cultivar type, and soil type are required by the crop model. In addition, fertilizer management, fertilizer type, time of fertilizer application and depth of application are needed as inputs. Recently recommended blended fertilizer (NPSB) was applied at a rate of 100 kg ha^{-1}. All the fertilizer was applied in side banding during sowing time. Two seeds per hill with spacing of 40 cm inter row and 10 cm intra row were sown to ensure germination and good stands of the variety and then thinned to one plant 10 days after the crop emergence.

Soil data

Two representative soil profiles were opened at depths of 160 cm which are 5 m and 6 m distances from the experimental sites of Sirinka and Chefa, respectively Samples were collected from each horizon in the profiles. Analysis was made for texture, pH, cation exchange capacity (CEC), electrical conductivity (EC), organic carbon (OC), total nitrogen (N) and available phosphorus (P). All the soil parameters were analyzed at Sirinka Agriculture Research Center Soil Laboratory using the standard procedures. Soil texture was determined by the modified Bouyoucos hydrometer method (Bouyoucos 1962) using sodium hexametaphosphate as dispersing agent. The soil pH was determined potentiometrically using a digital pH meter in a 1:2.5 soil water suspension (Van Reeuwijk 2002). Organic carbon was determined by wet digestion method whereas total nitrogen was determined through Kjeldahl digestion, distillation and titration procedures of the wet digestion method (Black 1965). Available phosphorus was determined colorimetrically using Olsen's method (Olsen, 1954). The Cation exchange capacity was estimated titrimetrically by distillation of ammonium that was displaced by sodium from NaCl solution (Chapman 1965). The soil water dynamics were estimated by inputting soil texture, soil organic matter content and soil bulk density into a soil file creation utility program of the DSSAT model. Bulk density, drained upper limit (DUL), drained lower limit (DLL), saturation (SAT), root growth factor (RGF) and saturated hydraulic conductivity (SKS) were estimated from the soil texture by using the software package (SBuild V 4.7) embedded in the Decision Support System for Agrotechnology Transfer (DSSAT V4.7 software).

Weather and climate parameters

Daily weather data during the growing season were collected and used as inputs to calibrate and evaluate the crop model. The collected weather data were daily maximum temperature, minimum temperatures (°C), precipitation (mm) and solar radiation (M J M^{-2} day^{-1}). The data were obtained from the nearest weather stations at Sirinka and Kombolcha stations which are 500 m and 10 km far from the field trial sites, respectively. There is no topographic variation between the Chefa site and the weather station at Kombolcha. Historical climate data (1981–2010) was used as baseline to simulate historical yield for comparison analysis. Solar radiation was estimated from latitude and temperature data using WeatherMan (Hoogenboom et al. 2010) software package embedded in the DSSAT model.

To predict response of common bean to future climate conditions, daily rainfall, maximum temperature, minimum temperature and solar radiation were obtained from the 17 CMIP5 GCM outputs run under RCP4.5 and RCP8.5 for the 2030s and the 2050s time period (Table 1). They were downloaded from CIAT's climate change portal (http://ccafs-climate.org/) and downscaled to the target site using MarkSim software package. The MarkSim uses the latitude, longitude and elevation of the location, and monthly rainfall, daily average temperature and daily average diurnal temperature variation. It also uses the temporal phase angle, that is, the degree by which the climate record is "rotated" in date. This rotation eliminates timing differences in climate events so that analysis can be done on standardized climate data. The climate record is rotated to a standard date, using the 12 point fast Fourier transform, on the basis of the first phase angle calculated using both rainfall and temperature (Jones et al. 2003). Almost all operations in MarkSim are done in rotated date space. The climate database WorldClim V1.3 was used to interpolate the climate at the required point. WorldClim may represent of the current climatic conditions. It uses historical weather data from a number of databases. WorldClim uses thin plate smoothing with a fixed lapse rate employing the program ANUSPLIN. Bicubic interpolation was used over a kernel of the nearest sixteen GCM cells on a 1×1○grid of GCM differentials. These are calculated from polynomials fitted to each GCM result which are used to return the values for any year or RCP regime. The ensemble (of 17 GCMs in this case) is calculated directly from the polynomial coefficients for each GCM. The estimated GCM differential values are added to the rotated record. This is an example of unintelligent downscaling (Wilby et al. 2009) to the monthly climate values. The method uses the spatial interpolation of grid-point data to the required local-scale. MarkSim then uses stochastic downscaling to simulate the daily weather sequences. The projected future scenario data were applied to evaluate the future production performances of the cultivar using DSSAT cropping system under the medium (4.5 W/m2) and maximum (8.5 W/m2) irradiance energy striking the earth. The Representative Concentration Pathways (RCP's) the recent approach on emission of greenhouse gases and pollutants, were used to develop future climate scenario. Representative Concentration Pathway's (RCP's) are time and space dependent trajectories of greenhouse gas concentrations and pollutants resulting from human activities, including change in land use and industrialization (IPCC 2014).

Models descriptions

Description of the DSSAT crop model

The DSSAT package provides models of 42 crops with new tools that facilitate the creation and management of experimental, soil, and weather data files (Hoogenboom

Table 1 The 17 CMIP5 models used in the simulation study

Models	Institutions	Resolutions Lat. × long
BCC-CSM 1.1 (Wu 2012)	Beijing Climate Center, China Meteorological Administration	2.8125 × 2.8125
BCC-CSM 1.1(m) (Wu 2012)	Beijing Climate Center, China Meteorological Administration	2.8125 × 2.8125
CSIRO-Mk 3.6.0 (Collier et al. 2011)	Commonwealth Scientific and Industrial Research Organization and the Queensland Climate Change Centre of Excellence	1.875 × 1.875
FIO-ESM (Song et al. 2012)	The First Institute of Oceanography, SOA, China	2.812 × 2.812
GFDL-CM 3 (Donner et al.2011)	Geophysical Fluid Dynamics Laboratory	2.0 × 2.5
GFDL-ESM 2G (Dunne et al. 2012)	Geophysical Fluid Dynamics Laboratory	2.0 × 2.5
GFDL-ESM2M (Dunne et al.2012)	Geophysical Fluid Dynamics Laboratory	2.0 × 2.5
GISS-E2-H (Schmidt et al. 2006)	NASA Goddard Institute for Space Studies	2.0 × 2.5
GISS-E2-R (Schmidt et al. 2006)	NASA Goddard Institute for Space Studies	2.0 × 2.5
HadGEM2-ES (Collins et al.2011)	Met Office Hadley Centre	1.2414 × 1.875
IPSL-CM5A-LR (Dufresne et al. 2013)	Institute Pierre-Simon Laplace	1.875 × 3.75
IPSL-CM5A-MR (Dufresne et al. 2013)	Institute Pierre-Simon Laplace	1.2587 × 2.5
MIROC-ESM (Watanabe et al. 2011)	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	2.8125 × 2.8125
MIROC-ESM-CHEM (Watanabe et al. 2011)	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	2.8125 × 2.8125
MIROC5 (Watanabe et al.2010)	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	1.4063 × 1.4063
MRI-CGCM3 (Yukimoto, 2012)	Meteorological Research Institute	1.125 × 1.125
Nor-ESM1-M (Kirkevag et al. 2008)	Norwegian Climate Centre	1.875 × 2.5

et al. 2015). DSSAT also includes improved application programs for seasonal, spatial, sequence and crop rotation analyses that assess the economic risks and environmental impacts associated with irrigation, fertilizer and nutrient management, climate variability, climate change, soil carbon sequestration, and precision management. Many changes have been incorporated to the latest version (DSSAT v4.7.5) from both the structure of the crop models and the interface to the models and associated analysis and utility programs. The DSSAT package has been widely used tool for testing cropping technologies, assessing management practices, and exploring climate change mitigation strategies (He et al. 2018). The DSSAT technology requires daily weather variables, soil physical and chemical characteristics, crop variety parameters, and crop managements (Hoogenboom et al. 2012; Jones and Thornton 2003).

Description of the CROPGRO-Model

The CROPGRO-dry bean model is one of the crop models available in DSSAT (Hoogenboom et al. 2010). The model has been used for many applications ranging from onfarm and precision management to regional assessment of impacts of climate variability and climate change (Hoogenboom et al. 2010; Jones et al. 2003). The CROPGRO-dry bean model employs soil, crop management and daily meteorological data as input. The vegetative and reproductive development, carbon balance, water balance and nitrogen balance are the major components of the model (Singh and Virmani 1996). The model simulates growth and development using a daily time step from sowing to maturity and ultimately predicts yield. Soil water balance is a function of rainfall, irrigation, transpiration, soil evaporation, runoff and drainage from the bottom of the soil profile. The soil water balance sub-model in CROPGRO-Dry bean model in the DSSAT model is described in detail by Ritchie (1998).

Model calibration and evaluation procedures

We followed stepwise procedures to calibrate the crop model. First, genetic coefficients were selected from a given genotype from those in the same maturity group and the model was run for treatments and values were assigned to specific genetic coefficients beginning with phenology followed by growth and yield parameters. A trial and error method was used by applying small change (+5%) on each parameter and by adjusting the genetic coefficients. The adjusted genetic coefficients were used in the subsequent evaluation of the crop model. For evaluating the model, data on flowering, physiological maturity, grain yield and above ground biomass yield were used. The model performance in prediction was evaluated using root mean square error (RMSE) (Wallach and Goffinet 1989). Willmot's Index of agreement (d) and coefficient of determination (R^2) which were computed from the observed and the simulated variables Root Mean Square Error is the standard deviation of the residuals (prediction errors). The residuals measure how far the data points are from the regression line. It tells us how concentrated the data is around the line of best fit. R^2 is a measure of the goodness of fit of a model. It is a statistical measure of how well the regression predictions approximate the real data points. An R^2 of 1 indicates that the regression predictions perfectly fit the data. The Index of Agreement (d) developed by Willmott (1981) is used as a standardized measure of the degree of model prediction error and varies between 0 and 1. A value of 1 indicates a perfect match, and 0 indicates no agreement at all (Willmott 1981). The nRMSE gives the measure (%) of the relative difference between simulated and observed data. Less value indicates good fit of the model.

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

where n = number of observations, Pi = predicted value for the ith measurement and Oi = observed value for the ith measurement. Thus, lower value indicates good fit of the model.

$$\mathrm{n}RMSE = \frac{RMSE}{N} \times 100$$

where N is the mean of the observed variables.

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (Pi - Oi)^2}{\sum_{i=0}^{n} (|Pi - O|) + (|Oi - O|)^2} \right]$$

The d-statistic was calculated as ($0 \le d \le 1$). The more values close to unity are regarded as best agreement between the predicted and observed data (Musongaleli et al. 2014). When d = 1 indicates excellent. Where n: number of observations, Oi and Pi are the observed and predicted values, respectively for the ith data pair; and O is the mean of the observed values.

Assessing impacts of future climate change on phenology and yield of common bean

For predicting impact of future climate change on common bean maximum and minimum temperatures, solar radiation and rainfall on daily bases with reference to the baseline climate (1981–2010) along with CO_2 increase (IPCC 2013) were used as input in the crop model. Simulation was carried out for the baseline period and for the projected climate in 2030s (2020–2049) and 2050s (2040–2069). The 17 Coupled Models Inter-Comparison Project (CMIP5) run under two greenhouse gas emission scenarios (RCP4.5 and RCP8.5) were downscaled to the target sites using MarkSim software package (Jones and Thornton 2013). In the simulation, 380 ppm of CO_2 was used for the baseline period while for the 2030s time period 423 ppm and 432 ppm CO_2 were used for RCP4.5 and RCP8.5, respectively. For the 2050s period, 449 ppm and 571 ppm CO_2 were used for the respective RCPs. The simulation was started on 30 June and soil profile was considered at the upper limit of soil water availability. 30 June is the normal/standard sowing date for common bean in the area. Most farmers start planting of common bean after the start of the main rain season. Thus, we assumed that soil moisture is at its field capacity in that day. The change in phenology and grain yield of the cultivar under the baseline and future climate changes were computed as follows:

$$\text{changeinphenology}(\%) = \frac{\text{X Predicted} - \text{X base}}{\text{X base}} * 100$$

where, X is phenology of the crop

$$\text{changeingrainyield}(\%) = \frac{\text{Y Predicted} - \text{Y base}}{\text{Y base}} * 100$$

where, y is grain yield of the crop.

Crop management Scenarios for common bean production

Grain yield of the cultivar in the base period and in future climates was predicted in response to change in sowing dates and supplemental irrigation. The sowing window for common bean in the study region extends from 15 June to 15 July. The standard sowing date (SSD) for the crop most practiced by farmers is 30 June. Thus, the early sowing date was set to SSD − 15 days whereas the late sowing date was set to SSD + 15 days. The two irrigation treatments were set (1) rainfed hereafter designated as RF and (2) supplemental irrigation hereafter designated as SI. In the irrigated treatment three irrigation of 100 mm water was applied in 10 days interval starting the flower initiation stage of the crop. The aim of the supplemental irrigation application was to reduce impact of terminal water deficit that occurs at critical crop growth stages of the crop. The amount and timing of irrigation were estimated based on water requirement of the crop in the study area. Thus, the effectiveness of sowing dates and supplemental irrigation were evaluated individually and in combinations. The multi-year output data from the simulation were analyzed using analysis of variance (ANOVA) based on the randomized complete block design (RCBD). Simulation years were considered as replications as the yield in one year under each treatment was not affected by another year. Therefore, years were considered as unpredictable weather characteristics. The following assumptions were considered when we used the ANOVA technique (1) individual observations are mutually independent; (2) the random errors are normally distributed; and (3) the random errors have homogenous (equal variance). The statistical analysis was done using (SAS 2008) software package and treatment means were compared using the least significance difference (LSD) at 5% probability. Descriptive statistics such as means and percentile characteristics were also used to compare treatments means.

Results and discussion

Model calibration

There are 18 eco-physiological coefficients in the CROPGRO-dry bean model for simulating phenology, growth and yield. The calibrated genetic coefficients are depicted in Table 2. Result showed that the RMSE values for flowering, physiological maturity, grain yield and above ground biomass yield were 3, 4, 292 and 497, respectively (Table 3) whereas the percent of normalized root mean square errors (NRMSE) for the respective parameters were 5.9%, 4.3%, 8.10% and 6.0% (Table 3). The results revealed that the cultivar specific parameters within the model were reasonably adjusted. However, the performance of the model needs further evaluation with an independent set of data before the model is used for application.

Table 3 Comparison between simulated and measured values for the cultivar *Awash Melka* during the model calibration phase

Parameters	Simulated	Observed	RMSE	nRMSE
Days to flowering	53	51	3	5.90
Days to maturity	96	93	4	4.30
Grain yield (kg ha^{-1})	3600	3400	292	8.10
Above ground biomass yield (kg ha^{-1})	8297	7800	497	6.00

Model evaluation

The performance of the CROPGRO-dry bean model was evaluated by comparing simulated and observed flowering date, physiological maturity date, grain yield, above ground biomass yield, leaf area index (maximum) and pods yield. The RMSE, R^2 and d-index values for days to flowering were 2.42, 0.76 and 0.82, respectively (Fig. 1) whereas the respective values for days to physiological maturity were RMSE = 3.19, R^2 = 0.70 and d-index value = 0.87. The RMSE, R^2 and d-index values for grain yield were 113.73, 0.95 and 0.89, respectively (Fig. 2). Aboveground biomass yield at maturity

Table 2 The calibrated genetic coefficients in the model for cultivar *Awash Melka*

Coefficients	Definition	Cultivar (Awash Melka)
CSDL	Critical Short Day Length below which reproductive development progresses with no daylength effect (for shortday plants) (hour)	12.17
PPSEN	Slope of the relative response of development to photoperiod with time (positive for shortday plants) (1/hour)	0.02
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	36.5
FL-SH	Time between first flower and first pod (R3) (photothermal days)	4.0
FL-SD	Time between first flower and first seed (R5) (photothermal days)	11.0
SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	24.5
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	24.0
LFMAX	Maximum leaf photosynthesis rate at 30 C, 350 vpm CO2, and high lightm (mg CO2/m2-s)	1.0
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm2/g)	300
SIZLF	Maximum size of full leaf (three leaflets) (cm2)	150
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	1.0
WTPSD	Maximum weight per seed (g)	0.40
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	22.5
SDPDV	Average seed per pod under standard growing conditions (#/pod)	5.0
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	15.0
THRSH	The maximum ratio of (seed/ (seed + shell)) at maturity. Causes seed to stop growing as their dry weight increase until shells are filled in a cohort. (Threshing percentage)	78.0
SDPRO	Fraction protein in seeds (g(protein)/g(seed))	0.235
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.03

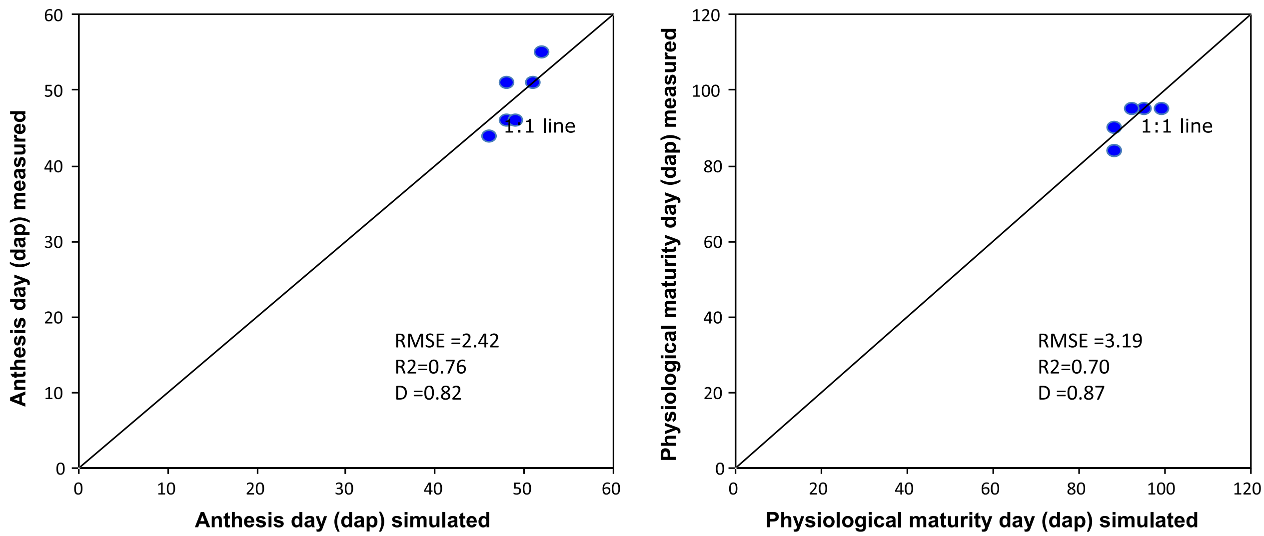

Fig. 1 Comparison between simulated and measured flowering and physiological maturity dates under different production years during the model evaluation phase at Chefa

also showed good agreement between the simulated and the observed values with RMSE = 290.63, $R^2 = 0.65$ and d-index value = 0.84 (Fig. 2). Pod yield and leaf area index (maximum) also showed strong agreement between the observed and simulated values (Fig. 2). The goodness of fit between the observed and simulated values revealed that the CROPGRO-dry bean model reasonably simulated and predicted flowering date, physiological maturity date, grain yield, aboveground biomass yield, pod yield and leaf area index of the cultivar. Therefore, the crop model can be used to study climate change impacts on common bean production and to evaluate various crop management strategies that can enhance the productivity of common bean in the study region.

Future climate changes in the study region

Result from the climate analysis showed that mean maximum and minimum temperatures of the study region may increase in 2030s and 2050s for both RCP4.5 and RCP8.5 climate scenarios. The result revealed that mean annual maximum temperature may increase by 1.36 °C in 2030s and increase by 1.9 °C in 2050s under RCP4.5 scenario. The mean annual temperature may also increase by 1.51 °C in 2030s and by 2.5 °C in 2050s for RCP8.5 scenario. The projected mean annual minimum temperature showed similar trend in 2030s and 2050s and it ma increase by 1.41 °C and 1.97 °C, respectively under RCP4.5 scenario whereas it is projected to increase by 1.65 °C in 2030s and by 2.73 °C in 2050s under RCP8.5. This results agrees well with previous reports that indicated future warming in different parts of Ethiopia (Hadgu, et al. 2015; Dereje et al. 2012; Conway and Schipper 2011; Setegn et al. 2011). Review of long-term climate data for Ethiopia shows increasing rainfall for some regions and decreasing rainfall for others with temperature rising for all regions (Energy Group of ECSNCC Network, 2011). Global circulation models predict a 1.7–2.1 °C rise in Ethiopia's mean temperature by 2050 (EPA, 2012). Average annual temperatures nationwide are expected to rise 3.1 °C by 2060, and 5.1 °C by 2090 (Kidanu et al. 2009). The National Meteorological Agency (NMA 2007) in Ethiopia also reported an increase in mean annual temperature by 0.2 °C per decade over Ethiopia between 1960 and 2006 period. Rainfall is projected to increase by 8% in 2030s and by 9% in 2050s under RCP4.5 scenario whereas it is projected to increase by 9% in 2030s and by 14% in 2050s under RCP8.5 scenario. This result agrees with those reported by Hadgu et al. (2015); Muluneh et al. (2015); Tesfaye et al. (2014); Kassie et al. (2015). An increase in annual rainfall was projected with the highest increase by 28 and 38% for RCP4.5 and RCP8.5, respectively (Kassie et al. (2015). The study by Muluneh et al. (2015) also showed that that the main season (*Kiremt*) rainfall may increase up to 32% in the Central Rift Valley of Ethiopia. Crop productivity (yield) is the results of environmental factors. Thus, variation in these climate parameters in the future may affect common bean production in semi-arid environments of northeastern Ethiopia.

Impact of future climate changes on common bean phenology and grain yield

The impacts of future climate on phenology and yield of cultivar *Awash Melka* are depicted in Fig. 3. Simulation results showed that both days to flowering and

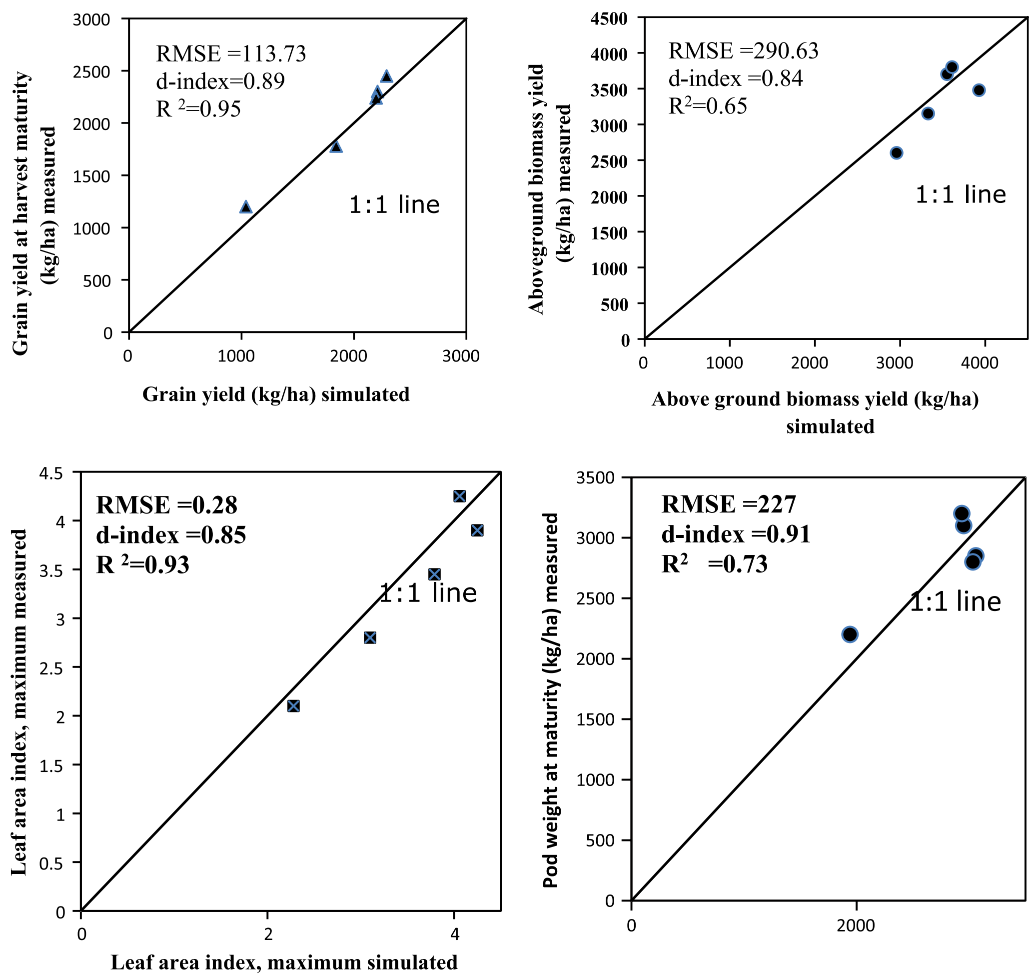

Fig. 2 Comparison between simulated and measured grain yield, aboveground biomass yield, leaf area index (maximum), and pod yield at maturity during the model evaluation phase at Chefa

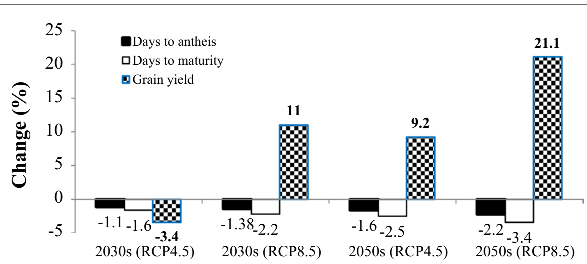

Fig. 3 Change (%) of flowering date, physiological maturity date and grain yield in 2030s and 2050s under RCP4.5 and RCP8.5 scenarios as compared to the baseline (1981–2010) at Sirinka

days to physiological maturity may decrease in 2030s and 2050s at both sites and under both RCP4.5 and RCP8.5 climate scenarios as compared to the simulated values for the baseline period (1981–2010). The highest significant reductions in flowering as well as physiological maturity dates were under scenario RCP8.5 in 2030s as well as in 2050s (Fig. 3). The reduction in flowering date of the cultivar (%) in 2030s is predicted to be 1.1% and 1.38% under RCP45 and RCP8.5, respectively whereas the reduction in physiological maturity date is predicted to be 1.6% and 2.2% under the respective RCPs. The result also revealed that flowering date of common bean may decrease in 2050s by 1.6% and 2.2% under RCP4.5 and RCP8.5 scenarios, respectively whereas physiological maturity date may decrease by 2.5% and 3.4% for the respective climate scenarios in 2050s (Fig. 3). However, the study showed that grain yield may increase in 2030s and 2050s as compared to the baseline yield except 3.4% yield reduction in 2030s under scenario RCP4.5. Grain yield is also predicted to increase in 2030s by about 11% under RCP8.5 and 9.2%

and 21.1% increase in 2050s under RCP4.5 and RCP8.5, respectively.

The decrease in flowering and physiological maturity dates of the cultivar under future climate conditions may be attributed to increase in future temperature from the base period which may accelerate the crop growth and development stages and ultimately reduce the life cycle of the crop. The reduction in growth period of the crop may affect the cultivar phenology, yield and yield components. On the other hand, the increase in grain yield of the cultivar in future climate may be due to the earliness of the cultivar which help it to escape from terminal water deficit as the study region is characterized as semi-arid where terminal water stress is common phenomenon. Other possible reason may be the increase in projected precipitation and/or increase in the CO_2 concentration that may influence yield positively. Hence, we concluded that common bean crop may be benefited from the future climate. Similar to this finding, Adem et al. 2016 reported that among the four climate scenarios (RCP2.6, RCP4.5, RCP6 and RCP8.5) days to maturity of chickpea was significantly reduced under RCP8.5 scenario which may be due to the highest increase in temperature. As the crop growth cycle is strongly related to temperature, crop life cycle may be conditioned by the daily temperatures absorbed. However, the study showed that the current yield of common bean in the study region is still low and may be continued to be low in future climate unless improved crop management practices are employed in the study region.

Effects of sowing dates and supplemental irrigation on grain yield of common bean

In the simulation, three sowing dates namely early sowing date (SSD − 15 days), standard sowing date (SSD) and late sowing date (SSD + 15 days) and two water regime (1) rainfed (no irrigation) and (2) supplementary irrigated were evaluated individually and in combination as climate adaptive measures for common bean at two agroecologies in northeastern Ethiopia (Sirinka and Chefa) for the baseline period (1981–2010) and for future climates in 2030s and 2050s under RCP4.5and RCP8.5 scenarios. The irrigated treatment received three irrigations of 100 mm each was applied in 10 days interval starting the flower initiation stage of the crop. The amount and time of irrigation is estimated based on the water requirement of the crop. Results showed that early sowing (SSD − 15 days) under rainfed condition significantly increased mean grain yield of the cultivar by 27%, 20% and 17% for the baseline period, 2030s and 2050s time periods, respectively under both RCPs (Table 4). On the other hand, early sowing under irrigated condition produced the highest increase in mean grain yield by about 89%, 71% and 56% for the respective time periods under both RCP. Late sowing date (SSD + 15) under l irrigated condition increased grain yield by 17%, 27% and 18% for the respective time periods. In contrast, late sowing under rainfed condition decreased grain yield by 24%, 19% and 19% for the respective time periods. The impacts of sowing dates and supplemental irrigation on grain yield of common bean showed similar trend at Chefa site in the present as well as in future climate conditions (Table 5). It can be generalized that early sowing of common bean significantly increased grain yield under both irrigated and rainfed conditions across time periods, climate scenarios and sites although the highest yield response was from the irrigated treatment. The result also showed that the cumulative effect of supplemental irrigation on grain yield was highly significant as compared to the rainfed condition across all the time periods and sites (Fig. 4 and Fig. 5). Hence, we concluded that early

Table 4 Combined effect of sowing dates and supplemental irrigation on grain yield of common bean under the projected climate changes as compared to baseline yield at Sirinka

Treatments	Grain yield (Baseline)	% change	(2030s)				2050s			
			RCP 4.5	% change	RCP8.5	% change	RCP 4.5	% change	RCP8.5	% change
SS + RF	1571	–	1523	–	1745	–	1723	–	1914	
SS + SI	2416	54	2475	63	2590	48	2576	50	2666	39
ES + RF	1995	27	1794	18	2131	22	2003	16	2254	18
ES + SI	2964	89	2712	78	2853	63	2749	60	2906	52
LS + RF	1192	− 24	1264	− 17	1398	− 20	1407	− 18	1534	− 20
LS + SI	1836	17	2026	33	2106	21	2111	23	2142	12
LSD (P = 0.05)	278		260		267		267		240	

LSD: Least significant difference at 5% probability level: % Change: Percent change in grain yield with reference to the grain yield of the standard sowing date under rainfed. SS, ES and LS stand for standard sowing date, early sowing date and late sowing dates, respectively. RF and SI stands for rainfed and supplemental irrigation, respectively

Table 5 Combined effect of sowing dates and supplemental irrigation on grain yield of common bean in the baseline, 2030s and 2050s under RCP4.5 and RCP8.5 scenarios at Chefa

Treatments	Baseline yield	% change	2030s				2050s			
			RCP 4.5	% change	RCP 8.5	% change	RCP 4.5	% change	RCP 8.5	% change
SS + RF	1894	–	1746	–	1857	–	1726	–	1947	
SS + SI	2553	35	2657	53	2693	45	2780	61	2827	45
ES + RF	2306	22	1989	14	2118	14	2014	17	2320	19
ES + SI	3060	62	2936	68	2936	58	2940	70	3112	60
LS + RF	1479	− 22	1497	− 14	1607	− 13	1630	− 6	1633	− 16
LS + SI	2030	7.0	2230	28	2276	23	2289	33	2333	20
LSD (P = 0.05)	251		289		268		267		274	

LSD: Least significant difference at 5% probability level: % Change: Percent change in grain yield with reference to the grain yield of the standard sowing date under rainfed. SS, ES and LS stand for standard, early and late sowing dates, respectively. RF and SI represent rainfed and supplemental irrigation, respectively

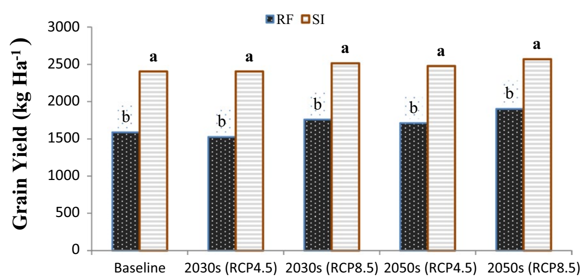

Fig. 4 Grain yield response of common bean to supplemental irrigation and rainfed conditions in the baseline period, 2030s and 2050s under RCP4.5 and RCP8.5 climate scenarios at Sirinka. Letters a and b indicates statistically significant difference at 5% probability level. RF and SI, indicates rainfed and supplemental irrigation, respectively

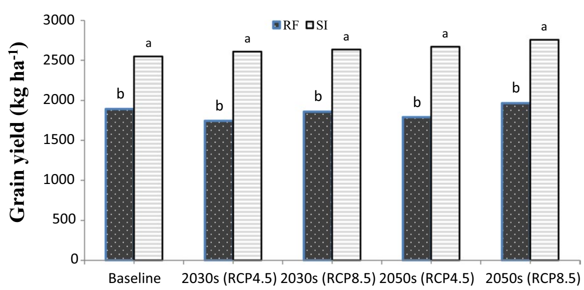

Fig. 5 Grain yield of common bean under supplemental irrigation and rainfed condition in the baseline, 2030s and 2050s under RCP4.5 and RCP8.5 climate scenarios at Chefa. Letters (a and b) indicates statistically significant difference at 5% probability level. RF and SI, indicates rainfed and supplemental irrigation, respectively

sowing of common bean (SSD-15) combined with supplemental irrigation may significantly increase grain yield across the time periods. The significant increase in grain yield under supplemental irrigation may be due to improvement in available soil moisture during the crop critical growth stages of the cultivar (flowering and grain filling stages) that reduced the effect of terminal water deficit on the crop.

Currently, water harvesting structures are widely practiced and utilized under the government interventions programme. Hence, farmers have the opportunity to apply supplemental irrigation for selected crops grown in the area. Terminal moisture deficit (drought) is common phenomenon in the semi-arid region of Ethiopia. The application of irrigation water during the flowering initiation stage of common bean may lead to significant increase in grain yield of in the present and future climate conditions of the study region. The result of this study showed that for many semi-arid areas in Ethiopia where drought is major crop production constraint, the application of supplemental irrigation at critical growth stages of common bean (flowering and grain filling stages) may significantly improve grain yield. Nayyar et al. (2006) reported that water shortage at chickpea generative stages prevents yield potential through flowers and pods shedding. Excellent responses to supplemental irrigation have been also reported by Rockström et al. (2007). Better responses from supplemental irrigation could be attained when the irrigation is applied at the critical time of the crop growth stages (flowering, grain yield including pod setting). In conclusion, supplemental irrigation may be used to alleviate soil water stress/drought which is major crop production constraint in most semi-arid areas. In agreement with this result, excellent response to supplemental irrigation on chickpea was reported by Adem et al (2016). As rainfall in the region is highly erratic and unpredictable, supplemental irrigation may be one of the most effective options to alleviate problem of terminal drought stress on common bean.

Conclusion

Common bean is the most important legume crop in Ethiopia. However, the national average yield remains 1600 kg ha^{-1} which is far below the yield in research fields (3500 kg ha^{-1}). The low productivity is mainly due to climate variability, climate change, low soil fertility, lack of improved crop management practices, lack of improved varieties, insect and disease problems. Currently, climate change is significantly impacting common bean production in the semi-arid areas of Ethiopia. There are limited studies conducted in the semi-arid areas respect to climate change impact and potential adaptation strategies.

This study assessed impact of future climate changes on common bean productivity and identified possible adaptation strategies in two agroecologies of common bean growing areas in the semi-arid region of northeastern Ethiopia. The climate impact assessment and evaluation of management scenarios were done by using the CROPGRO-dry bean model in DSSAT crop model for the baseline climate and for the projected climate in 2030s and 2050s using the 17 CMIP5 models under two climate scenarios (RCP4.5 and RCP8.5). Baseline daily climate data, soil and crop managements were collected from the study sites. The model was calibrated using data of flowering date, physiological maturity date, grain yield, pod yield, above ground biomass yield and leaf area index (LAI). Three sowing dates and two water regime (rainfed (not irrigated) and (2) Supplementary Irrigated) were evaluated as management strategies for common bean under projected climate change conditions.

The result showed that the CROPGRO-dry bean model was reasonably calibrated as the model successfully predicted flowering date, physiological maturity date, grain yield, aboveground biomass yield, pod yield and leaf area index (maximum) of common bean. The result of impact analysis indicated that days to flowering and days to physiological maturity of common bean may decrease in 2030s and 2050s under both RCPs and at both sites. However, grain yield may increase in 2030s and 2050s. The management scenarios showed that early sowing (SSD − 15 days) under rainfed condition will likely increase mean grain yield by 27%, 20% and 17% for the baseline, 2030s and 2050s time periods respectively under both RCPs. The highest and significant grain yield will likely be from the early sowing (SSD − 15 days) under irrigation may increase grain yield by 89%, 71% and 56% for the baseline, 2030s and 2050s, respectively. Late sowing (SSD + 15) under supplemental irrigation may also increase grain yield by about 17%, 27% and 18% for the respective time periods. In contrast, grain yield is predicted to decrease by 24%, 19% and 19% due to the delayed sowing dates under rainfed conditions for the respective time periods Thus, it can be generalized that early sowing combined with supplemental irrigation may significantly increase grain yield in the present and future climate conditions of the study region.. Thus, it can be concluded that better understanding of the cumulative effects of climate change is important to develop climate resilient common bean production system in the study region.

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Author contributions
AM was involved in analyzing and interpreting the data regarding the crop modeling and calibration process. EF has been involved in the evaluation and analysis of the climate data and also contributed in giving constructive comments and suggestion. AM was a major contributor in writing this manuscript. Both authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval and consent to participate
The manuscript is submitted based on the journal requirement and ethical consideration.

Consent for publication
The authors are agreed to publication the article in the journal.

Competing interests
"The authors declare that they have no any competing interests" in this section.

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