Climate change/variability is a global concern that is seriously affecting developing and least developed countries which rain-fed based agriculture is predominantly the basis for their livelihood and socio-economic system. Adverse impacts of climate change and variability, in most developing and least developed countries like Ethiopia, is growing in time and exert pressure on agricultural systems which changes the balance among the key determinants of crop growth and yield. As a result, the demand for investigating and understanding the expected negative impacts of climate change and variability on food production is increasing. Accordingly, this study tried to investigate impacts of climate change on sorghum production using projected future climate scenarios data. Climate change scenario data for 20 global climate models were downscaled from the fifth assessment report on coupled model intercomparison project of intergovernmental panel on climate change. CERES-Sorghum model was calibrated and validated using soil, weather and crop management data conducted at Kobo agricultural experiment site. The result revealed that yield variation was observed across locations, climate models and time periods considered. Despite uncertainties, maximum yield reduction in sorghum is projected by the end of the 21st century when maximum insolation has reached 8.5 W/m². In general, the result indicated that, sorghum production in north eastern Ethiopia is expected to be affected negatively in the future. Therefore, this finding would give a preliminary information for policy and decision making process to enhance climate change adaptation.

**Key words:** Climate change, impact assessment, crop, models, climate, sorghum.

**INTRODUCTION**

Climate change/variability is a global concern that is seriously affecting developing and least developed countries which rain-fed based agriculture is predominantly the basis for their livelihood and socio-economic system (Hellmuth et al., 2007; Kotir, 2011; FAO, 2015; Zacharias et al., 2015). The adverse impacts of climate change and variability, in most developing and least developed countries like Ethiopia, is growing in time and exert pressure on agricultural systems which changes the balance among the key determinants of crop growth and yield. As a result, the demand for investigating and understanding the expected negative impacts of climate change and variability on food production is increasing. Accordingly, this study tried to investigate impacts of climate change on sorghum production using projected future climate scenarios data. Climate change scenario data for 20 global climate models were downscaled from the fifth assessment report on coupled model intercomparison project of intergovernmental panel on climate change. CERES-Sorghum model was calibrated and validated using soil, weather and crop management data conducted at Kobo agricultural experiment site. The result revealed that yield variation was observed across locations, climate models and time periods considered. Despite uncertainties, maximum yield reduction in sorghum is projected by the end of the 21st century when maximum insolation has reached 8.5 W/m². In general, the result indicated that, sorghum production in north eastern Ethiopia is expected to be affected negatively in the future. Therefore, this finding would give a preliminary information for policy and decision making process to enhance climate change adaptation.

**Key words:** Climate change, impact assessment, crop, models, climate, sorghum.
growth and yield (Aggarwal, 2009). Agriculture, in Ethiopia, is largely susceptible for climate variability and extremes, due to its high dependency nature of rainfed based system (Deressa, 2007; NMA, 2007; MoA, 2011). Climate change induced variations contribute to frequent drought, flooding and rising mean temperatures which seriously affect agricultural production over large areas of Ethiopia (Aragie, 2013).

Agriculture is the back bone of the entire economy of Ethiopia which currently contributes about 42% to the GDP, employs more than 85% of the total population, and contributes around 90% of the national export (NMA, 2007; Irish AID, 2018). Evidences show that whatever is happening in agriculture sector, the country’s economy would be profoundly affected (Gebrehiwot and Veen, 2013; World Bank, 2016, 2019). Rainfall and temperature are the most important climatic factors that tend to affect production potential of the agricultural sector (Irish AID, 2018). The changing rainfall pattern in combination with the warming trends could make rain-fed agriculture more risky and aggravate food insecurity in Ethiopia. According to FAO (2010) report, production performance of agriculture in Ethiopia is highly linked with the rainfall performance of the cropping season in which wet season is associated with higher production and vice versa. The report by Aragie (2013) also indicated that uneven and erratic rainfall during the last four decades makes a clear divergence of Ethiopian economy from the rest of the world.

The results from most climate models also indicate projected high inter-annual rainfall variability in combination with warming will lead to recurrent droughts in Ethiopia, which negatively impacts crop production and alleviates the food security challenges (NMA, 2007; WFP, 2014; World Bank, 2016). Furthermore, heavy rains and floods are projected to increase, which causes production loss and nurturing stress.

In Ethiopia, most of the risk and impact assessments studies are more generalized and region wide rather than location specific and descriptive even if sensitivity is varied across sectors, geographic locations, time, socioeconomic and environmental considerations (NMA, 2007). As a result, the information generated are uncertain to design appropriate adaptation strategies that reduce the adverse impacts of climate variability and extremes. In addition, limited capacity, to carry out analysis for advocacy and enhanced understanding of risks and impacts, is another constraint for climate change adaptation (NMA, 2007; Irish AID, 2018).

The northern parts of Ethiopia is highly characterized by low, erratic, uneven rainfall distribution and recurrent droughts. This region is seriously affected by adverse impacts of climate variability and extreme events which any variation in rainfall during the cropping season causes production loses (NMA, 2007; MoA, 2011; Irish AID, 2018). The well recognized recurrent droughts occurring in the region poses a serious threat to agricultural production and livelihood of the communities and aggravating the ongoing food shortage (FAO, 2010, 2015; Irish AID, 2018).

Nowadays, the demand of identifying production risks and designing appropriate contingency plan for possible adverse impacts of climate change and variability is increasing. This is to understand and identify cropping patterns (crops or varieties suitable for a given production environment) and management practices for optimum utilization of resources that enhance climate change adaptation (FAO, 2010). New thinking and advanced approaches are needed to precise agriculture decision that minimize production risks under a given environment and season.

The process of adaptation emphasizes understanding of the production environment, learning about risks, evaluating response options, creating the conditions that enable adaptation, mobilizing resources, implementing adaptations and revising choices with new learning (NMA, 2007; FAO, 2015). Since recent tools and scientific approaches have been used to predict and precise farming practices which are good risk management approach that reduced climate uncertainties. Process based cropping system models are a set of tools that have been used widely to answer complex questions related to crop production, economics and environmental impacts (Hoogenboom, 2000; Hoogenboom et al., 1992; Jones et al., 2003, 2010). Crop growth models integrate soils, weather, management, genetics, and pest effects in daily pattern that simulates growth, development and yields (Jones et al., 2003, 2010a and b; Hoogenboom et al., 2012). Among several crop growth models, the most widely used is a decision support system for agrotechnology transfer (DSSAT), which is designed to stimulate growth, development, and yield of a crop growing on a uniform area of land, as well as change in soil water, carbon, and nitrogen interactions that takes place over time (Hoogenboom, 2000; Jones et al., 2003; Hoogenboom et al., 2010).

Herewith, 20-global climate model outputs, from intergovernmental panel on climate change fifth assessment report of IPCC-AR5 and decision support system for agro-technology transfer (DSSATv4.6) were used. The objective of this study is to evaluate the response of selected sorghum varieties for future climate in north eastern region of Ethiopia.

Ethiopia is a center of origin and diversity for sorghum (Sorghum bicolor (L) Moench). The country contributed considerably a number of genetic resources for the global germplasm collections and genes. The crop is primarily grown as a food crop used for preparation different food types mainly leavened bread (locally known as Injera) and locally prepared alcoholic beverages (e.g. tala and areke) (EIAR, 2020).

Sorghum stands third in area coverage next to tef and maize and fourth in total production next to maize, teff and wheat (ATA, 2015; CSA, 2018). It covers around
16.79% of the total area allocated to grains and 16.89% of cereal production (CSA, 2018; EIAR, 2020). Sorghum is the major crop grown in dry lowland environment which accounts for more than 60% of the cultivated land. Productivity of sorghum is constrained by a number of biotic and abiotic factors which drought is the most abiotic factor in dry lowland region (ATA, 2015; EIAR, 2020).

MATERIALS AND METHODS

Description of study sites

The study was undertaken in north eastern parts of Ethiopia, one of the major sorghum production belts of the country. Two production districts, Sirinka and Kobo, were considered to undertake this study. Sirinka is situated in between 11°41’ and 11°49’ N latitude; and 39°07’ and 39°42’E longitude with an elevation range of 1749 to 2033 m.a.s.l. Whereas Kobo is found in between 12°09’ and 12°15’ N latitude and 39.38° and 39.63°E longitude; which has an elevation of around 1468 m.a.s.l (Figure 1).

Climate of the study areas

Kobo has a semi-arid climate characteristic, which the mean annual temperature ranges from 18 to 27°C and a mean annual rainfall of 410 to 820 mm. Whereas, Sirinka has a tropical climate type in which mean annual rainfall ranges from 680 to 1200 mm. Regarding rainfall distribution, Kobo and Sirinka experience a bimodal rainfall pattern with little or unreliable rain from mid-February to end of April (locally known as belg) and more reliable and peak rain from June to September (locally known as kiremt) which more than 50% of the annual total rain recorded. In both districts, the mean monthly maximum temperature was recorded in June, first month of the main growing season; known as Kiremt (JJAS). June is the warmer month that a maximum day/night temperature reach its peak value in both locations. Figure 2 shows mean monthly rainfall and temperature distribution at Kobo and Sirinka districts.

Farming system

Crop dominating mixed (crop-livestock) subsistence farming system is practiced under the region (FAO, 2010; Assefa et al., 2016). Rain-fed based small scale farming system, employed under traditional farming technology, is a source of livelihood for the majority of the population. Low potential and high risks are major characteristic of the production system in the region (World Bank, 2004; Assefa et al., 2016.). Teff and sorghum are dominant crops grown in well-known region of sorghum diversity in Ethiopia (Assefa et al., 2016). Sorghum is an important food crop next to teff in the dryland region, including Kobo and Sirinka, for human diet and feed for animals (Assefa et al., 2016).

Data collection

Crop and management data

Commonly grown sorghum cultivars (Teshale and Melkam) were used as testing cultivars to evaluate production performances in the future under the changing climate. Melkam and Teshale are categorized under early and medium maturing groups, respectively. Growth, development and grain yield data for model calibration and validation were obtained from sorghum and millet improvement research program of Melkassa Agricultural Research Center (MARC). Teshale and Melkam sorghum varieties were released in 2002 and 2009 for moisture stress (dry lowland) areas.

Climate data

Long-term observed daily rainfall, maximum and minimum temperature data for Sirinka and Kobo districts were obtained from Ethiopian Institutes of Agricultural Research and National Meteorology Agency of Ethiopia. Historical climate data from 1985 to 2014 were used as a baseline data to generate future climate scenario and to simulate historical yield for comparison analysis. Solar radiation, one of the important data to run the cropping system model were estimated from latitude and temperature data using WeatherMan (Bristow and Campbell, 1984; Hoogenboom et al., 2010) software package embedded in DSSAT-GSM.

Future climate scenario data

The concept of Representative Concentration Pathways (RCP’s), the recent approach on emission of greenhouse gasses and pollutants, were used to develop future climate scenario data for the study sites. 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). Agricultural Model Inter-comparison and Improvement Project (AgMIP) climate scenario generation tool was used to downscale future climate scenario data for 20 global climate models (20-GCM’s) for two RCP’s (RCP4.5 and RCP8.5) and two time periods; 2050s (2040-2069) and 2080s (2070-2099) using delta method downscaling approach. The global climate models (GCM’s) used for this study are displayed in Table 1 below. The projected future scenario data were applied to evaluate the future production performances of the two sorghum cultivars using DSSAT cropping system under the medium (4.5 W/m²) and maximum (8.5 W/m²) irradiance energy striking the earth.

Soil data

Soil physical properties like texture and chemical properties like pH, cation exchange capacity (CEC), organic carbon (OC), and total N were determined for the experiment site using Melkassa Agriculture Research Center soil laboratory. In addition, important soil properties such as bulk density, drained upper limit (DUL), drained lower limit (DLL), saturation (SAT), root growth factor (RGF) and saturated hydraulic conductivity (SKS) were estimated from soil texture using SBUILD software package embedded under Decision Support System for Agro-technology Transfer (DSSAT4.6). Soil physical and chemical properties for Kobo and Sirinka districts are presented in Tables 2 and 3 respectively.

DSSAT crop model

Decision Support System for Agro-Technology Transfer (DSSAT) is a generic cropping system model developed to simulate crop growth, development and yield of several crops grown under uniform area of land and a set of management conditions. It have been used for more than 25 years by researchers, educators, consultants, extension agents, growers, policy and decision makers over more than 100 countries worldwide (Jones et al., 2003). Crop Environment Resource Synthesis (CERES) of sorghum model, which is embedded within DSSAT version 4.6 was used to simulate growth, development and yield as a function of the soil-
plant-atmosphere dynamics, and it has been used for many applications ranging from on-farm and precision management to regional assessment of the impacts of climate variability and climate change (Hoogenboom et al., 2010; Jones et al., 2003). CERES-Sorghum model employs soil, crop management and daily meteorological data as input to simulate daily leaf area index (LAI) and vegetation status parameters, biomass production and final yield. The model calculates phasic and morphological development of crops using temperature, day length and genetic characteristics (Ritchie, 2016). The water and nitrogen balance sub models, on the other hand, provide feedback that influences developmental and growth processes (Ritchie, 2016).

Model calibration and evaluation

Decision Support System for Agro-technology Transfer (DSSAT) cropping system models need genetic coefficients to simulate growth, development and yield of specific genotypes, taking into account weather, soil water and nitrogen dynamics in soil and crop in mechanistic manner (Hunt et al., 1993; Choudhury et al., 2018). Genotype coefficient may be determined in controlled environments or under field conditions (Hunt et al., 1993). Under this study, cultivar specific genetic coefficients for two sorghum cultivars, Teshale and Melkam, were estimated using GENCAL software packages embedded in DSSAT cropping system model. In

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**Figure 1.** Map of study sites (Kobo and Sirinka).

**Figure 2.** Mean monthly rainfall and temperature distribution at Sirinka and Kobo station (1985-2014).
Table 1. Coupled Model Inter-comparison Project phase 5 (CMIP5) general circulation models (GCM’s) used for this study.

| No. | Modelling center                                                                 | Country       | Model                | Lat. | Lon. | Res. |
|-----|---------------------------------------------------------------------------------|---------------|----------------------|------|------|------|
| 1   | Commonwealth Scientific and Industrial Research Organization/Bureau of Meteorology (CSIRO-BOM) | Australia     | ACCESS1.0            | 1.87 | 1.25 | MR   |
| 2   | Beijing Climate Centre, China Meteorological Administration                      | China         | BCC-SM1.1            | 2.81 | 2.79 | LR   |
| 3   | College of Global Change and Earth System Science, Beijing Normal University       | China         | BNU-ESM              | 2.81 | 2.79 | LR   |
| 4   | Community Climate System Model, Climate and Global Dynamics Division/ National Centre for Atmospheric Research | USA           | CCSM4                | -    | -    |      |
| 5   | Community Earth System Model, Climate and Global Dynamics Division/ National Centre for Atmospheric Research | USA           | CESM1-BGC            | -    | -    |      |
| 6   | Commonwealth Scientific and Industrial Research organization/Queensland Climate Change Centre of Excellence (QCCCE) | Australia     | CSIRO-Mk3.6          | 1.87 | 1.87 | MR   |
|     | Canadian Centre for Climate Modelling and Analysis                               | Canada        | CanESM2              | 2.81 | 2.79 | LR   |
| 7   | Geophysical Fluid Dynamics Laboratory                                            | US-JNJ        | GFDL-SM2G 2          | 2.5  | 2.0  | LR   |
|     |                                                                                 | US-JNJ        | GFDL-ESM2M           | 2.5  | 2.0  | LR   |
| 8   | Met Office Hadley Centre                                                         | UK-Exeter     | HadGEM2-CC           | 1.87 | 1.25 | MR   |
|     |                                                                                 | UK-Exeter     | HadGEM2-ES           | 1.75 | 1.25 | MR   |
| 9   | Institute Pierre-Simon Laplace                                                  | France        | IPSL-CM5A-LR         | 3.75 | 1.89 | LR   |
|     |                                                                                 | France        | IPSL-CM5A-MR         | 2.50 | 1.26 | LR   |
| 10  | Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology | Japan         | MIROC-ESM           | 2.81 | 2.79 | LR   |
|     |                                                                                 | Japan         | MIROC5               | 1.40 | 1.40 | HR   |
| 11  | Max Planck Institute for Meteorology (MPI-M)                                     | Germany       | MPI-ESM              | 1.87 | 1.87 | LR   |
|     |                                                                                 | Germany       | MPI-ESM-MR           | 1.87 | 1.87 | MR   |
| 12  | Meteorological Research Institute                                               | Japan         | MRI-GCM3             | 1.12 | 1.12 | HR   |
| 13  | Norwegian Climate Centre                                                        | Norway        | Nor-ESM1-M           | 2.50 | 1.89 | LR   |
| 14  | Institute for Numerical Mathematics                                              | Russia        | INM-CM4              | 2.0  | 1.5  | MR   |

GENCALC, coefficients for genotypes are estimated iteratively by comparing the predicted model outputs (days to anthesis, days to maturity and grain yield) to the actual observed data and altering the coefficients until the predicted and observed values approximately matched (Hunt et al., 1993). The coefficients related to phonological aspects such as flowering and maturity date were determined first and then growth related to such yield related aspect was determined (Jones et al., 2003; Hunt et al., 1993). The soil, weather and crop management data obtained during 2007 and 2008 growing season were used to adjust model parameters for Melkam; and data obtained during 2005, 2007 and 2008 cropping season for Teshale undertaken at Kobo agricultural research site were used to adjust the required model parameters.

Once the model is well adjusted, the performance is evaluated using independent data sets which was not used during model calibration process (Jones et al., 2003; Hunt et al., 1993; Romero et al., 2012). The field experiment data for model evaluation were also undertaken from the same field during 2010, 2011 and 2013 main growing season. Indicator statistics like coefficient of determination ($R^2$), root mean square error (RMSE), normalized root mean square error (RMSEn) and index of agreement were used to evaluate the performance or to quantify the errors of the adjusted model. The Root Mean Square Error (RMSE) which measures the agreement between...
measured and simulated data. The simulation is considered 

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

where \( n \) is the number of observations, \( P_i \) is predicted value for the \( i \)th measurement, and \( O_i \) is observed value for the \( i \)th measurement.

The normalized root mean square error (RMSEn) is also used to evaluate the performance of the model and computed as follows:

\[ \text{RMSEn} = \frac{\text{RMSE} \times 100}{\bar{O}} \]

where RMSE is root mean square error and \( \bar{O} \) is the overall mean of observed values.

RMSEn (%) gives a measure of the relative difference of simulated versus observed data. The simulation is considered excellent if the RMSEn is less than 10%, good if it is greater than 10% and less than 20%, fair if RMSEn is greater than 20% and less than 30%, and poor if the RMSEn is greater than 30% (Aronica et al., 2002).

In addition, the \( d \)-statistic was also employed. It has been reported that this index provides better model performance indications that encompasses bias and variability than \( R^2 \) (Willmott et al., 1982). The closer the index value is to unity, the better the agreement between the two variables that are being compared and vice versa.

\[ d = 1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (P_i + O_i)^2}, 0 < d < 1 \]

where \( n \) is the number of observations, \( P_i \) is predicted value for the \( i \)th measurement, \( O_i \) is observed value for the \( i \)th measurement, \( \bar{O} \) is the mean of observed values, \( P_x \) is the overall mean of observed values, and \( d \) is the \( d \)-statistic.

Moreover, linear regression was applied between simulations and observations to evaluate model performance and correlation coefficient (\( R^2 \)) for each simulation (Loague and Green, 1991).

Impact assessment

Finally, to quantify the impacts of projected future climate on sorghum production in parts of the Great Rift Valley of Ethiopia, historical yield was simulated using the calibrated genetic coefficients under the historical climate (1985-2014) data. The following equation was used to estimate the yield difference in percent between simulated and historical yield.

\[ \text{Δyield} = \left( \frac{Y_{\text{predicted}} - Y_{\text{base}}}{Y_{\text{base}}} \right) \times 100 \]
Figure 3. Projected changes in rainfall (percent deviation from historic rainfall) in mid-century (2040-2069) for Sirinka and Kobo stations.

where $Y_{\text{predicted}}$ is predicted yield (kg ha$^{-1}$), $Y_{\text{base}}$ is yield of the base period (kg ha$^{-1}$) and $\Delta$yield is the yield difference (%).

RESULTS AND DISCUSSION

Future climate of the study districts

According to the downscaled Atmosphere Ocean General Circulation Models (AOGCMs), the overall mean model projected climate change scenarios showed a general increase in temperature and precipitation over the two selected stations in mid and end-century. Nonetheless, the projected change in seasonal and annual rainfall varied across GCMs, RCPs and time periods considered. The projected change in rainfall is highly uncertain that models are inconsistent in rainfall projections. Given that, the BNU-ESM, CanESM2, CESM1-BGC, CSIRO-Mk3-6-0, GFDL-ESM2, GFDL-ESM2M, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM, MPI-ESM-MR, MRI-CGCM3, and NorESM1-M climate models showed a positive deviation in JIAS (Kiremt) rainfall, whereas the JJAS rainfall under ACCESS1-0, CSIRO-Mk3-6-0, HadGEM2-ES and MPI-ESM-LR is projected to be declined at Sirinka and Kobo by mid (2040-2069) and the end (2070-2099) of the 21st century. Two climate models IPSL-CM5A-LR and IPSL-CM5A-MR projected a maximum increase in annual rainfall from 68.7 to 137.4 mm by the end of the century. On the other hand, the seasonal rainfall amount during Belg is projected to be declined from 30 to 40% under MIROC-ESM model in both stations by 2050 and 2080s. Figure 3 shows a projected seasonal and annual rainfall deviation from 2040 to 2069 under 20-GCMs at Sirinka and Kobo districts.

In general, the mean model ensemble results showed that a general increase in seasonal and annual rainfall amount in Sirinka and Kobo districts relative to the 1985-2014 mean observed climate. The projected rainfall varied across emission scenarios, time periods and locations considered. Mean model projected seasonal and annual rainfall amount is shown in Figure 4. The result also revealed that, the deviation of annual and seasonal rainfall amount would be higher by 2080s. During the major growing season (June to September), amount of rainfall is expected to be increased by 18.1% (Kobo) and 25.5% (Sirinka) by 2080s under RCP8.5.

The downscaled climate change scenarios concluded a consistent increase in projected maximum and minimum temperature in the study districts. The model based projected climate change scenarios showed a consistent warming trend during the short (MAM) and the main (JJAS) growing season. The day/night warming trend is projected to be higher during the short (MAM) season relative to comparison to the main (JJAS) cropping season in both districts by mid and end of the 21st century. The scenarios from the 20-GCMs furthermore indicated that, the day/night temperature at kobo would be higher compared to its counterpart (Sirinka) under RCP4.5 and RCP8.5 scenario assumptions. Besides that, the higher increase in seasonal and annual temperature is also anticipated by most of the models considered under this study, however, variation in magnitude is well-
thought-out across location and time periods. Figures 4 and 5 present the projected annual maximum and minimum temperature changes of 20-AOGCMs by 2050s under the respective stations is presented in Figure 5 and 6.

The model ensemble output of the 20-GCM’s under the two RCP scenario assumption (RCP4.5 and RCP8.5) revealed a consistent day/night warming trend of the study sites, which the magnitude of change is varied depending on locations and time periods. As a result, annual day time warming is projected to be increased between 1.8 (RCP4.5) and 2.4°C (RCP8.4) by 2050s and 2.1 (RCP4.5) to 3.4°C (RCP8.5) by 2080s. Likewise, a probable increase of night time temperature from 1.8 to 2.8°C by 2050s and 2.2 to 4.8°C by 2080s is expected in the study area. Moreover, the model ensemble output
also emphasized that a higher increase in night temperature is projected by the end of 21st century. The mean observed and projected temperature changes at Kobo and Sirinka is shown in Table 5.

**Model calibration**

The model performance test for the estimated cultivar specific genotype coefficient is shown in Table 4. According to the root mean square error (RMSEn) statistics, CERES-sorghum is parameterized excellently for date of flowering and physiological maturity with less variation (RMSEn < 10%) expected between observed and simulated. Whereas, the model parameters for grain yield is moderately adjusted according to the RMSEn (RMSEn = 10 to 20%) statistics. The index of agreement (d-index) and coefficient of determination (R²) statistics for model calibration indicated that parameterization done for the two sorghum cultivars is in a mode of making less uncertainty between the simulated and the observed values. Performance evaluation statistics during model parameterization is shown in Table 6.

**Model validation**

The model performance evaluation statistics and graphs for adjusted cultivars of the two sorghum cultivars are shown in Table 7 and Figures 7 and 8. Based on the evaluation result, the adjusted model parameters explained the observed values used for model evaluation in acceptable range for both sorghum cultivars indicated that the model is well adjusted for further application. The root mean square and the index of agreement results for both varieties showed a good fit of agreement between the observed and simulated values for grain yield, days to flowering and days to maturity days shown in Table 7. Besides this, coefficient of determination values for days to flowering and days to maturity also indicated that the model is well parameterized during calibration to simulate the observed values during validation test. In general the performance evaluation statistics indicated that the adjusted model parameters (genetic coefficients) explained well the observed values with less and tolerable differences for the two sorghum cultivars.

Hence, CERES-sorghum CSM for the two sorghum cultivars is parameterized well and showed that using the model for other application is valid.

As a result, the model is used to simulate historical yields for the two cultivars under a baseline climate (1985 to 2014) and projected climate for two time periods (2040 to 2069) and (2070 to 2099) by keeping the soil, cultivar, and management parameters constant.

**Sorghum yield response for projected future climate**

Future production response of the two sorghum cultivars for different GCMs at Sirinka and Kobo districts are shown in Figures 9 and 10. The result revealed that, the yield response for the two sorghum varieties is varied with the type of climate models, the time period and assumptions of scenarios considered. CanESM2, HadGEM2-ES, and IPSL-CM5A-MR climate models show a consistent decline in yield by 2050 and 2080s under the highest (RCP85) and a moderate (RCP45) emission scenario assumptions for both cultivars of sorghum. Under the highest emission scenario (RCP8.5) sorghum production is projected to decline in a range of 1 to 30% from the baseline yield. However, the projected yield, under BNU-ESM climate model, is expected to be increased from 7.6 to 18.3% at Sirinka and 1.5 to 14.3% at Kobo by 2050 and 2080s.
Table 4. Estimated Genetic Coefficients for two sorghum cultivars (Teshale and Melkam) using data obtained from Kobo agricultural research site, Northern Ethiopia.

| Genetic parameter | Description                                                                 | Initial coef. | Estimated coef. |
|-------------------|-----------------------------------------------------------------------------|---------------|-----------------|
|                   |                                                                             | CARGIL_1090   | Teshale         | Melkam          |
| P1                | Thermal time from seedling emergence to the end of the juvenile phase       | 460.0         | 250.1           | 311.7           |
|                   | (expressed in degree days above a base temperature of 8°C) during which     |               |                 |                 |
|                   | the plant is not responsive to changes in photoperiod                       |               |                 |                 |
| P2O               | Critical photoperiod or the longest day length (in hours) at which          | 12.50         | 12.46           | 12.46           |
|                   | development occurs at a maximum rate. At values higher than P20, the rate |               |                 |                 |
|                   | of development is reduced                                                   |               |                 |                 |
| P2R               | Extent to which phasic development leading to panicle initiation (expressed | 90.0          | 101.7           | 154.4           |
|                   | in degree days) is delayed for each hour increase in photoperiod above      |               |                 |                 |
|                   | P20.                                                                        |               |                 |                 |
| P5                | Thermal time (degree days above a base temperature of 8°C) from             | 600.0         | 492.8           | 480.8           |
|                   | beginning of grain filling (3-4 days after flowering) to physiological      |               |                 |                 |
|                   | maturity                                                                    |               |                 |                 |
| G1                | Scaler for relative leaf size                                              | 5.0           | 5.512           | 6.4             |
| G2                | Scaler for partitioning of assimilates to the panicle (head).               | 6.0           | 5.255           | 5.0             |

Table 5. Summary of observed and projected mean annual and seasonal (Kiremt and Belg) temperature at Kobo and Sirinka.

| Station | Season | Historical observed (Mean) | Maximum temperature | Minimum temperature |
|---------|--------|----------------------------|---------------------|---------------------|
|         |        | TMAX | TMIN | RCP45 | RCP85 | RCP45 | RCP85 | RCP45 | RCP85 | RCP45 | RCP85 |
| Sirinka | Annual | 26.5 | 13.6 | 1.8 | 2.4 | 2.3 | 3.4 | 1.8 | 2.8 | 2.4 | 4.7 |
|         | Kiremt | 28.5 | 15.6 | 1.8 | 2.3 | 2.2 | 3.4 | 1.8 | 2.7 | 2.3 | 4.6 |
|         | Belg   | 26.7 | 13.9 | 1.8 | 2.3 | 2.2 | 3.4 | 1.8 | 2.6 | 2.2 | 4.3 |
| Sirinka | Annual | 30.1 | 14.9 | 1.8 | 2.3 | 2.1 | 4.0 | 1.7 | 2.7 | 2.4 | 4.7 |
|         | Kiremt | 31.9 | 17.1 | 1.8 | 2.3 | 2.2 | 4.0 | 1.7 | 2.5 | 2.2 | 4.4 |
|         | Belg   | 30.4 | 15.2 | 1.9 | 2.4 | 2.3 | 4.2 | 1.8 | 2.8 | 2.6 | 4.8 |

Table 6. Evaluation results of CERES-sorghum for anthesis, physiological maturity and grain yield of Teshale and Melkam cultivars during model calibration under Kobo experimental site.

| Crop type | Variety | Variable        | Mean |          |     |     |     |
|-----------|---------|-----------------|------|----------|-----|-----|-----|
|           |         |                 |      | Observed | Simulated | R²  | RMSE | RMSEn | d-Stat. |
| Sorghum   | Teshale | Anthesis day    | 73   | 73       | 0.79 | 0.8 | 1.1  | 0.92  |
|           |         | Yield (kg/ha)   | 2809 | 2688     | 0.61 | 289.4 | 10.3 | 0.84  |
|           |         | Maturity day    | 111  | 110      | 0.92 | 1.4  | 1.2  | 0.85  |
|           | Melkam  | Anthesis day    | 81   | 81       | 1.0  | 0.82 | 1.0  | 0.96  |
|           |         | Yield (kg/ha)   | 2504 | 2021     | 0.96 | 520.1 | 20.7 | 0.87  |
|           |         | Maturity day    | 110  | 109      | 0.97 | 1.3  | 1.2  | 0.92  |

The model result showed that the projected yield, for both cultivars of sorghum, is expected to be affected more negatively by the end of the century (2070-2099) in both locations under the medium and highest emission.
Table 7. Model performance indicator statistical output for Model validation for Sorghum and wheat crop variety.

| Crop type | Variety | Variable       | Observed | Simulated | r-Square | RMSE  | d-Stat. |
|-----------|---------|----------------|----------|-----------|----------|-------|--------|
|           |         | Anthesis day   | 73       | 73        | 0.79     | 0.82  | 0.92   |
| Sorghum   | Teshale | Yield (kg/ha)  | 2809     | 2688      | 0.62     | 289.4 | 0.85   |
|           |         | Maturity day   | 111      | 110       | 0.92     | 1.4   | 0.86   |
|           |         | Anthesis day   | 81       | 81        | 1        | 0.82  | 0.95   |
| Melkam    | Yield (kg/ha) | 2504 | 2021      | 0.96     | 520.1   | 0.87  |
|           |         | Maturity day   | 110      | 109       | 0.97     | 1.3   | 0.92   |

The regression line was near to the 1:1 line, indicating that the model was performed well under the test environment of calibration.

Figure 7. Relationship between simulated and observed values of anthesis, maturity and final grain yield for sorghum (Teshale) at Kobo.

Analysis result from the 20 GCMs revealed that future production of sorghum at Kobo and Sirinka is predicted to decline. Yield loss due to the projected impacts of temperature and precipitation is slightly higher for Melkam sorghum variety relative to Teshale. On average, sorghum yield is expected to decrease by 1.2 to 23% according to the assumptions of emission scenarios considered for this study by the mid and end of the 21st century under the study districts. Future production of sorghum in Kobo is more risky relative to Sirinka. In this regard, Teshale variety would be affected more due to
Figure 8. Relationship between simulated and observed values of anthesis, maturity and final grain yield for sorghum (Melkam) at Kobo.

Figure 9. Yield response of two sorghum cultivars (percentage change in grain yield relative to the baseline yield) for projected future climate of 20 GCMs under RCP4.5 and RCP8.5 during mid-century (2040-2069) and end century (2070-2099) at Sirinka district.

future climate change than its counterpart (Melkam) did. Likewise, regardless of location, variety and emission scenarios, productivity of sorghum will decrease drastically towards the end of the century (2080s).
compared to mid-century (2050s). The simulated yield for two sorghum cultivars (Teshale and Melkam) by 2050 and 2080s averaged over 20 GCMs under two representative concentration pathways is shown in Figures 11 and 12.

According to the projected model result, the projected increase in temperature and precipitation causes a reduction in sorghum yield at Kobo and Sirinka. Moreover, the risk of future projected climate is very negatively influenced by the end of 21st century which the incoming solar radiation is reached to 8.5 W/m². However, the magnitude of risk varied depending on the varieties which Melkam is less risky relative to Teshale variety. The consistent increase in projected temperature and variable rainfall may...
contribute to the predicted yield reduction through accelerating growth and development of plants which lead to less dry matter production (carbon assimilation and biomass accumulation) which highly contribute to a decline in yield (Rawson, 1992; Morison, 1996). On the other hand, the increase in temperature would increase the evapotranspiration demand of the atmosphere and hence create moisture deficit in the root zone, which in turn lead less synthesis of sugars for limited plant growth and development processes. According to Gupta (1975) high temperature is involved in a direct cause for death of plants, even adequate water is provided. Furthermore, beyond certain limit, the detrimental effects of high temperature on crop production depends on the crop, the stage of development, and the physiological processes involved in (Amon, 1975).

In general, the projected climate change in the study area will have a far-reaching effect on the livelihood of the community who is highly dependent on sorghum production for food, feed, fuel and construction materials. Therefore, it might be critical to adapt some in situ moisture conservation and utilization practices as well as envisaging sorghum breeding strategies that target the development of heat tolerant varieties to improve and sustain productivity of sorghum in the study area.

Conclusion

To investigate the projected impacts of climate change on future sorghum production, crop-climate simulation modeling approaches were used. For this study, Decision Support System for Agro-technology Transfer (DSSAT) were used to evaluate yield response of sorghum for the projected future climate scenarios. The crop simulation model were also calibrated and validated using soil, weather and crop management field data. To simulate future production performance of sorghum, site specific future climate scenarios were developed using delta method downscaling approach for mid and end time periods under two emission scenario assumptions (RCP4.5 and RCP8.5) for Kobo and Sirinka sites. The calibration and validation results for the two sorghum cultivars indicated that CERES-sorghum is reasonably adjusted to investigate future sorghum production in relation with projected future climate.

In general, the result revealed that future climate has a significant negative impact on sorghum yield, however, the magnitude of severity and yield variation differs depending on the type of varieties, time periods projected, emission scenarios considered and agro-ecology zone of the study area. The output from the model ensemble showed that sorghum production would be very risky by 2080 under the assumption of maximum emission of GHGs and incoming irradiance by the end of 21st century.

As a whole, unless technical and tactical measures are taken, future production of sorghum would be adversely affected by the consequences of climate change. Therefore, it is strongly recommended that more detail and further investigation should be undertaken to clearly explain and interpret the negative impacts of climate change on future food production and to explore alternative measures in order to enhance and sustain productivity.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.
ACKNOWLEDGEMENTS

This research was funded by Ethiopian Institutes of Agriculture Research (EIAR). The authors thank the administrative and research staffs of EIAR for their continuous support and facilitation for the successful accomplishment of this research work.

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