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Projecting maize yield under local-scale climate change scenarios using crop models: Sensitivity to sowing dates, cultivar, and nitrogen fertilizer rates

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Abstract

The APSIM-Maize and CERES-Maize models are widely used in impact studies to analyze the effect of climate change on future maize yield. The study objectives were to develop climate scenarios, assess crop model's sensitivity, and predict the impact of climate change on rainfed maize yield based on five global climate models under two RCP (RCP4.5 and RCP8.5) scenarios. The scenarios were based on the mid-century and tested for sowing dates (SDs), maize cultivars, and nitrogen fertilizer rates (N). For field calibration and validation, the split-split-plot experimental design with three replicates was set up at Mount Makulu, Zambia. The treatments were SD, cultivar, and N-rate were the main plot, subplot, and subsub plot, respectively. The APSIM-Maize and CERES-Maize models were used to run simulations using seasonal analysis. The impacts of climate change on maize yield were simulated for the future 2040–2069/1980–2010 using the AgMIP Protocols. The ensemble means from the simulation result in precipitation decrease and temperature increase. Days after planting to anthesis and maturity would reduce in 2050 (2040–2069). The % change in grain yield would range from 2.78% to 9.94%, −3.81% to −8.88%, and −2.33% to 10.63% under N1 (55.2 N kg/ha), N2 (110.4 N kg/ha), and N3 (165.6 N kg/ha) as affected by SDs, respectively. The simulation showed evidence of climate change and hence affect maize growth and yield. Therefore, there is a need to put in place strategies for alleviating the impact of climate change in maize production in Zambia.

KEYWORDS

AgMIP Protocols, APSIM-Maize, calibration, CERES-Maize, CMIP5, crop models, delta-based method, global climate models

1 | INTRODUCTION

Maize (*Zea mays* L.) is an important cereal crop after wheat and rice in the world (FAO, 2016; Lukeba, Vumilia, Nkongolo, Mwabila, & Tsumbu, 2013; Macauley & Ramadjita, 2015). It is grown for human consumption, livestock feed, and industrial raw materials (Lukeba et al., 2013). Maize yields have increased over the last decades due to an increase in nitrogen (N) fertilizer use, improvement in crop management, and enhanced stress tolerance in maize cultivars (Yakoub, Lloveras, Biau, Lindquist, & Lizaso, 2017). African agriculture production is dominated by small-scale farms and is mainly rainfed (Turral, Burke, & Faurès, 2011). In Zambia, maize is grown by 80% and 20% of small-scale and commercial farmers, respectively (Mulenga & Wineman, 2014). High intra-seasonal rainfall variability, drought, floods, lack of adaptive capacities, and widespread poverty among small-scale farmers are major constraints facing rainfed agricultural production in Sub-Saharan Africa (Waongo, Laux, & Kunstmann, 2015). It is estimated that 64% of Zambia's population live in rural areas and practice rainfed subsistence agriculture (Arslan et al., 2015). Prolonged shorter rainfall seasons and dry spells have reduced maize yields by 40% of the long-term average in agro-ecological regions (AERs) I and II (UNDP, 2010).

Climate change and variability are two important aspects of climatic change affecting sectors such as agriculture. Variability in precipitation and temperature affect rainfed agricultural productivity (Ojeda, Caviglia, Irisarri, & Agnusdei, 2018). By 2050s, the world population would be 9.1 billion (Rosenzweig et al., 2012), the climate warmer by 2°C and CO_2 concentration at 550 ppm (Jaggard, Qi, & Ober, 2010). Increasing CO_2 in the atmosphere would increase most crop yields by approximately 13% (Jaggard et al., 2010). However, the increase in air temperature will negatively impact crop growth and yield (Tigchelaar, Battisti, Naylor, & Ray, 2018). Climate change would reduce water consumption by all crops, but increased rates of evapotranspiration would negate this effect due to an increase in air temperature (Jaggard et al., 2010). For every degree increase in global mean air temperature, maize yield is projected to reduce by 7.4% (Tigchelaar et al., 2018; Zhao et al., 2017). Climate change by 2050 would reduce maize yields globally and in Africa by 3%–10% and 20%, respectively (FAO, 2016; Macauley & Ramadjita, 2015; Thornton & Cramer, 2012).

Global Climate Models (GCMs) from Intergovernmental Panel on Climate Change (IPCC) are tools used to simulate the present and project the future climate of the earth under different climate scenarios due to increasing greenhouse gases (GHGs; Osman, Al-Ansari, Abdellatif, Aljawad, & Knutsson, 2014). The Representative Concentration Pathways (RCPs) are being used for the new climate model simulations carried out under Fifth Coupled Model Intercomparison Projects Phase 5 (CMIP5) of the World Climate Research Programme (IPCC, 2014a). Four different RCPs were developed for the Fifth Assessment Report (AR5; IPCC, 2014b). Furthermore, the RCPS correspond to four different levels of radiative forcing or GHG concentration (not emissions) trajectories in the atmosphere by 2,100 relative to preindustrial levels with 48 CMIP5 experiments. The four RCPs are as follows: radiative forcing levels of stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high GHG emissions (RCP8.5) Watts per square meter (W/m^2) and correspond to concentrations of 450, 650, 850, and 1,370 ppm CO_2eq, respectively.

The GCM outputs have coarse spatial resolution and cannot be used directly as inputs into crop simulation models for impact studies. Therefore, dynamical and statistical downscaling models (delta-based method) are used to bridge the gap between the large- and local-scale variables. The Agricultural Model Intercomparison and Improvement Project (AgMIP) Protocols (delta-based approach) (Rosenzweig et al., 2012) have not been used locally in Zambia to generate future climate scenarios from GCMs. Crop simulation models are widely used to evaluate the likely possible impacts of changes in climate parameters on crop growth and yield (Kang, Khan, & Ma, 2009). The application of GCMs, crop simulation (APSIM-Maize [Agricultural Production Systems Simulator] and CERES-Maize [Crop Environment Resource Synthesis] models), and statistical downscaling models to study and quantify the potential impact of climate change and variability provides a direct link between models, agro-meteorology, and the needs of society. The effect of climate change on future crop yield could be reversed by manipulating the sowing dates (Liu, Hubbard, Lin, & Yang, 2013).

The APSIM and CERES-Maize models have been used to determine the optimal maize sowing dates and nitrogen fertilizer rates (Myoung, Hee Kim, Kim, & Kafatos, 2016; Soler, Sentelhas, & Hoogenboom, 2007). The AgMIP Protocols use multiple climate and crop simulation models to simulate future climate and crop yields, respectively. Limited published scientific information exists at the local scale on impacts due to changes in climatic parameters on maize yield and adaptability in AERII. The study objectives were to develop climate change scenarios using AgMIP Protocols; to assess the sensitivity of crop models to simulate maize yield; and to predict the impact of climate change and variability on maize growth and yield based on five GCMs under two RCP (RCP4.5 and RCP8.5) scenarios. These scenarios were assessed for mid-century (the 2050s) using three sowing dates, maize cultivars, and nitrogen fertilizer levels.

2 | MATERIALS AND METHODS

2.1 | Description of the study site and weather data

A study was conducted at the Zambia Agricultural Research Institute (ZARI) Central Research Station at Mount Makulu (latitude: 15.550° S, longitude: 28.250° E, altitude: 1,213 m) in Agro-ecological Region II (AERII), Zambia. The daily weather data (latitude and longitude of the weather station, rainfall, maximum, and minimum temperature, solar radiation) were obtained from the Zambia Meteorological Department. Weather data, namely rainfall, solar radiation, mean maximum, and minimum temperature for Mount Makulu during the 2016/2017 season, were 930.17 mm, 18.93 MJ m^{-2} day^{-1}, 21.83, 15.36, and 28.29°C, respectively, as shown in Figure 1.

2.2 | Rainfed and irrigated field experiments

Two field experiments were conducted, irrigated (split-plot design), and rainfed (split–split-plot design). A rainfed field experiment was arranged in a split–split-plot design with sowing dates (SDs; 12th December 2016, 26th December 2016, and 9th January 2017), maize cultivars (ZMS 606 [V1], PHB 30G19 [V2], and PHB 30B50 [V3]), and N levels (N1, N2, and N3) as the main plots, subplot, and sub-subplots, respectively. The treatments were replicated thrice. Two days before sowing the maize seeds, the site was plowed to a depth of about 30 cm and harrowed. Individual plot sizes were 6 m (seven rows) by 5 m and were separated from each other by a 2-m distance. Three seeds were sown by hand at 5 cm depth in a flat seedbed in 0.75-m row spacing by 0.50 m spacing between plants per station. The nitrogen fertilizer levels (120 [N1], 240 [N2], and 360 [N3] kg/ha NPK 10-20-10 [N, P_2O_5, K_2O]) were applied as a basal dressing at sowing. The 120 (N1), 240 (N2), and 360 (N3) kg urea (46% N) were applied as a top dressing. The rainfed field experiment was used to calibrate APSIM-Maize and DSSAT CERES Maize models (Table 4).

The irrigated field experiment was used to validate the APSIM-Maize and DSSAT CERES Maize models. Two days before planting, the site was plowed to a depth of about 30 cm and harrowed. Individual plot sizes were 6 m (12 rows) by 5 m. The plots were separated from each other by a 2-m distance to prevent cross-contamination of treatments. Seeds were sown by hand at 5 cm depth in a flat seedbed in 0.50-m row spacing and 0.30-m spacing between plants. Weeds were controlled using herbicides and hand hoes during the growing period. The experiment design under irrigated field experimental site was a split-plot design consisting of three maize cultivars (ZMS 606, PHB 30G19, and PHB 30B50) and three nitrogen fertilizer rates (N1, N2, and N3) with three replicates. Maize cultivar and N rate were the main plot and subplots, respectively. 120 (N1), 240 (N2), and 360 (N3) kg/ha NPK 10–20–10 (N, P_2O_5, K_2O) were applied as a basal dressing at sowing. 120 (N1), 240 (N2), and 360 (N3) kg urea (46% N) were applied as a top dressing. All field observations for the irrigated experimental site are shown in Table 3.

2.3 | Description of the crop simulation models

The Agricultural Production Systems Simulator (APSIM) version 7.9 (Holzworth et al., 2014) and Decision Support Systems for Agrotechnology Transfer (DSSAT) version 4.6 (Jones et al., 2003; Jones, Hoogenboom, Wilkens, Porter, & Tsuji, 2010a) models were used in this study to simulate maize grain yield using the baseline and future climate scenarios. APSIM runs on a daily time-step and simulates biophysical processes in response to management and climate scenarios (Gaydon, 2014). The model is driven by daily temperature, precipitation, and solar radiation and is capable of simulating soil carbon (C), soil water, phosphorus (P), and nitrogen (N) dynamics and their interaction (Keating et al., 2003).

On the other hand, the DSSAT-CERES-Maize model was designed to simulate maize phenology, dry matter partitioning, yield, rootzone soil water, soil temperature, and nitrogen dynamics at a field scale on a daily time step from inputs of climate data, management, genotype, and soil (Jones, Kiniry, & Dyke, 1986; Jones et al., 2003). The APSIM-Maize and CERES-Maize models are different in the parameterization

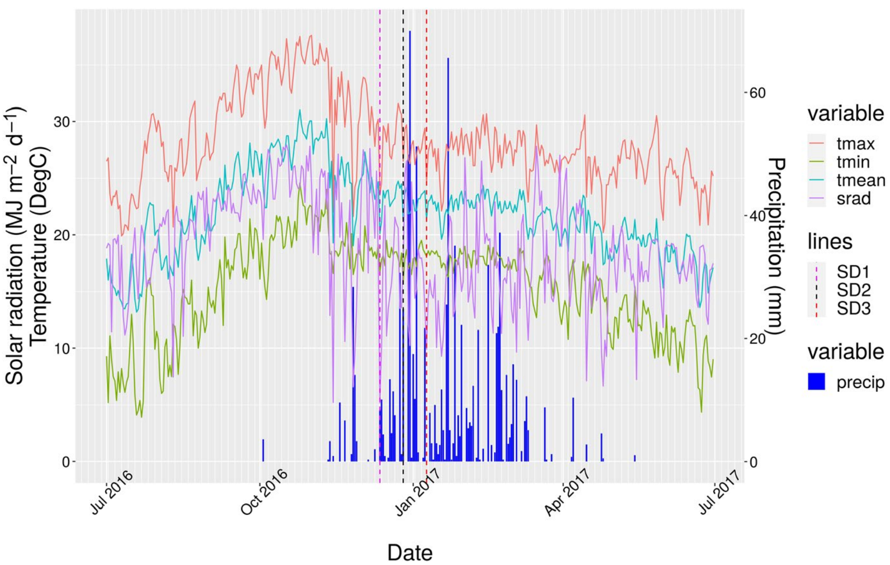


FIGURE 1 Daily weather data collected from the Zambia Meteorological Department for Mt Makulu during the 2016/2017 season. The data were used to create the climate data file

TABLE 1 Soil physical characteristics at experimental site

Depth (cm)	0–20	20–40	40–60	60–80	80–100	Analysis method
Soil texture	Clay	Clay	Clay	Clay	Clay	SPAW
Silt (%)	12.80	16.80	12.80	18.80	2.80	Hydrometer method
Sand (%)	39.60	35.60	37.60	41.60	37.60	
Clay (%)	47.60	47.60	49.60	39.60	59.60	
Bulk density (g/cm^3)	1.43	1.41	1.41	1.46	1.36	SPAW
LL (cm^3/cm^3)	0.287	0.287	0.299	0.244	0.350	
DUL (cm^3/cm^3)	0.407	0.409	0.419	0.363	0.470	
SAT (cm^3/cm^3)	0.459	0.467	0.468	0.447	0.487	
SHC (mm/hr)	0.350	0.500	0.290	1.480	0.010	

Abbreviations: DUL, drained upper limit (field capacity); LL, lower limit (wilting point); SAT, saturation; SHC, saturated hydraulic conductivity; SPAW, soil–plant–air–water.

Source: Chisanga, Phiri, and Chinene (2019).

TABLE 2 Soil chemical characteristics at experimental sites

Depth (cm)	0–20	20–40	40–60	60–80	80–100	Analysis method
Total *N* (%)	0.031	0.042	0.054	0.061	0.036	Modified Kjeldahl
NO_3N (ppm)	29.90	48.70	56.40	70.10	42.80	
NH_4N (ppm)	18.00	29.20	33.90	42.10	25.70	
P (mg/kg)	10.00	11.00	10.00	18.00	12.00	Bray 1
K (mg/kg)	1.05	0.99	1.12	0.59	0.89	Ammonium acetate
Ca (cmol(+)/kg)	11.00	9.30	3.40	2.90	3.20	Ammonium acetate
Mg (cmol(+)/kg)	3.50	2.70	2.30	1.00	1.30	Ammonium acetate
OC (%)	0.35	0.57	0.66	0.82	0.50	Walkley & Black
CEC (cmol(+)/kg)	15.57	13.02	6.85	4.52	5.42	Ammonium acetate

Abbreviations: Mg, magnesium; OC, organic carbon; P, phosphorus; P, potassium.

Source: Chisanga et al. (2019).

of soil, calibration, and management options, and in the initial minimum data required and outputs. APSIM-Maize and CERES-Maize models were used to simulate the number of days after planting (DAP) to anthesis and physiological maturity and maize yield as a function of the present and future climate scenarios.

2.4 | Crop management and soil input data

The maize cultivars, ZMS 606 (V1), PHB 30G19 (V2), and PHB 30G50 (V3), are medium maturity (120–130 days). PHB30B50 is recommended to be grown under irrigation, while PHB30G19 and ZMS 606 can be grown under irrigated and rainfed conditions in Zambia, respectively. PHB30G19 and PHB30B50 are white and yellow cultivars, respectively, produced by Pioneer. The ZMS 606 is an excellent drought-tolerant cultivar. These cultivars were selected based on having a long commercial life, adaptability, good heat, drought resistance, and major cultivars planted by the small scale farmers.

The soil samples were collected before plowing the field and analyzed for the chemical and physical properties at the Zambia Agriculture Research Institute laboratory. The soil at the study site was classified in USDA Soil Taxonomy (Soil Survey Staff, 2014) as Clayey, Mixed, Hyperthermic, Typic Paleustalfs in Soil Taxonomy. It is well-drained, yellowish red to red (2.55YR), deep to very deep, clayey soil with high activity clayey, medium base saturation, and clayey topsoil. The soil analysis results used as the initial conditions in the simulation are shown in Tables 1 and 2.

2.5 | Field observation and measurements

Field observation and biomass sampling were done at vegetative (VE, V6) and reproductive (R1, R4, and R6) stages

TABLE 3 Agronomic practices and field observations for the irrigated field experiment site

Cultivars	ZMS 606			30G19			30B50		
N (kg N/ha)	N1	N2	N3	N1	N2	N3	N1	N2	N3
Pre-plant sampling	26 May 2016			26 May 2016			26 May 2016		
Land preparation	26 May 2016								
Basal dressing and planting	5 June 2016								
Seeding rate	80,000 seeds/ha								
Top dressing	29 August 2016								
Herbicide	7 July 2016 (Stellar star and Nicosulfuron 750 WDG)								
Pesticide	1 September 2016 (AVI-Monocrotophos)								
Phenological stage									
Emergence (VE)	19 June 2016			19 June 2016			18 June 2016		
V6	24 July 2016			22 July 2016			22 July 2016		
V8	6 September 2016			5 September 2016			2 September 2016		
R1	17 September 2016			18 September 2016			13 September 2016		
R4	10 October 2016			10 October 2016			6 October 2016		
R6	5 November 2016			5 November 2016			3 November 2016		
Biomass sampling									
V6	26 July 2016			26 July 2016			26 July 2016		
V8	8 August 2016			8 August 2016			8 August 2016		
R1 (Anthesis)	19 September 2016			19 September 2016			19 September 2016		
R4	12 October 2016			12 October 2016			7 October 2016		
Final harvest	10 November 2016								

using guidelines provided by Hoogenboom, Wilkens, and Tsuji (1999). The maize leaf area index (LAI) was computed by multiplying the manually measured length and maximum width and multiplied by 0.75, the maize calibration factor (Karuma, Gachene, Gicheru, Mtakwa, & Amuri, 2016). The agronomic practices and field observations for the irrigated and rainfed field experiments are presented in Tables 3 and 4. Biomass was oven-dried at 70°C for 72 hr after being sorted.

2.6 | Baseline and future climate scenarios

The baseline (1980–2010) and future (2040–2069) climate scenarios were obtained from the Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) Climate Forcing Dataset for Agricultural Modeling with global coverage of climate variables required for crop modeling (Ruane, Goldberg, & Chryssanthacopoulos, 2015). The AgMERRA data were created as an element of the Agricultural Model Intercomparison and Improvement Project (AgMIP), and it has global coverage. The baseline climate data are used to calibrate crop models for improved intercomparison, and it is a basis upon which future climate scenarios can be downscaled dynamically and statistically.

The protocols developed by the global AgMIP team (Rosenzweig, Jones, Antle, & Hatfield, 2016) were used to generate the baseline and future climate scenarios (RCP4.5, RCP8.5) for Mount Makulu for 1980–2010 and 2040–2069 (2050) using the delta-based method. The delta-based method is a direct method of generating higher spatial resolution climate scenarios by applying coarse-resolution GCM outputs to a high quality observed time series (Fowler, Blenkinsop, & Tebaldi, 2007). The main goal of this method was to modify the daily time series in future years by adding monthly mean changes of GCM outputs. Five deltas were computed as the changes from five GCMs control to future projections, then monthly applied on baseline climate to produce five future daily sets (Rosenzweig et al., 2013). The deltas were computed using RCP scenarios from 2040 to 2069. For temperature, the same delta was applied to a minimum temperature and maximum temperature. Changes in temperature and rainfall in 2040–2069 relative to the baseline were estimated based on GCM outputs. The adjusted formula for modified daily precipitation is expressed in Equation 1, while modified daily temperature was computed using in Equation 2 (Abera, Crespo, Seid, & Mequanent, 2018).

$$\mathrm{P}_{\mathrm{adj.fur,d}} = \mathrm{P}_{\mathrm{obs,d}} * \sum_{i=1}^{k} \mathrm{P}_i \left(\frac{\overline{\mathrm{P}}_{\mathrm{GCM.fur,m}}}{\overline{\mathrm{P}}_{\mathrm{GCM.ref.m}}} \right) \tag{1}$$

TABLE 4 Summary of data collected from the rainfed experiment site

	PD1			PD2			PD3		
Cultivars	ZMS 606	30G19	PHB 30B50	ZMS 606	PHB 30G19	PHB 30B50	ZMS 606	PHB 30G19	PHB 30B50
N rate	1 2 3	1 2 3	1 2 3	1 2 3	1 2 3	1 2 3	1 2 3	1 2 3	1 2 3
Land preparation	29-November-16								
Basal dressing/ planting	12-December-16			26-December-16			09-January-17		
Top dressing	30-January-17			17-February-17			03-March-17		
Herbicides	14-December-16								
Herbicides	23-December-2016 & 18-January-2017								
Weeding	17-January-17								
Pesticides	29-December-16								
Phenological stages									
Emergence	19-December-16	19-December-16	18-December-16	04-January-17	04-January-17	03-January-17	17-January-17	16-January-17	17-January-17
V6	06-January-17	06-January-17	06-January-17	20-January-17	20-January-17	19-January-17	06-February-17	06-February-17	05-February-17
R1	15-February-17	15-February-17	13-February-17	04-March-17	2-March-17	04-March-17	19-March-17	19-March-17	17-March-17
R4	14-March-17	14-March-17	12-March-17	28-March-17	28-March-17	26-March-17	12-April-17	12-April-17	10-April-17
R6	14-April-17	15-April-17	13-April-17	28-April-17	27-April-17	27-April-17	18-May-17	18-May-17	19-May-17
Biomass sampling									
V6	06-January-17	06-January-17	06-January-17	20-January-17	20-January-17	20-January-17	06-February-17	06-February-17	06-February-17
R1	15-February-17	15-February-17	13-February-17	04-March-17	04-March-17	2-March-17	21-March-17	21-March-17	21-March-17
R4	16-March-17	16-March-17	16-March-17	30-March-17	30-March-17	28-March-17	13-April-17	13-April-17	13-April-17
Final harvest	03-May-17			15-May-17			01-June-17		

Note: pd = sowing date; 1 = N1; 2 = N2; 3 = N3; Pesticide = Monocrotophos, Fustac; Herbicide = Nicosulfuron; Termites: Terminator (Imidacloprid 30.5% SC) 350 g of Imidacloprid per litre.

Source: Chisanga et al. (2019).

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

However, the adjusted daily temperature $T_{adj.fur,d}$ is given by

$$T_{\text{adj.fur,d}} = T_{\text{obs,d}} * \sum_{i=1}^{k} P_i \left(\overline{T}_{\text{GCM.fur,m}} - \overline{T}_{\text{GCM,ref,m}} \right) \quad (2)$$

where $T_{adj.fur,d}$ is the adjusted daily temperature (maximum and minimum temperatures) for the future years, $T_{obs,d}$ is the observed daily temperature for the base years, $-\overline{T}_{GCM.fur,m}$ is the monthly mean temperature of the GCM outputs for the future years, $-\overline{T}_{GCM,ref.m}$ is the monthly mean temperature of the GCM outputs for the baseline, P_i is the weight of each grid cell, and k is the number of the grid cells.

The mid-century (2040–2069) RCP8.5 is the priority period for the assessment using the AgMIP Protocols (Rosenzweig et al., 2016). The baseline was assumed to have 360 ppm CO_2, while the mid-century RCP4.5 and RCP8.5 have 499 and 571 ppm CO_2, respectively. Future climate and mean change scenarios were generated for five CMIP5 GCMs presented in Table 5. The five GCMs were selected due to their long history of development and evaluation, higher resolution, and established performance (Msongaleli, Rwehumbiza, Tumbo, & Kihupi, 2015). Climate impacts, mitigation, and adaptation research are increasingly using multimodel ensembles of local-scale climate change scenarios. The simple multimodel averaging was used to compute the ensemble mean (Hao, Ju, Jiang, & Zhu, 2013; Wallach, Mearns, Ruane, Rötter, & Asseng, 2016). The probability density functions (PDFs) were also computed for the climate scenarios.

2.7 | Calibration and validation of APSIM-Maize and CERES-Maize models

The simulation files were created using the minimum data collected from the rainfed and irrigated field experiments at Mount Makulu (Figure 1, Tables 1–4). In DSSAT, the experimental (FileX), soil (FileS), weather (FileW), and experiment (average time series [FileT], average summary [FileA]) data files were created using Xbuild, Sbuild, WeatherMan, and ATCreate programs within DSSAT (Hoogenboom et al., 1999, 2010). The APSIM simulations were created using the procedures provided by the APSIM Initiative (www.apsim.info).

The parameterized APSIM-Maize and DSSAT CERES-Maize models were run using the rainfed maize growing season, treatments, and the best initial estimates for the input parameters to be calibrated. The simulated outputs (DAP to anthesis, and physiological maturity, grain yield) were then compared with observed values from the rainfed experiment. The genetic coefficients for the new maize cultivars were generated using the Generalized Likelihood Uncertainty Estimation (GLUE) in the DSSAT CERES-Maize model (Hoogenboom et al., 1999). In the APSIM-Maize model, the genetic coefficients were computed using the manual trial and error method until the simulated values were within 9%–20% of the observed values (Ahmed & Hassan, 2011). The computed genetic coefficients used in the simulations for the APSIM-Maize and CERES-Maize models are shown in Tables 6 and 7.

Crop simulation models have been evaluated by comparing simulated versus observed values (DAP to anthesis, and maturity, grain yield; Lin et al., 2017). The crop models were evaluated using root mean square error (RMSE), normalized RMSE (RMSEn), and d-stat (Jones, Hoogenboom, Wilkens, Porter, & Tsuji, 2010b; Jones & Thornton, 2003). The simulation was considered excellent with RMSEn < 10%, good if 10%–20%, acceptable or fair if 20%–30%, and poor >30% (Jamieson, Brooking, Porter, & Wilson, 1995).

2.8 | Simulation protocol and data analysis

The AgMIP Quick and Dirty [File Translation] User Interface (QUADUI) tool (http://www.agmip.org/tools) was used to convert weather files from AgMIP format to APSIM (met) and DSSAT (weather) file formats into ready model run files for the simulations. The generated synthetic weather data using AgMIP Protocols were used as inputs into APSIM-Maize and DSSAT CERES-Maize models to simulate the change in maize yield using sowing dates (SD1, SD2, SD3), nitrogen fertilizer rates (N1, N2, N3) under RCP4.5 and RCP8.5 scenarios, respectively. The calibrated APSIM-Maize and CERES-Maize models (Chisanga, 2019) were simulated with 30 years of baseline data (360 ppm CO_2), 2040–2069 (RCP4.5, 499 ppm CO_2 and RCP8.5, 571 ppm CO_2) climate scenarios using an ensemble of the five GCMs shown in Table 8. The climate, field observations, soil, and crop management practice were used in creating soil data files, climate files, and end-of-season files used to run the simulations using APSIM-Maize and CERES-Maize models.

The effects of climate change on SD, N rate, cultivar, maize growth, and yield were simulated for 30-year baseline (1980–2010) and future (2040–2069) climate scenarios. The APSIM-Maize and CERES-Maize models were calibrated and validated by Chisanga (2019) using genetic cultivar coefficients shown in Tables 5 and 6. The seasonal analysis program in APSIM and DSSAT was used to generate 30-year simulations and examined the year-to-year

TABLE 5 Coupled Model Intercomparison Project Phase 5 (CMIP5) subset GCMs considered under AgMIP

GCM scenario ID	Modeling Centre	Country	Lat	Lon
CCSM4 (E)	Community Climate System Model, Climate and Global Dynamics Division/National Centre for Atmospheric Research	USA	3.758	3.758
GFDL-ESM2M (I)	Geophysical Fluid Dynamics Laboratory	US-NJ	2.5	2.5
HadGEM2-ES (K)	Met Office Hadley Centre	UK-Exeter	1.75	1.25
MIROC5 (O)	Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	Japan	1.4	1.4
MPI-ESM-MR (R)	Max Planck Institute for Meteorology (MPI-M)	Germany	1.87	1.87

TABLE 6 Genetic cultivar coefficients used in APSIM-Maize model

Coefficients	Explanation	Units	ZMS 606	PHB 30G19	PHB 30B50
tt_emerg_to_endjuv	tt from emergence to end of juvenile stage	°Cd	240	238.5	242
tt_flower_to_maturity	tt from silking to physiological maturity	°Cd	820	817	805
tt_flag_to_flower	tt from flag leaf to silking	°Cd	1	1	1
tt_emerg_to_endjuv	tt from emergence to end of juvenile stage	°Cd	240	238.5	242
tt_endjuv_to_init	tt from end of juvenile to floral initiation	°Cd	0	0	0
tt_flower_to_start_grain	tt from silking to start effective grain fill period	°Cd	150	190	192
grain_gth_rate units	Grain growth rate	mg grain^{-1} day^{-1}	9.00	9.17	9.17
head_grain_no_max	Potential kernel number per ear	°Cd	640	655	520

Abbreviation: tt, thermal time.

variation in maize growth and yield relative to the baseline. The initial soil conditions for each year were reset to those used during the calibration exercise (Chisanga, 2019). Intercomparison studies using multiple crop models and climate model ensembles provide valuable information on uncertainty and accuracy. The multimodel ensemble mean of the two crop models was computed using simple model averaging. The impact of climate scenarios on days after planting (DAP) to anthesis, and maturity and maize yield was compiled and relative yield deviation from the baseline computed. The maize yield scenarios were analyzed using SDs, cultivars, and N rates. Maize biomass and grain yield coefficient of variation (CV = std/mean), standard deviation, and means were computed relative to the baseline. The significance of future grain yield was evaluated using the standard deviations.

3 | RESULTS AND DISCUSSION

3.1 | Calibration and validation of the crop models

The APSIM-Maize and CERES-Maize models were calibrated and validated by Chisanga (2019) using rainfed and irrigated field experiments conducted at Mount Makulu, respectively. The calibration and validation of APSIM-Maize and CERES-Maize models were necessary for their application to new cultivars.

APSIM-Maize and CERES-Maize models were parameterized to simulate DAP to anthesis, and maturity, grain size, grain number/m^2, biomass, and grain yield under three N fertilizer application rates for the three maize cultivars. The simulated days after planting to anthesis and maturity were excellent with NRMSEn < 10% for both crop models. The pooled value for RMSE on DAP to anthesis and maturity was 2.89 and 3.13 days in the CERES-Maize model, respectively. In APSIM-Maize, the RMSE on DAP to anthesis and maturity was 1.91 and 3.35 days, respectively. Observed and simulated values for grain yield, grain size, and grain number/m^2 for APSIM-Maize and CERES-Maize had RMSEn between 20% and 30% and considered acceptable in crop model evaluation. The RMSE between the observed and simulated value of grain yield for ZMS 606, PHB 30G19, and PHP 30B50 using the APSIM-Maize model were 1.28, 1.27, 1.56 ton/ha, respectively. However, the RMSE for grain yield was 0.67 ton/ha (ZMS 606), 0.68 ton/ha (PHB 30G19), and 1.11 ton/ha (PHB 30B50) in the CERES-Maize model.

The validation statistics showed that the simulated grain size (RMSEn = 6.25%, R^2 = .80, d-stat = 0.75), grain number/m^2 (RMSEn = 18.51%), and grain yield (RMSE = 1.34 t/ha, RMSEn = 20.18%) using APSIM-Maize were excellent and good, respectively. The simulated grain size (RMSEn = 21.14%, R^2 = .72, d = 0.55) and grain number/m^2 (NRMSE = 26.91%, R^2 = .10, d = 0.52) using CERES-Maze were good. The simulated grain yield (NRMSE = 45.08%) using CERES-Maize model was considered poor. The APSIM-Maize performed better in evaluating grain yield, grain size, and grain number/m^2 compared to CERES-Maize. The accuracy of the simulated outcome in crop models using new cultivars depends on rigorous calibration to minimize uncertainties.

3.2 | Climate change scenarios for temperature and precipitation

The baseline precipitation, maximum, and minimum temperature are 797.96 mm, 28.8, and 15.45°C, respectively. Climate change is projected to increase temperatures and shift precipitation patterns. Simulated results for the RCP4.5 and RCP8.5 indicated increasing positive trends for temperature relative to the baseline (Table 2 and Figure 1). All GCMs show warming, while precipitation response is decidedly more variable and uncertain, as shown in Table 2. Multimodel GCM ensemble projections have been recommended for climate change impact studies to take care of uncertainties embedded within GCMs (Araya et al., 2015). With the ensemble GCM, mean changes would be −1.46% (RCP4.5) and −15.24% (RCP8.5). There is a large decrease in precipitation under the RCP8.5 scenario compared to RCP4.5, as shown in Figure 1. The delta-based method used in the AgMIP protocols is considered to be a robust, easily understood, and accurate statistical downscaling technique. Unfortunately, its weakness is that the number of rain days per month in the future does not change, and solar radiation is assumed to be constant relative to the baseline (Jones, Singels,

TABLE 7 Genetic cultivar coefficients used in CERES-Maize model

Coefficients	Development aspects	Units	ZMS 606	PHB 30G19	PHB 30B50
P1	GDDs (based on 8°C) from emergence to end of the juvenile phase	°Cd	159.00	209.90	155.10
P2	Photoperiod sensitivity coefficient (01.0)		1.8500	0.4410	1.7630
P5	GDDs (based on 8°C) from silking to maturity	°Cd	810.20	815.90	800.40
	Growth aspects				
G2	Maximum possible number of kernels per plant		945.00	840.80	795.60
G3	Potential kernel growth rate (mg/day)	mg/day	8.559	8.840	15.340
PHINT	GDDs required for a leaf tip to appear(based on 8°C)	°Cd	59.700	56.00	59.730

TABLE 8 Simulated annual climatic changes for precipitation (prcp), maximum (t_{max}), and minimum (t_{min}) temperatures for the mid-century under RCP4.5 and RCP8.5 relative to the baseline data

	RCP4.5				RCP8.5			
GCM	prcp (mm)	%	t_{max}	t_{min}	prcp (mm)	%	t_{max}	t_{min}
CCSM4	−46.70	−5.85	1.76	1.51	−56.98	−7.14	2.37	2.36
GFDL-ESM2M	0.26	0.03	1.73	1.66	−8.45	−1.06	2.14	2.06
HadGEM2-ES	48.27	6.04	2.36	2.28	68.53	8.59	3.09	3.01
MIROC5	−12.49	−1.56	1.99	1.58	−21.03	−2.63	2.56	2.41
MPI-ESM-LR	−47.56	−5.96	1.76	1.51	−58.27	−7.30	2.37	2.35
Ensemble mean	−11.63	−1.46	1.92	1.71	−15.24	−1.91	2.51	2.44

& Ruane, 2015). Adhikari, Nejadhashemi, and Woznicki (2015) observed that large uncertainty exists in projecting precipitation, and changes would range from −15% to +27% by 2060s in Africa. In sub-Saharan Africa, the projected rainfall would be uncertain in 2050 (Waongo et al., 2015). The simulated temperature ranges at the study site are suitable for growing maize as a document by Araya et al. (2015) and Cairns et al. (2013). Maize grows well in between mean temperatures of 15 and 35°C (Araya et al., 2015).

3.3 | Probability distribution functions

The PDF shapes for maximum (T_{max}), mean (T_{mean}), and minimum (T_{min}) temperatures follow the shapes of observed PDFs under both RCP4.5 and RCP8.5 scenarios and are in agreement with the findings of Boberg, Berg, Thejll, Gutowski, and Christensen (2009) and Masanganise, Magodora, Mapuwei, and Basira (2014). The PDFs for temperature show a horizontal shifting relative to the baseline, as shown in Figure 2. The simulation indicates that temperature would increase during the 2050s (2040–2069) under RCP4.5 and RCP8.5 relative to the baseline. However, rainfall showed a vertical upward or downward shift in probability (Figure 3).

3.4 | Projected impact of climate change on anthesis and maturity using APSIM-Maize and CERES-Maize models

The baseline simulated days after planting (DAP) at anthesis, and maturity using APSIM-Maize and CERES-Maize models were 63.57–65.77 days (anthesis), and 118.13–122.73 days (maturity) and 43.83–46.87 days (anthesis), and 99.17–104.50 days (maturity), respectively. Using a crop model ensemble mean relative to the baseline, the percent DAP to anthesis (−11.28 to −9.39% [RCP4.5]; −14.28 to −12.65% [RCP8.5]) and maturity (−10.52 to −9.43% [RCP4.5]; −14.01 to −12.75% [RCP8.5]) would reduce in 2050. The crop models simulated a reduced DAP to anthesis and maturity at all treatment levels, which is attributed to climate change. As noted in this study, warmer climate speeds up crop development and thereby decreases DAP to anthesis and maturity. Results show that there is a higher percent change in the simulated DAP to anthesis and maturity using CERES-Maize compared to the APSIM-Maize model. SD affects the duration and timing of the vegetative and reproductive stages (Nape, 2011). As a result of this, small-holder farmers use different SDs to ensure crop yield success. A reduction in DAP to anthesis and maturity under future climate scenarios has been reported by Adnan, Jibrin, Kamara, Abdulrahman, and Shaibu (2017) and Zhang, Zhao, Chen, Guo, and Wang (2015).

3.5 | Projected impact of climate change on maize yield using APSIM-Maize and CERES-Maize models

The mean and standard deviation of the simulated grain yields for the baseline (1980–2010) and future (2040–2069) scenarios are presented in Figure 4. The simulated mean change in maize yield using the CERES-Maize model at the N1 rate for the ZMS 606 for SD1, SD2, and SD3 under RCP4.5 was within the second standard deviation of the baseline yield of 5.40 ± 0.52, 5.38 ± 0.51, and 5.38 ± 0.51 ton/ha, respectively. The simulated mean

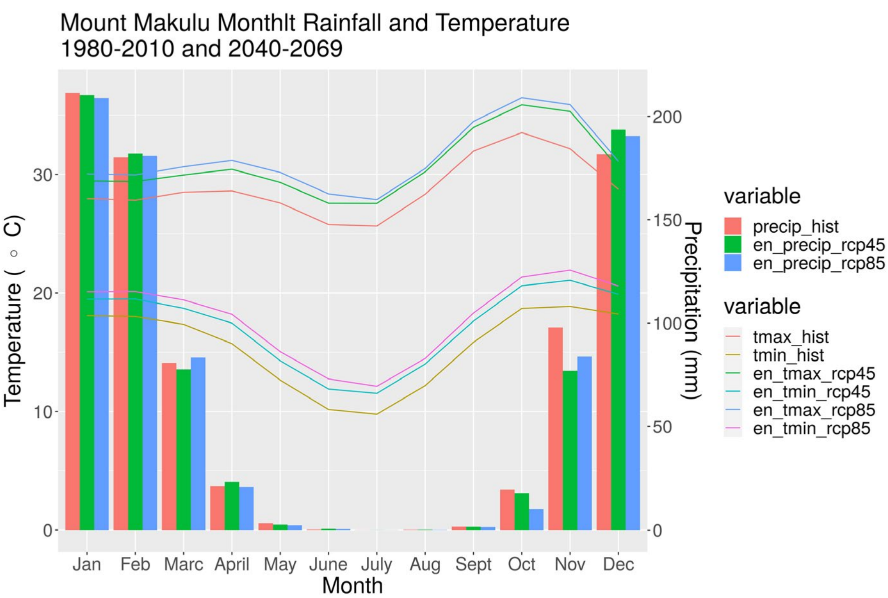


FIGURE 2 Mount Makulu Monthly Rainfall and Temperature for 1980–2010 (baseline), 2040–2069 (RCP4.5), and 2040–2069 (RCP8.5)

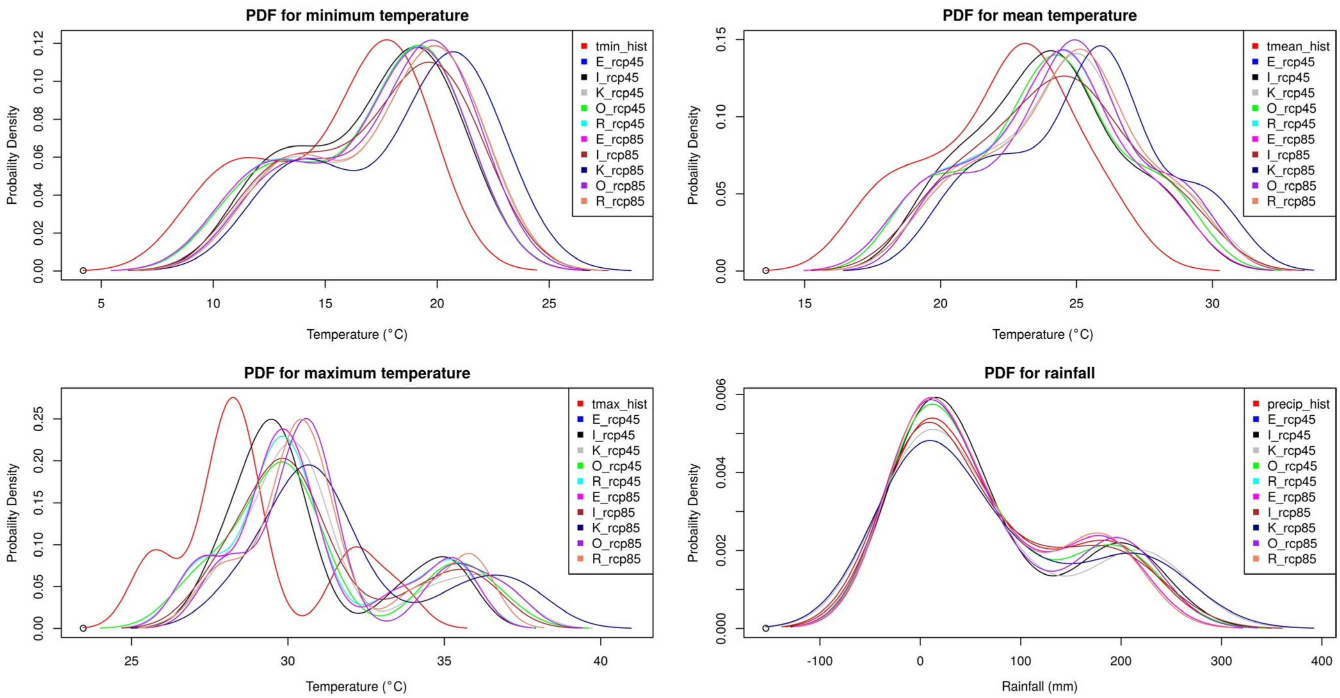


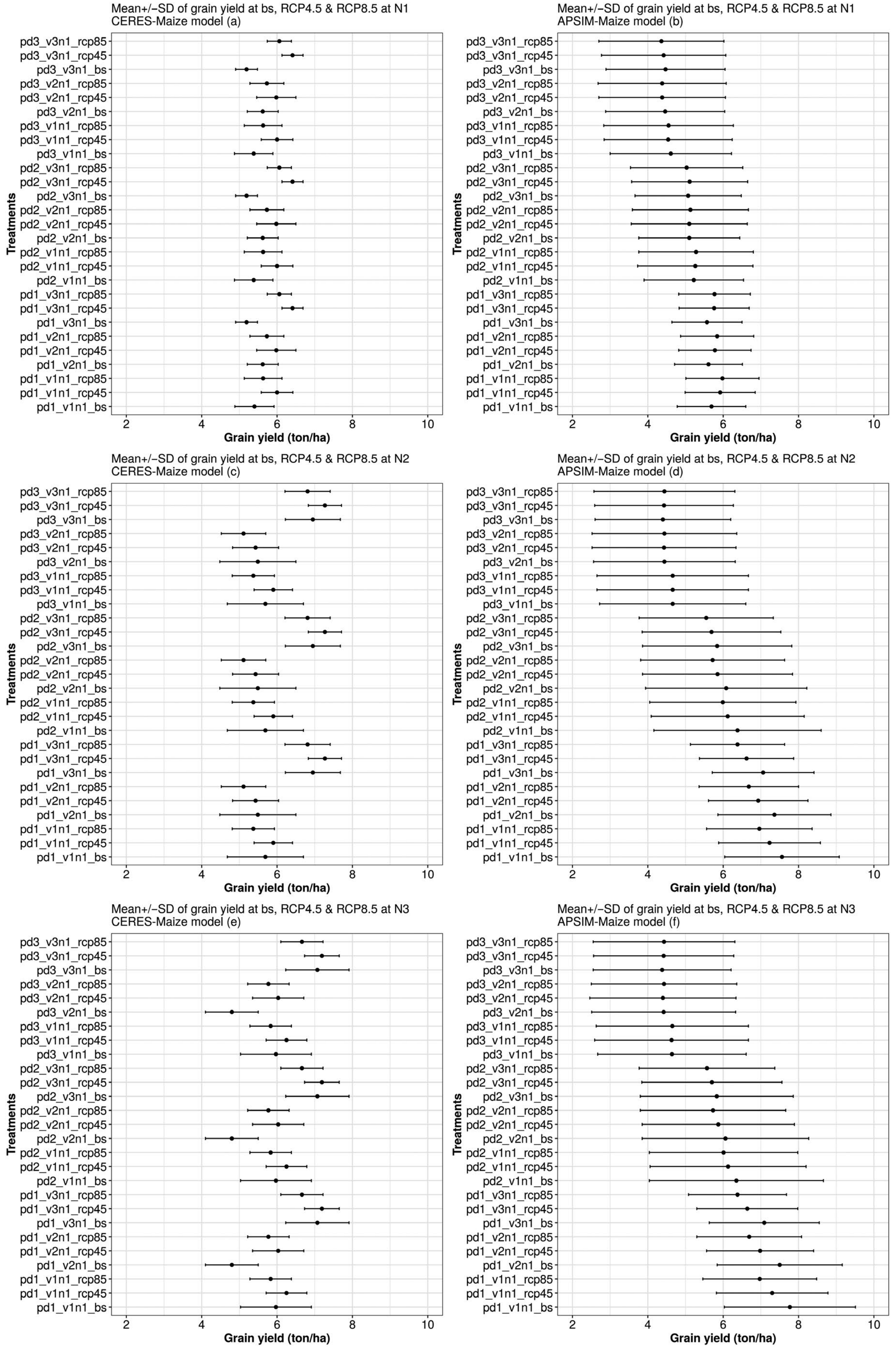
FIGURE 3 Probability Distribution Functions (PDF) for minimum, mean, and maximum temperature and rainfall for 1980–2010 (baseline), 2040–2069 (RCP4.5), and 2040–2069 (RCP8.5) climate scenarios

change in maize yield for PHB 30B50 cultivar under RCP4.5 and RCP8.5 is within the third standard deviation of the baseline yield of 5.40 ± 0.52, 5.38 ± 0.51, and 5.38 ± 0.51 ton/ha, respectively. The grain yield for PHB 30G19 cultivar at RCP4.5 (SD1 = 4.80 ± 0.70 ton/ha, SD2 = 4.8 ± 0.7 ton/ha, SD3 = 4.8 ± 0.7 ton/ha) and RCP8.5 (SD1 = 4.80 ± 0.70 ton/ha, SD2 = 4.8 ± 0.7 ton/ha, SD3 = 4.8 ± 0.7 ton/ha) with application of N3 fertilizer is within the second standard deviation. However, the mean yield change simulated using the DSSAT CERES-Maize model with the application of N2 (ZMS 606 and PHB 30B50) and N3 (ZMS 606, PHB 30G19, PHB 30B50) for the rest of the treatments is within the first standard deviations and therefore, nonsignificant statistically. All the treatments simulated with the APSIM-Maize model are within the first standard deviation and, therefore, considered statistically nonsignificant. APSIM-Maize has higher standard deviations compared to the CERES-Maize model, as shown in Figure 4. Results of standard deviations showed similar trends in grain yield, and this suggests that variability normally scales with the means. The grain yield would reduce with delay in SD of 7 and 14 days due to cooler air temperature, lower solar radiation, and reduced precipitation. However, APSIM-Maize exhibited an increased risk of yield variability, and Guan, Sultan, Biasutti, Baron, and Lobell (2017) agree with the finding of this study. It has also been reported in northern Nigeria that grain yield reduces with delay in sowing date (Adnan et al., 2017).

3.6 | Percent change in grain yield under sowing date, N rate, and cultivar using APSIM-Maize and CERES-Maize models

The percent change in grain yield is shown in Figure 5. Using the APSIM-Maize, the mean percent change in maize grain yield in 2050 would range from −2.88 to +4.37% (N1), −5.83 to +0.20% (N2), −6.21 to +0.58% (N3) (RCP4.5) and −3.86 to +5.42% (N1), −9.10 to +0.03% (N2), −9.99 to +0.69% (N3) (RCP8.5). The mean percent change in grain yield simulated using the CERES-Maize in 2050 would range from 6.85% to 23.86% (N1), 2.00% to 6.96% (N2), 2.99% to 27.96% (N3) (RCP4.5) and 2.55% to 17.04% (N1), −3.99% to −0.83% (N2), −4.61% to +22.80% (N3) (RCP8.5). Results show that the simulated changes in grain yield would be lower under RCP8.5 compared to the RCP4.5 climate scenario.

According to the analysis, maize cultivars would perform differently varying sowing dates (SDs) and nitrogen fertilizer application rates. Low N fertilizer rate would be better with low maintenance at SD1. Grain yield variation caused by weather was much greater under N3 than at N1 at SD1 and SD2 for both crop models (Figure 5). Delayed SD (SD3) at a higher N fertilizer rate would increase grain and biomass yield than at SD1. Lower N fertilizer rate (N1) in the future would give a higher increase in grain yield at SD1 than at SD3. FAO (2016) and Zhang et al. (2015) agree with the findings of this study that maize yield would reduce in the future due to climate change. Simulated


Mean+/−SD of grain yield at bs, RCP4.5 & RCP8.5 at N1
CERES-Maize model (a)
Mean+/−SD of grain yield at bs, RCP4.5 & RCP8.5 at N1
APSIM-Maize model (b)
Mean+/−SD of grain yield at bs, RCP4.5 & RCP8.5 at N2
CERES-Maize model (c)
Mean+/−SD of grain yield at bs, RCP4.5 & RCP8.5 at N2
APSIM-Maize model (d)
Mean+/−SD of grain yield at bs, RCP4.5 & RCP8.5 at N3
CERES-Maize model (e)
Mean+/−SD of grain yield at bs, RCP4.5 & RCP8.5 at N3
APSIM-Maize model (f)
pd3_v3n1_rcp85
pd3_v3n1_rcp45
pd3_v3n1_bs
pd3_v2n1_rcp85
pd3_v2n1_rcp45
pd3_v2n1_bs
pd3_v1n1_rcp85
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pd1_v2n1_rcp45
pd1_v2n1_bs
pd1_v1n1_rcp85
pd1_v1n1_rcp45
pd1_v1n1_bs
Treatments
2
4
6
8
10
Grain yield (ton/ha)

FIGURE 4 Mean ± *SD* of maize grain yield at 1980–2010 (baseline), 2040–2069 (RCP4.5), and 2040–2069 (RCP8.5) with varying sowing dates, maize cultivars, and nitrogen fertilizer application rates; (a) mean ± *SD* of maize grain yield in ton/ha at N1 using CERES-Maize model; (b) mean ± *SD* of maize grain yield in ton/ha at N3 using APSIM-Maize model; (c) mean ± *SD* of maize grain yield in ton/ha at N1 using CERES-Maize model; (d) mean ± *SD* of maize grain yield in ton/ha at N2 using APSIM-Maize model; (e) mean ± *SD* of maize grain yield in ton/ha at N3 using CERES-Maize model; and (f) mean ± *SD* of maize grain yield in ton/ha at N3 using APSIM-Maize model

percent change in grain yield would decrease in 2050 due to reduced duration of the phenological stages and higher air temperatures. Shorter crop growth duration entails that the crop would utilize less solar radiation and rootzone soil water. The management of SD and N fertilizer rates could be beneficial mitigation and adaptation of maize to climate change at Mount Makulu. Projected changes in temperature and precipitation would decrease maize yield in Africa as a result of the shortening DAP to anthesis and maturity (Adhikari et al., 2015).

Inadequate use of crop models is attributed to a lack of application in policy formulation and low capacity (MacCarthy, Kihara, Masikati, & Adiku, 2017). Using crop models as decision support tools by both end-users, researchers, planners, and policymakers could lead to efficient use of nutrients in agricultural productivity. The observed differences between APSIM-Maize and CERES-Maize model projections are due to differences in sensitivity to temperature and CO_2 increases (Waha, Huth, Carberry, & Wang, 2015). Araya et al. (2015) reported an increase in maize yield for the mid-century using DSSAT and 20 GCMs and his findings to agree with this study. A prediction of a 3%–19% reduction in maize yield by 2050 was observed by Jones and Thornton (2003) using the CERES-Maize model. Challinor, Koehler, Ramirez-Villegas, Whitfield, and Das (2016) also found that the increase in air temperature shortens the number of days to anthesis and physiological maturity and hence, reduces grain and biomass yield, and they agree with the findings of this study.

3.7 | Ensemble mean of the crop models outputs

The simulated ensemble mean (Figure 6) of grain yield using APSIM-Maize and CERES-Maize models due to the impact of climate change and management has been quantified for Mount Makulu. The mean change in maize grain yield would be −0.25 to 0.71 and −0.56 to 0.54 ton/ha under RCP4.5 and RCP8.5, respectively. There is higher grain reduction under RCP8.5 compared to RCP4.5 relative to the baseline, as shown in Figure 6. The ZMS 606 grain yield would increase in future relative to the baseline at SD1 (0.41 ton/ha [RCP4.5]; 0.26 ton/ha [RCP8.5]), SD2

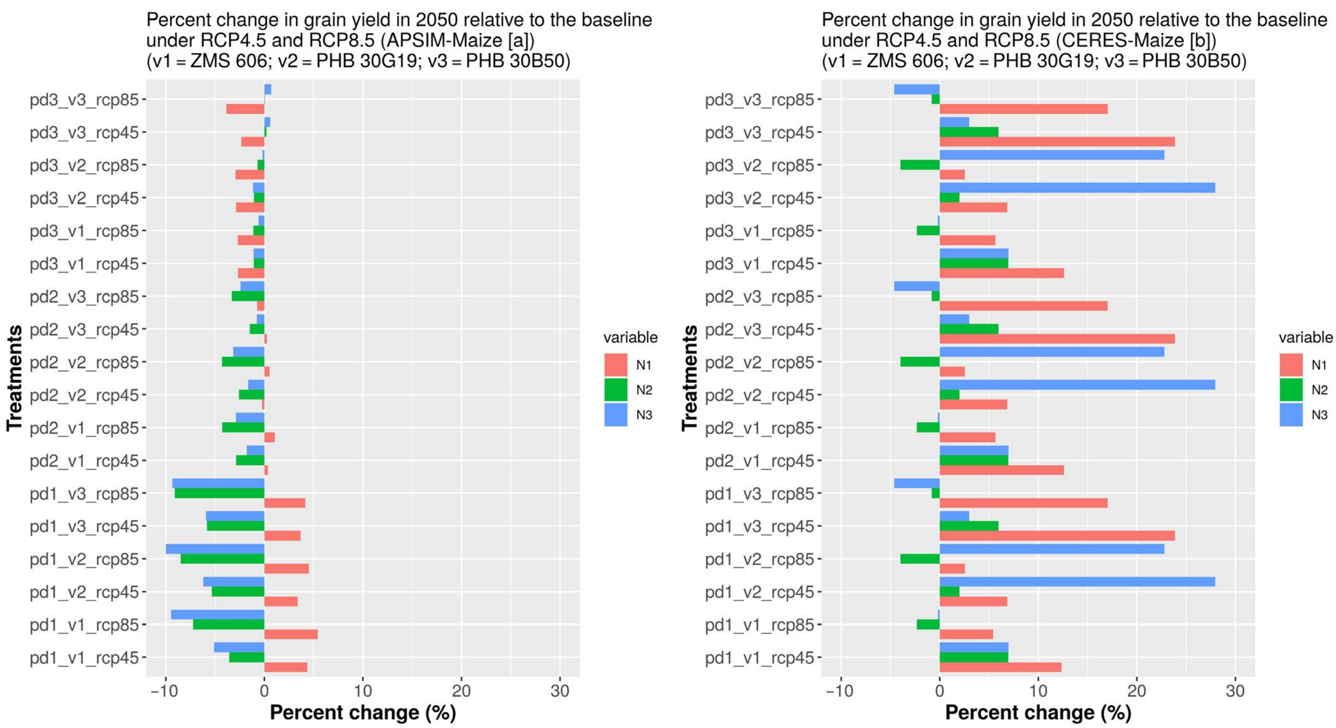

FIGURE 5 Percent change in maize grain yield under sowing dates, and maize cultivar and nitrogen fertilizer rates in 2040–2069/1980–2010 under RCP4.5 and RCP8.5 (APSIM-Maize [a]; CERES-Maize [b])

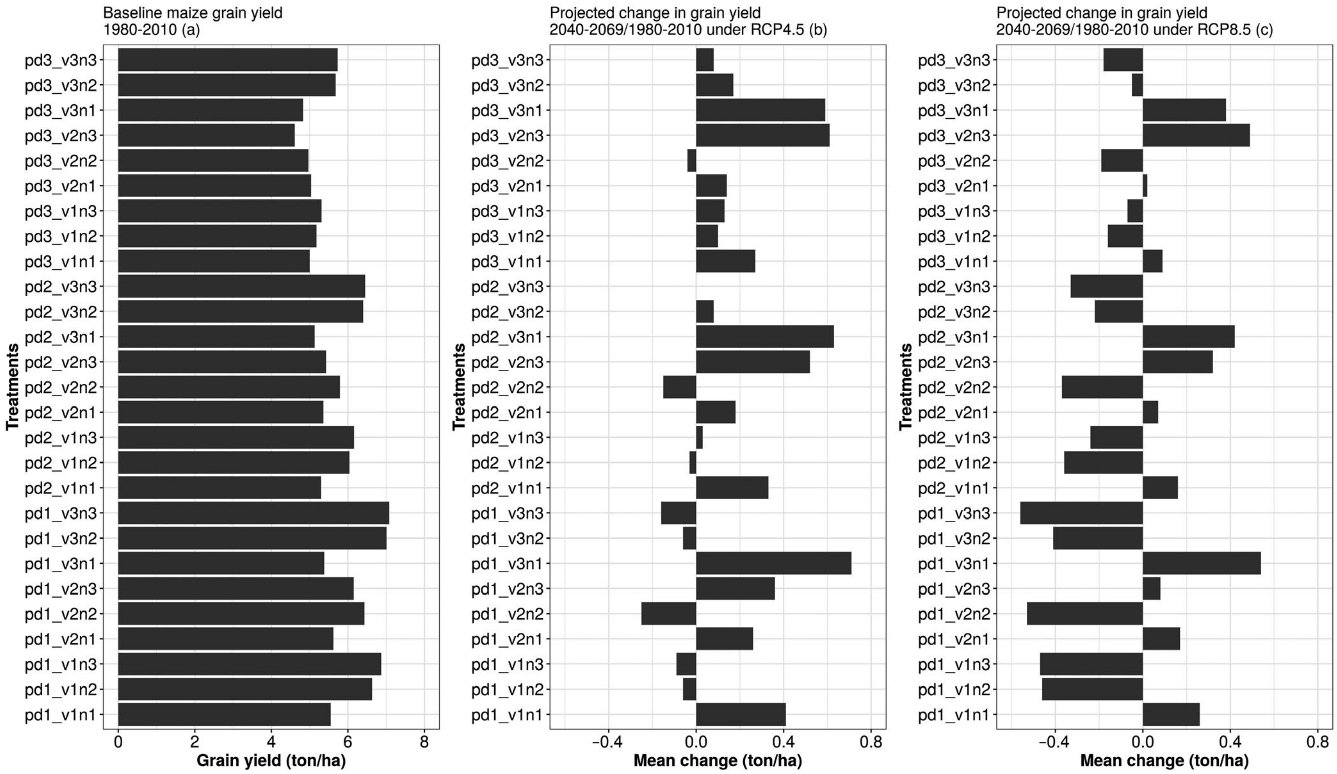

FIGURE 6 (a) Maize grain yield in 1980–2010 with varying sowing dates, maize cultivars, and nitrogen fertilizer application rates; (b) projected changes in maize grain yield in 2040–2069/1980–2010 with varying sowing dates, maize cultivars, and nitrogen fertilizer application rates under RCP4.5; (c) projected changes in maize grain yield in 2040–2069/1980–2010 with varying sowing dates, maize cultivars, and nitrogen fertilizer application rates under RCP8.5

(0.33 ton/ha [RCP4.5]; 0.16 ton/ha [RCP8.5]), and SD3 (0.27 ton/ha [RCP4.5]; 0.09 ton/ha [RCP8.5]) with N1 application rates. However, the application of N1, N2, and N3 would increase grain yield at SD3. The PHB 30G19 grain yield would increase in future under both scenarios at all sowing dates ([SD1 = 0.14 ton/ha; SD2 = −0.04 ton/ha; SD3 = 0.61 ton/ha (RCP4.5)]; [SD1 = 0.02 ton/ha; SD2 = −0.19 ton/ha; SD3 = 0.49 ton/ha [RCP8.5]) with application of N1 and N3 fertilizer rates. The cultivar would have a higher increase in grain yield with the application of N3 at all sowing dates, as shown in Figure 6.

The PHB 30B50 at SD3 would experience a reduction in maize yield with an increase in N application rate (N1 = 0.59 ton/ha; N2 = 0.17 ton/ha; N3 = 0.08 ton/ha [RCP4.5]) and (N1 = 0.38 ton/ha; N2 = −0.05 ton/ha; N3 = −0.18 ton/ha [RCP8.5]). The PHB 30G50 exhibits similar trends at SD1 and SD2. The grain yield would increase in the future under both climate scenarios for the PHB 30B50 with a lower N application (N1). The cultivar would only benefit from N2 and N3 applications at SD2 and SD3 under the RCP4.5 scenario, as shown in Figure 6. The PHB 30B50 would perform better at all sowing dates and N rates compared to ZMS 606 and PHB 30G19 under both climate scenarios. The PHB 30G19 will outperform ZMS 606 and PHB 30B50 at SD3 under both scenarios.

Less soil water content has an effect on soil fertility, which becomes less significant. Earlier SD (SD1) with a lower N application rate (N1) is an effective adaptation strategy in dealing with the adverse effects of future climate change. If smallholder farmers maintain N1 at all SDs, climate change would be inconsequential due to the over-riding constraint of fertility on crop yield. Adaptation and mitigation strategies that should be used by farmers are planting drought, heat resistant and open pollinating cultivars, N management, and varying SDs. Other strategies include early and late SDs with lower and higher N fertilizer rates, respectively. Management strategies such as tillage, soil water conservation measures, and improved irrigation technologies were not considered in this study. Their effectiveness in counteracting projected negative climate change impacts needs to be quantified in the future. An increase in temperature and precipitation variability is the main mechanism by which climate change would have a significant impact on crop growth and yield through reduced DAP to anthesis and maturity. The most effective approach in assessing the impact of climate change on crop yield and in formulating mitigation and adaptation strategies is the use of a multimodel ensemble of crop models and GCMs. Crop models can also be used in plant breeding targeted at specific mitigation and adaptation strategies.

Multimodal ensembles improve the simulation of maize growth and grain yield consistently and accurately. Martre et al. (2015) noted that studies using an ensemble of crop models provide valuable information about model accuracy and uncertainty.

4 | CONCLUSION

The simulated effects of climate change and variability on maize cultivars provided an understanding of the possible impacts of the changes in temperature and rainfall on maize yield varying SDs and N fertilizer rate in the future (2040–2069). Crop models could be applied in assessing the impact of climate change on maize yield using future climate scenarios. The APSIM-Maize and CERES-Maize models simulated reduced DAP to anthesis and maturity. The projected changes in temperature and rainfall would adversely reduce simulated maize yield, depending on SD in 2050. Therefore, new cultivars are needed that are drought resistant and efficient at utilizing N. Using multimodel ensembles of crop models provides robust estimates of growth and yield. Significant changes in DAP to anthesis and maturity, biomass, and grain yield were observed under RCP4.5 and RCP8.5 scenarios. The DAP to anthesis and maturity would reduce in 2050. The pooled % change in grain would range from 2.78% to 9.94%, −3.81 to −8.88%, and −2.33 to 10.63% under N1, N2, and N3, respectively. The percent change in grain yield would increase with delay in SD (RCP4.5 [SD1 = 2.57%; SD2 = 3.31%; SD3 = 4.37%]; RCP8.5 [SD1 = −1.11%; SD2 = −0.29%; SD3 = 1.08%]). The current SDs and cultivars with lower N (N1) would increase grain yield in the future. However, grain yield would increase at SD3 with a higher N rate (N3). Climate models should be linked to crop simulation models to generate short-term and long-term local weather forecasts. The findings provide evidence that climate change at the study site would affect maize yield. Therefore, there is a need to put in place strategies of addressing the impacts of climate change in maize production in Zambia.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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