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Assessing the impacts of projected climate changes on maize (*Zea mays*) productivity using crop models and climate scenario simulation

Xuan Yang[A], Dorothy Menefee[B], Song Cui[C,*] and Nithya Rajan[D,*]

For full list of author affiliations and declarations see end of paper

*Correspondence to:
Song Cui
School of Agriculture, Middle Tennessee State University, Murfreesboro, TN 37132, USA
Email: song.cui@mtsu.edu;
Nithya Rajan
Department of Soil and Crop Sciences, Texas A&M University, College Station, TX 77843, USA
Email: nrajan@tamu.edu

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ABSTRACT

Context. Investigating agronomic responses of dryland maize (*Zea mays* L.) systems under global change could provide important insights in designing climate-resilient cropping systems. **Aims and methods.** In this study, we integrated Agricultural Production Systems sIMulator (APSIM) with Representative Concentration Pathways 8.5 and 20 Global Climate Models to systematically: (1) calibrate and validate APSIM using large-field study conducted in East-Central Texas; (2) evaluate the impacts of climate change on maize productivity and risks; and (3) investigate the variations in growth stage lengths. **Key results.** Results indicated that APSIM simulated grain yield, biomass production, precipitation productivity (PP; kg ha^{-1} mm^{-1}) and developmental stage transition agreed well with observation (NRMSE < 14.9%). Changes in temperature and precipitation shortened growing seasons and affected available water, resulting in widely varied yield and PP. Mean grain yield changed from −34.8 to +19.7%, mean PP were improved 9.2–36.5%. The grain production could be maintained at least the standard of 75% of historical in most cases, but with greater risks for achieving higher threshold (50% of baseline). Finally, simulations indicated shortened days (4–13 days) for reaching key developmental stages for maize. **Conclusions and implications.** The results advocate adoptions of management practice that incorporating early sowing, irrigations at sowing/VT stages, and selections of late-maturing cultivars for better sustainability and higher productivity.

Keywords: APSIM, climate change, climate risk, crop productivity, growing season duration, maize, precipitation productivity, the East-Central Texas.

Introduction

Global climate change, characterised by increasing average temperature and number of extreme weather incidences (IPCC 2014), has greatly challenged the productivity and sustainability of agronomic production on a global scale (Piao *et al.* 2010). In particular, yield loss caused by storms, prolonged dry spell, as well as increasing outbreaks of insects/pathogen directly contributed by rising atmospheric temperature are currently, and will remain one of the most serious issues threatening global food security in the future (FAO *et al.* 2013). For example, a former study estimated that as a temperature-sensitive crop, the global maize (*Zea mays* L.) grain yield would decrease by as much as 30% in the 2080s (Xiong *et al.* 2016).

The East-Central Texas (ECT) represents a major agricultural production region in the United States, featuring large acreage of row-crop and forage production, long growing season, and adequate precipitation. However, precipitation variability and warmer summer temperature have become major concerns in recent years (Chavez *et al.* 2019). Furthermore, the majority of farmland in this region remains idle and/or non-irrigated due to high water input costs and low profit margin (DeLaune *et al.* 2012; Chavez *et al.* 2019), thus, making crop production of ECT particularly sensitive to climate change, casting great uncertainties over economic sustainability of major grain cropping systems (e.g. maize and sorghum [*Sorghum bicolor* L. Moench]) in the future (Mjelde *et al.* 1997).

Interests in using climate projections and simulation modelling for yield estimation and decision making have been growing rapidly. Former studies indicated that the evaporation and grain yield of maize in Texas would decrease 3–25% due to accelerating climate warming during 2020–2099 (Chipanshi *et al.* 2003; Chen *et al.* 2019). It was also noted that yield variability of main staple crops [wheat (*Triticum aestivum* L.), rice (*Oryza sativa* L.), and maize] will be increased as a result of warmer temperatures and alterations in precipitation patterns across the globe, forecasting huge risks of production in the future (Leng 2017; Leisner 2020). A commonly accepted issue was that the yield instability/reduction and increasing production risks caused by changes in weather patterns should greatly offset the positive effects of increasing ambient CO_2 concentration on photosynthesis for both C_3 and C_4 plants (Hatfield *et al.* 2011; Adhikari *et al.* 2016). However, the response differences of such influences across crops and regions are pronounced (Leisner 2020). In particular, the information relating to the impact of elevated CO_2 concentration in conjunction with other climate factors on the risk of dry-farming maize production in the ECT still remains scanty. Thus, we expect the effects of elevated atmospheric CO_2 concentration and climatic variability on dryland maize production should be more pronounced, and greatly depend on agroclimatic regions, implying the necessity of conducting multi-scenarios analysis based on locally collected field data.

Crop models are useful tools for exploring the impact of climate and management scenarios on agricultural response indicators, such as yield. Particularly, Agricultural Production Systems sIMulator (APSIM) is a widely used process-based model for simulating biological and physical processes in production risk management and crop adaptation studies (Keating *et al.* 2003; Archontoulis *et al.* 2014; Holzworth *et al.* 2014; Yang *et al.* 2020). The modular nature and pluggable framework of APSIM make it accommodating to a wide array of different managerial and environmental factors such as crop species, soil classes, year patterns and climate conditions (Holzworth *et al.* 2014). Thus for ECT region, linking climate change scenario analysis with APSIM-based simulation modelling could provide a comprehensive assessment on how maize production could be impacted in response to future climate change, offering invaluable information for strategic decision-making processes and filling the scarcity of long-term estimation on maize production.

In this study, a systematic investigation was conducted based on field-level data to evaluate how climate will change, and how such changes will affect maize productivity and risk under dryland cropping in the ECT region. The overall data analytic paradigm involves field-data based calibration/validation coupled with climate scenario analysis. The primary objects of the current study are to: (1) calibrate and validate APSIM model for accurately predicting maize growth process and grain yield in ECT; (2) investigate the effects of projected future climate changes on maize grain yield and precipitation productivity (PP), as well as the climate risks of long-term production based on the baseline and an ensemble of 20 Global Climate Model (GCMs), under high emission scenarios; and (3) elucidate the transitions of key maize growth stages under projected climate conditions using multi-GCMs.

Methods and materials

Site information

The study area is located at the Burleson County of Texas, constituting a major maize (*Zea mays* L.) production area in a sub-tropical region of the East-Central Texas (ECT). The long-term average annual temperature of this site was 20.6°C, and the long-term average annual precipitation was 1018 mm. The rainfall pattern in this region is bimodal with the highest rainfall in May, June and October. Two dominant yet very similar soil types in the major farmland of ECT were focused on: (1) a Ships clay (Chromic Halpludert, 42% clay in the surface horizon; hereinafter soil type I) and; (2) a Weswood silt loam (Udifluventic Haplustepts, 38% clay in surface horizon, floodplain; hereinafter soil type II).

Field experiment

The experiment was conducted on the Texas A&M Agrilife Research Farm in Burleson County, Texas (30°32′46.2″N, 96°25′19.7″W). The entire field was measured at 34 ha and was dedicated to dryland maize production, where planting was completed on 10 March 2017 and 6 March 2018. Disc-tillage was performed prior to planting. The variety planted was B-H 8845 VTB in 2017, and Pioneer P1602 AM in 2018. Nitrogen fertiliser was broadcast at a rate of 135 kg N ha^{-1} annually as urea ammonium nitrate (32-0-0) immediately after planting. Maize was harvested on 25 July 2017 and 19 July 2018, and the crop stalks and leaf residues were shredded post-harvest and incorporated into the soils using disc tillage. No irrigation water was supplied throughout the growing season during each year.

Maize dry matter biomass and plant height were measured and recorded at different maize developmental stages in each year, including: emergency (VE), end of juvenile (V6), flowering (VT) and physiological maturity (R6) according to Feekes Growth Scale. At each sampling, six areas (three from each soil type) within the field were randomly selected for plant sampling, and then 15 plants from each area were randomly selected for height, growth stage, and aboveground biomass measurements. Phenological stages were determined by visual inspection. Biomass was determined on dry matter basis following destructive sampling and oven drying at 40°C until constant weight. Annual grain yield was determined using similar protocols of hand threshing and seed separation. The meteorological data, including daily maximum/minimum air temperature, daily cumulative precipitation and solar radiation, was obtained from a nearby weather station located at the Texas A&M Agrilife Research Farm near College Station, TX. Particularly, cumulative precipitations for the maize growing seasons during 2017 and 2018 were 472 and 259 mm, respectively, and the mean daily temperatures were 23.8 and 23.1°C, respectively.

Model calibration and validation

Agricultural Production Systems sIMulator (APSIM) ver. 7.10 (available at www.apsim.info) in conjunction with crop module APSIM-Maize was used to simulate crop development and production in this study. In order to calibrate the model for the field experiment, we used basic crop data, including Dates After Sowing (DAS) for reaching various crop stages (VE, V6, VT and R6), biomass production, grain yield, maximal plant height, and weather data each growing season to obtaining crop parameters using a trial-and-error method based on the field data of soil type I (Table 1). The key soil parameters (Table 2) from soil particle composition (0–10, 10–30 and 30–50 cm, three layers for soil type I and II) were calculated using the methods described by Saxton and Rawls (2006).

APSIM simulations were performed separately for soil type I (calibration) and soil type II (validation). The variables of interest include maize biomass production, grain yield, precipitation productivity (PP) and DAS of key developmental stages (V6, VT, and R6). PP (kg ha^{-1} mm^{-1}) was calculated as:

$$PP = GY/GSP \tag{1}$$

where GY and GSP are grain yield and growing season precipitation, respectively.

The performance statistics were calculated based on the data collected from the field experiment component and APSIM simulation, while the root mean square error (RMSE) and normalised root mean square error (NRMSE; 0–100%) were used. The maize biomass contained 12 pairs of values, while the grain yield, PP, and the DAS of each tested phenology contained four pairs of values. Particularly, model evaluation metrics were calculated as:

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

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2}}{\bar{O}} \times 100\% \tag{3}$$

where O_i, P_i and $\bar{O}$ are observed, simulated, and mean of observed values, respectively. N is the number of observations in the dataset.

Scenario simulations

Climate scenarios

Climate change scenarios are widely used in modelling studies to evaluate the responses of different indices in agricultural production to projected climatic conditions in the future (White *et al.* 2011; Traore *et al.* 2017). Particularly, the Representative Concentration Pathways

Table 1. Values of the main ecophysiological parameters used for calibrating APSIM model based on a dryland maize experiment conducted in Burleson County of Texas from 2017 to 2018.

Maize cultivar	Parameter description	Coefficient name	Validated value
B-H 8845 VTB	Thermal time from emergence and end of juvenile stage	tt_emerg_to_endjuv description (°C day)	270
	Thermal time from end of juvenile stage to floral initiation	tt_endjuv_to_init (°C day)	0
	Thermal time from appearance of flag leaf to flowering	tt_flag_to_flower (°C day)	1
	Thermal time from flowering to start of grain filling	tt_flower_to_start_grain (°C day)	160
	Thermal time from flowering to physiological maturity	tt_flower_to_maturity (°C day)	660
	Degree days to initiate each leaf primordium until floral initiation	leaf_init_rate (°C day)	33
	Plant canopy height	y_height (mm)	0–1500
	Radiation use efficiency	RUE (g (biomass) MJ^{-1})	1.50
Pioneer P1602	Thermal time from emergence and end of juvenile stage	tt_emerg_to_endjuv description (°C day)	360
	Thermal time from end of juvenile stage to floral initiation	tt_endjuv_to_init (°C day)	120
	Thermal time from appearance of flag leaf to flowering	tt_flag_to_flower (°C day)	1
	Thermal time from flowering to start of grain filling	tt_flower_to_start_grain (°C day)	210
	Thermal time from flowering to physiological maturity	tt_flower_to_maturity (°C day)	780
	Degree days to initiate each leaf primordium until flora initiation	leaf_init_rate (°C day)	48
	Plant canopy height	y_height (mm)	0–3000
	Radiation use efficiency	RUE (g (biomass) MJ^{-1})	1.60

Table 2. Values of the main soil parameters used for calibrating APSIM model based on a dryland maize experiment conducted in Burleson County of Texas from 2017 to 2018.

Soil type	Parameter description	Coefficient name	Soil layer (cm)		
			0–10	10–30	30–50
Soil type I (Chromic Halpludert, 42% clay in the surface horizon)	Percentage of clay	N/A (%)	42	34	34
	Percentage of sand	N/A (%)	24	32	13
	Bulk density	BD (g cm^{-3})	1.329	1.349	1.226
	Hydroscopic water content	AirDry (mm mm^{-1})	0.070	0.126	0.140
	Permanent wilting point	LL15 (mm mm^{-1})	0.255	0.216	0.214
	Field capacity	DUL (mm mm^{-1})	0.391	0.357	0.381
	Saturation	SAT (mm mm^{-1})	0.498	0.491	0.537
Soil type II (Udifluventic Haplustepts, 38% clay in surface horizon, floodplain)	Percentage of clay	N/A (%)	38	38	28
	Percentage of sand	N/A (%)	31	29	43
	Bulk density	BD (g cm^{-3})	1.349	1.339	1.392
	Hydroscopic water content	AirDry (mm mm^{-1})	0.070	0.126	0.140
	Permanent wilting point	LL15 (mm mm^{-1})	0.237	0.237	0.186
	Field capacity	DUL (mm mm^{-1})	0.373	0.374	0.318
	Saturation	SAT (mm mm^{-1})	0.491	0.495	0.475

(RCPs), which represent a series of trajectories of greenhouse gas (GHG) and air pollutant emission, energy and land use, technological development and socio-economic changes; were reported by IPCC based on different 21st century pathways. Particularly, the higher-emission scenario relative to the baseline, RCP8.5 (CMIP5 climate modelling results; Taylor *et al.* 2012), was used in our scenario analysis, which represents the 'business-as-usual' scenario, the future projection based on a very high level of greenhouse gas emission due to human activities and industrial development (Guan *et al.* 2017). For this study, particularly, the projected climate scenarios of 2040–2065 under RCP8.5 were compared to the reference time slice of 1981–2005 under the baseline.

Historical daily weather data (1981–2005) for Burleson County, Texas, including minimum and maximum air temperatures and daily precipitation was obtained from the Integrated Agricultural Information and Management System (iAIMS) website (https://beaumont.tamu.edu/climaticdata/WorldMap.aspx), while the historical daily solar radiation (1981–2005) was obtained from the National Solar Radiation Database (http://rredc.nrel.gov/solar/old_data/nsrdb/). The mean general maize growing season (from March to July) precipitation during 1981–2005 (baseline scenario) at the Burleson County of ECT was 416 mm with high inter-annual variability, ranging from 107 to 733 mm (Fig. 1*a*). The mean growing season temperature was 23.4°C in these 25 years, ranging from 21.2 to 24.3°C (Fig. 1*b*).

To better consider the uncertainties induced by different climate change projections, the datasets from 20 Global Climate Model (GCMs; Table 3) were used in our scenario simulations (baseline scenario and 20 × GCMs of RCP8.5 generated scenarios). Particularly, the RCP8.5 projections (2041–2065), corresponding to the period of 1981–2005) were generated using the protocols specified by ACSGTR (AgMIP Climate Scenario Generation Tools with R; www.agmip.org). The climate data (GCM files) was downloaded from NASA Goddard's Online File Depot provided by AgMIP. With the input of the longitude and latitude of study site (farm in Burleson County, Texas), ACSGTR produced the projected climate scenarios using the 'Delta Method' that adjusts daily historical observations to match mean monthly climate changes as determined by GCM simulations (Ruane *et al.* 2015): the future scenarios of RCP8.5 were generated by imposing the monthly changes in temperature and percentage changes in precipitation on the filled historical record year by year.

Moreover, we fitted the yearly CO_2 concentration values according to concentration pathway for each RCP scenario of CMIP5 reported by the International Institute for Applied Systems Analysis (IIASA) RCP Database (http://tntcat.iiasa.ac.at/RcpDb) for simulating the responses in maize production referring to CO_2 in APSIM. Eqn 4 showed the empirical equation to calculate yearly CO_2 concentration values for RCP 8.5 as (Xiao *et al.* 2020):

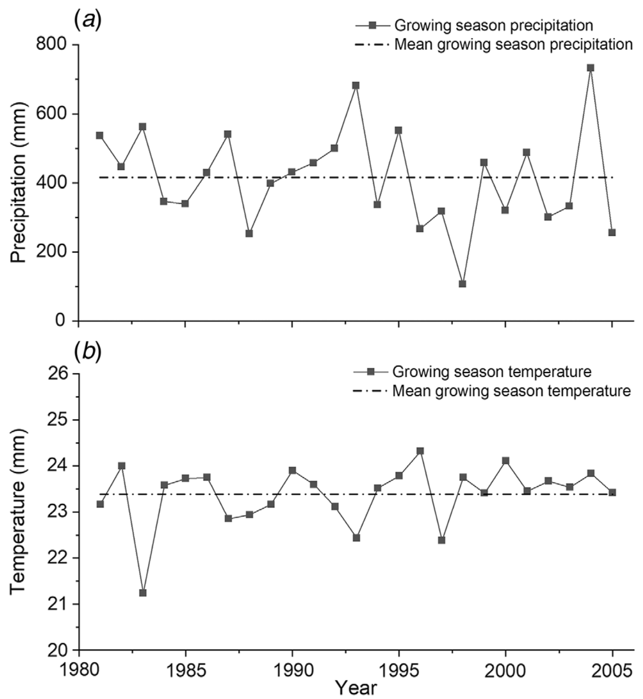

Fig. 1. General maize growing season (from March to July) precipitation and air temperature during 1981–2005 (baseline scenario) in Burleson County, Texas, USA. (*a*) precipitation; (*b*) air temperature.

$$[CO_2]_y = 1034.3 + \frac{267.78 - 1.6188y}{4.0143 - 53.342y^{-5.2882}} + 21.746 \times \left(\frac{y - 2020}{100}\right)^3 + 100.65 \times \left(\frac{y - 1911}{100}\right)^3 \quad (4)$$

where y is the year for 1971–2100 ($y = 1971, 1972, \ldots, 2100$) and $[CO_2]_y$ is the value of CO_2 concentration (mg kg^{-1}) in y. As indicated, yearly CO_2 concentration values were integrated in both baseline simulation (1981–2005) and future scenario simulations (2041–2065).

In the scenario analysis of the current study, the response of transpiration efficiency (TE) to CO_2 concentration is specified in the file 'Maize-7.3-CO2.xml' of APSIM supporting file repository (https://www.apsim.info/support/apsim-training-manuals/apsim-training-simlesa/climate-change-projections/), which estimates TE based on a function embedded in the file 'Maize.xml' (Eqn 5).

$$\mathrm{TE}(CO_2) = \mathrm{TE}(350) \times (1 + \frac{[CO_2] - 350}{100} \times 0.106) \quad (5)$$

where $\mathrm{TE}(CO_2)$ and TE(350) are the customised TE value and the value under the CO_2 concentration of 350 mg kg^{-1}, respectively. $[CO_2]$ represents the customised value of CO_2 concentration.

In summary, the scenario analysis of these future projections provided implications on how dryland maize production would change under projected climate change with a general increase in air temperature, variability in precipitation quantity and pattern, and elevated CO_2 concentration in the near future (near 25-year future period).

Simulation setting

Based on the field data, Pioneer P1602 AM cultivar, which was planted in 2018, is generally taller and capable of producing more biomass than B-H 8845 VTB. Meanwhile, Pioneer P1602 AM needs higher thermal time for reaching physiological maturity than B-H 8845 VTB (Table 1). Therefore, Pioneer P1602 AM has the potential to be used as a dual-purpose cultivar (grain and forage cultivar), and B-H 8845 VTB was selected to represent the main grain-producing cultivar in scenario simulations of the current study. The two dominant soil types in major farmland of the ECT, soil type I (the Ships clay) and soil type II (the Weswood silt loam), were specifically included in the simulations to enhance the robustness and accuracy of our scenario analysis. Therefore, there were 42 of 25-year of APSIM simulations in our scenario simulations (totally, 21 GCMs and two soil types with 25-year).

For our simulation, maize planting density was set at 6.93 plants m^{-2} (30 kg ha^{-1}) in each year (25-year for a scenario) for both baseline scenario and projected scenarios, which initialled in 1981 and 2041, respectively. Maize has a specific sowing time window (1–10 March) with a requirement for accumulated precipitation (5 mm) for sowing, or a latest date of 10 March; whichever comes first. Harvesting was performed in maturity stage (R6) of maize. To ensure sufficient soil N for optimum crop growth, 280 kg N ha^{-1} was applied at each sowing event in the scenario simulations. The initial soil water storage of each simulation was set at 75% of Drained Upper Limit (DUL) for each soil layer (Table 2), and was reset at the sowing of each year for all scenario simulations. Based on common field operation practices for main production in ECT, we modified each simulation as no post-harvest organic matter (residuals) remaining on the soil surface, while the subsequent residuals of maize (5% of plant standing) were reserved in the fields before the next sowing event. No irrigation inputs were included for all scenario simulations. The effects of climates and soil types were investigated based on the outputs of APSIM simulations, specifically, simulated maize grain yield, PP, as well as DAS of maize flowering and maturity were compared across different climate scenario-soil types.

The cumulative probability distributions (CPD) were used to characterise maize yield variability and climate risk in the current study. Thus the guarantee rate (Eqn 6) and the climate risk (Eqn 7) were calculated referenced by Zhang *et al.* (2019). For maize yield, 'not passing the threshold' means that the yield is above certain critical minimum level, and 'passing the threshold' means that the yield is less than the threshold:

Table 3. List of the GCMs (Global Climate Model) used in the scenario simulations of this study, and their corresponding changes of total precipitation and daily air temperature of general maize growing seasons in the Burleson County of Texas (from March to July) for each climate scenario compared with the baseline scenario.

GCMs	Institute ID	Country	The change of air temperature (°C $season^{-1}$)	The change of precipitation (mm $season^{-1}$)
ACCESS1-0	ACCESS	Australia	+2.4	−78.2
bcc-csm1-1	BCC	China	+2.1	−101.5
BNU-ESM	GCESS	China	+2.0	+1.1
CanESM2	CCCMA	Canada	+2.6	−101.8
CCSM4	NCAR	USA	+2.1	+37.4
CESM1-BGC	NSF-DOENCAR	USA	+2.1	−8.5
CSIRO-Mk3-6-0	CSIRO-QCCCE	Australia	+2.4	+53.1
GFDL-ESM2G	NOAA GFDL	USA	+2.5	−88.7
GFDL-ESM2M	NOAA GFDL	USA	+2.1	−21.6
HadGEM2-CC	NIMR/KMA	Korea	+2.9	+15.2
HadGEM2-ES	NIMR/KMA	Korea	+3.4	−105.0
inmcm4	INM	Russia	+1.2	+60.6
IPSL-CM5A-LR	IPSL	France	+2.9	+14.0
IPSL-CM5A-MR	IPSL	France	+3.5	−151.9
MIROC5	MIROC	Japan	+2.9	+11.2
MIROC-ESM	MIROC	Japan	+2.4	+49.1
MPI-ESM-LR	MPI-M	Germany	+2.2	−21.8
MPI-ESM-MR	MPI-M	Germany	+1.7	+54.5
MRI-CGCM3	MRI	Japan	+1.5	−5.1
NorESM1-M	NCC	Norway	+2.8	−43.2

$$pr = m/25 \times 100\% \tag{6}$$

$$ri = 100\% - pr \tag{7}$$

where m is the number of years that the variable is not passing the threshold and the number '25' is total number of simulated years in a scenario. Higher guarantee rate pr means lower risk ri (Eqn 7). The yield threshold of 10%, 25%, 50%, 75% and 90% for both 42 scenario simulations were recorded and presented by box plots. The 50% and 75% yield threshold of baseline scenario were selected to designate as the 'key threshold' for calculating pr and ri in the projected scenario simulation.

Data analysis

Data analyses were performed using Genstat (Edition 20th; VSN International, Hemel Hempstead, United Kingdom) statistics software. The maize grain yield, DAS of flowering and DAS of maturity were compared among different scenarios (including baseline scenario and 20 projected scenarios of GCMs) and soil types (including soil type I – the Ships clay and soil type II – the Weswood silt loam). The analysis of variances-based (ANOVA) mean separation between scenarios was performed using the Duncan Multi-Range Test at $P < 0.05$, while the differences between two soil types were tested using the Fisher's protected least significant difference test. The annual values of maize grain yield, PP and DAS during 25-year in a scenario simulation were considered repeated measures in the ANOVA analyses.

Results

Model calibration and validation

APSIM simulated the DAS (V6) of calibration and validation with the RMSE of 1.4 and 2.8 day, respectively (Table 4). For the DAS of VT, the simulations showed RMSE of 0.7 and 2.1 day for calibration and validation, respectively (Table 4). For the DAS of R6, APSIM showed the RMSE values of 0.7 and 3.6 day for calibration and validation, respectively (Table 4). Overall, the model presented great accuracies in predicting three key growth stages of maize (V6, VT and R6), the RMSE values only accounted for 0.7–6.8% (NRMSE) of mean observed values (Table 4).

Maize biomass production, grain yield and PP indicated good agreement between simulated and observed values in

Table 4. The statistics of calibration and validation for the DAS of key phenological stages, maize biomass production and grain yield based on a dryland maize experiment conducted in Burleson County of Texas during 2017–2018.

Calibration or validation	Data	RMSE	NRMSE (%)
Calibration (soil type I)	DAS of end of juvenile (V6)	1.4 day	3.4
	DAS of flowering (VT)	0.7 day	1.1
	DAS of maturity (R6)	0.7 day	0.7
	Maize biomass	438 kg ha^{-1}	8.7
	Maize grain yield	146 kg ha^{-1}	2.0
	Maize PP	0.47 kg ha^{-1} mm^{-1}	2.0
Validation (soil type II)	DAS of end of juvenile (V6)	2.8 day	6.8
	DAS of flowering (VT)	2.1 day	3.2
	DAS of maturity (R6)	3.6 day	3.4
	Maize biomass	757 kg ha^{-1}	14.9
	Maize grain yield	335 kg ha^{-1}	5.6
	Maize PP	1.27 kg ha^{-1} mm^{-1}	6.7

PP, precipitation productivity; RMSE, root mean square error; NRMSE, normalised root mean square error.

both calibration and validation (Table 4). The average differences between simulated and observed biomass production, grain yield and PP were 10.4%, 1.9% and 1.9% for calibration (soil type I), and 13.4%, 5.7% and 5.7% for validation. The detailed performance of APSIM in predicting maize production is presented in Table 4. For calibration, particularly, the RMSE values of biomass production, grain yield and PP were 438 kg ha^{-1}, 146 kg ha^{-1} and 0.47 kg ha^{-1} mm^{-1}, accounting mean observation for 2.0–8.7% (NRMSE), The corresponding values of RMSE in validation were 757 kg ha^{-1}, 335 kg ha^{-1} and 1.27 kg ha^{-1} mm^{-1} for biomass production, grain yield and PP, respectively, with NRMSE of 5.6–14.9%. The results indicated satisfactory ability in simulating maize production (Table 4).

Scenario analysis

Climate conditions of projected scenarios

Compared with the baseline data, the projected temperature of RCPs yielded a mean temperature increase of 1.2–3.5°C $season^{-1}$ for general maize growing season (from March to July), implying the warmer climate for both 20 GCMs. The mean projected precipitation changed between −151.9 and +60.6 mm $season^{-1}$ for general maize growing season (Table 3). Five GCMs (CCSM4, CSIRO-Mk3-6-0, inmcm4, MIROC-ESM and MPI-ESM-MR) indicated relatively 'warm-wet' conditions compared to baseline scenario (precipitation > +5% change), while six GCMs (BNU-ESM, CESM1-BGC, HadGEM2-CC, IPSL-CM5A-LR, MIROC5 and MRI-CGCM3) were considered as relatively 'mitigated' GCMs on precipitation (<±5% change). Other nine GCMs (ACCESS1-0, bcc-csm1-1, CanESM2, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-MR, MPI-ESM-LR and NorESM1-M) were deemed as relatively 'warm-dry' conditions compared to baseline (>−5% change). Averaged by GCMs, the mean growing season temperature ranged from 23.6°C (in 2043) to 26.7°C (in 2056), and the mean growing season precipitation ranged from 81 (in 2058) to 556 (in 2064) mm (Fig. 2). Notably, the maximum difference of mean growing season temperatures between GCMs was 2.4°C, while the growing season precipitations varied from 264 to 476 mm (Fig. 2).

Maize grain yield predictions

For baseline scenario (1981–2005), the mean annual predicted maize grain yield was 5415 and 4920 kg ha^{-1} on soil type I and II, respectively. For the scenarios of GCMs, mean annual yield varied from −29.8 to +16.0% on soil type I, and from −34.8 to +19.7% on soil type II. Two relatively drastic warm-dry GCMs (HadGEM2-ES and IPSL-CM5A-MR) presented the significant reductions in annual grain yield relative to the baseline data ($P < 0.05$; 27.1–30.0% and 29.8–34.8%, respectively; Fig. 3). Three relatively drastic warm-wet GCMs, CSIRO-MK3-6-0, inmcm4 and MPI-ESM-MR predicted the greatest annual grain yield across 20 GCMs, which was significantly higher than the values of eight warn-dry or mitigated GCMs (Fig. 3). Though soil type I had 6.1–18.6% greater annual maize yield than soil type II under GCMs and baseline scenario, the differences remained insignificant ($P > 0.05$).

The distribution of the annual maize grain yield during the 25-year of the scenarios is presented in Fig. 4. The median predicted grain yield under the baseline scenario (1981–2005) was 6473 and 5972 kg ha^{-1} for soil type I and II, respectively (Fig. 4). For the future climate scenarios projected by GCMs, the median grain yield changed from −2403 to +627 kg ha^{-1} and from −2211 to +847 kg ha^{-1} for soil type I and II, respectively. The median grain yield in each scenario tended to greater than the average values, indicating the skewed/unbalanced distribution of data (Fig. 4). Production failures were encountered in the baseline and the RCP8.5 scenarios (Fig. 4). Meanwhile, soil type II showed more or identical times of failures compared with soil type I under identical scenario, implying that soil type I of Burleson County, Texas should be more suitable for maize production in the future. Under the baseline scenario, the 75 percentiles of maize yield were 3315 and 2923 kg ha^{-1} for soil type I and II, while the 25 percentiles were 7249 and 6922 kg ha^{-1} for soil type I and II, respectively (Fig. 4). In comparison with baseline scenario, the projected future scenarios reduced the 75 and 25 percentiles of maize yield by 2.3–39.5%.

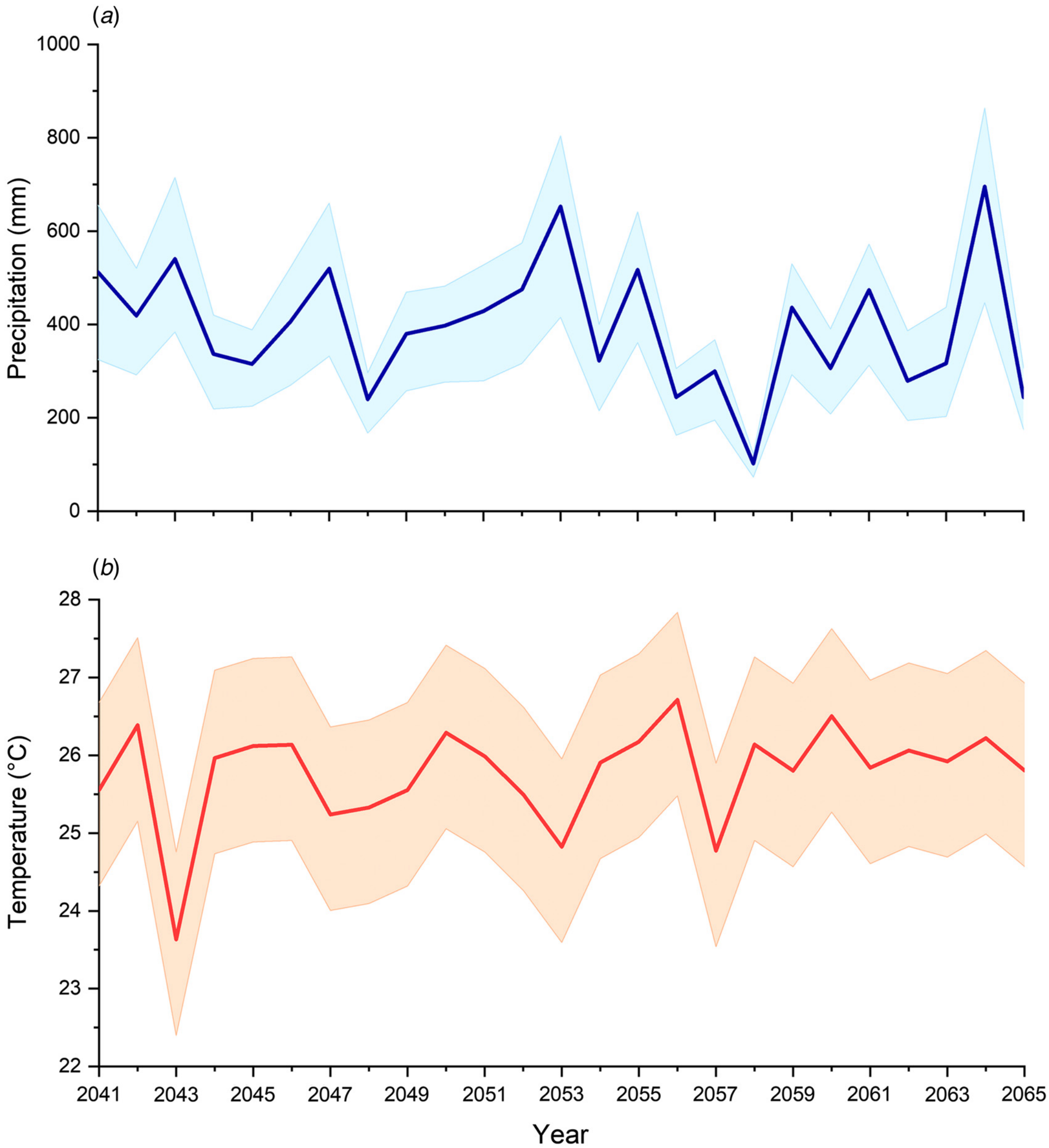

Fig. 2. General maize growing season (from March to July) precipitation and air temperature during 2041–2065 in the RCP8.5 scenarios (refers to Table 3) for Burleson County, Texas. The values of bold solid lines are the multi-GCM (Global Climate Model) average values, and the shading represents estimated uncertainty ranges. (*a*) Precipitation and (*b*) temperature.

Precipitation productivity (PP) predictions

The mean maize PP for baseline scenario (1981–2005) was 17.4 and 15.3 kg^{-1} mm^{-1} for soil type I and II, respectively. The values of PP under GCMs presented higher trends than baseline scenario, showing 12.2–34.4% and 9.2–36.5% of increases for soil type I and II, respectively. There were nine GCMs (three for both warm-wet, mitigated and warm-dry) predicting significantly higher PP than baseline scenario with the improvement from 21.0 to 36.5% ($P < 0.05$; Fig. 5). The greatest values of PP were projected under bcc-csm1-1 and BNU-ESM. Inconsistent with maize grain yield, the PP values of soil type I were significantly higher than that of soil type II with differences between 7.1% and 27.7%.

Guarantee rate (*pr*) and climate risk (*ri*) under baseline and climate change conditions

The guarantee rates (*pr*) in Fig. 6 indicated that the annual yield of eight GCMs (both of them were warm-wet and mitigated) failed to pass the 50% threshold of the baseline scenario (6473 and 5972 kg ha^{-1} for soil type I and II, respectively). Moreover, there were 14 and 13 GCMs (most

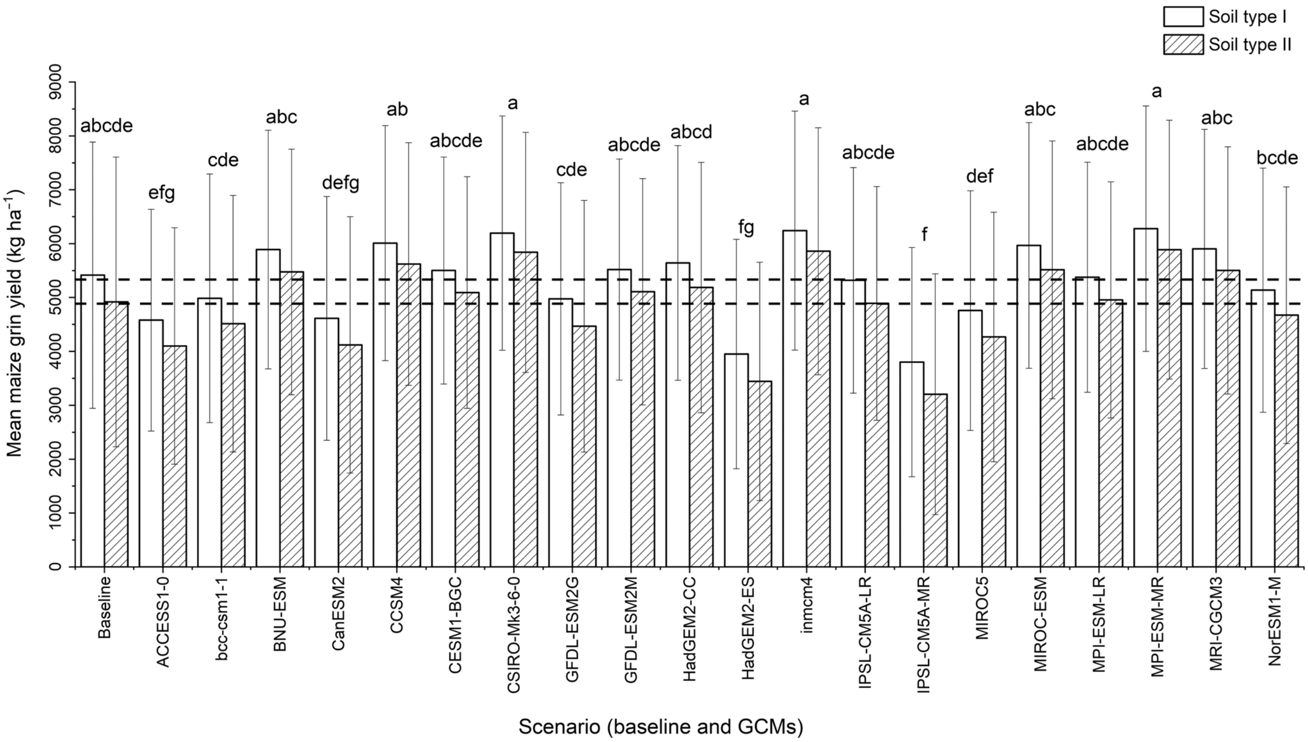

Fig. 3. Mean predicted grain yield with error bars of maize under different scenario simulations and soil types. The bold dashed line represents the mean grain yield of multi-GCMs simulation ensemble (20 GCMs, with the mean values of 5332 and 4887 kg ha^{-1} for soil type I and II, respectively). The same lowercase letter indicates insignificant differences of maize grain yield (both soil type I and II) among different scenarios at level of $P = 0.05$.

of them were warm-wet and mitigated) not passing the 75% threshold of baselines for soil type I (3316 kg ha^{-1}) and II (2923 kg ha^{-1}), respectively; thus, with *pr* values less than 75%. Projected climate scenarios of RCP8.5 predicted the climate risk (*ri*) of 36–84% for not passing the 50% yield threshold baseline, and 12–48% for not passing the 75% yield threshold baseline. Overall, great variations in *pr* and *ri* were observed from the simulation outputs of GCMs. Additionally, the ANOVA results indicated that *pr* and *ri* values for 50% or 75% threshold of baseline between two soil types were insignificantly different from each other ($P > 0.05$).

DAS of maize flowering and maturity under baseline and climate change conditions

The DAS of maize flowering and maturity in baseline scenario were 56–72 and 93–111 day, respectively. Due to the climate warming and accelerated heat unit accumulation, the future scenarios predicted shortened time for reaching flowering (VT) and maturity (R6). The decrease of projected DAS values for flowering was about 3–11 day for the period 2041–2065 compared to the baseline scenario (Fig. 7). Meanwhile, the reduction of days to maturity in future scenarios ranged from 4 to 14 day compared to the baseline data. Averaged over all maize seasons (excluding the seasons with crop failures), the baseline scenario indicated that the mean DAS for reaching flowering and maturity were 61.8 and 98.4 day, respectively (Fig. 7), which were significantly longer than the values of multi-GCM (53.0–58.4 and 87.0–93.1 day for reaching flowering and maturity, respectively; $P < 0.01$). The mean temperature from March to May (month of sowing to month of flowering), and from March to July (general maize growing season: month of sowing to month of maturity) showed significant linear relationship with the DAS of flowering and Maturity, respectively (Fig. 7).

Discussion

Summary of model calibration and validation

This study calibrated and validated APSIM-Maize on two quintessential soil types based on a dryland large plot (>34 ha) field study located in the Burleson County of the ECT. Again, the information related to this is extremely limited, which helps establishing foundational knowledge for conducting further simulation/modelling cropping system studies based on environments that suffer severe ecological pressure and production hardship such as the ECT. Additionally, the large production footprint of the

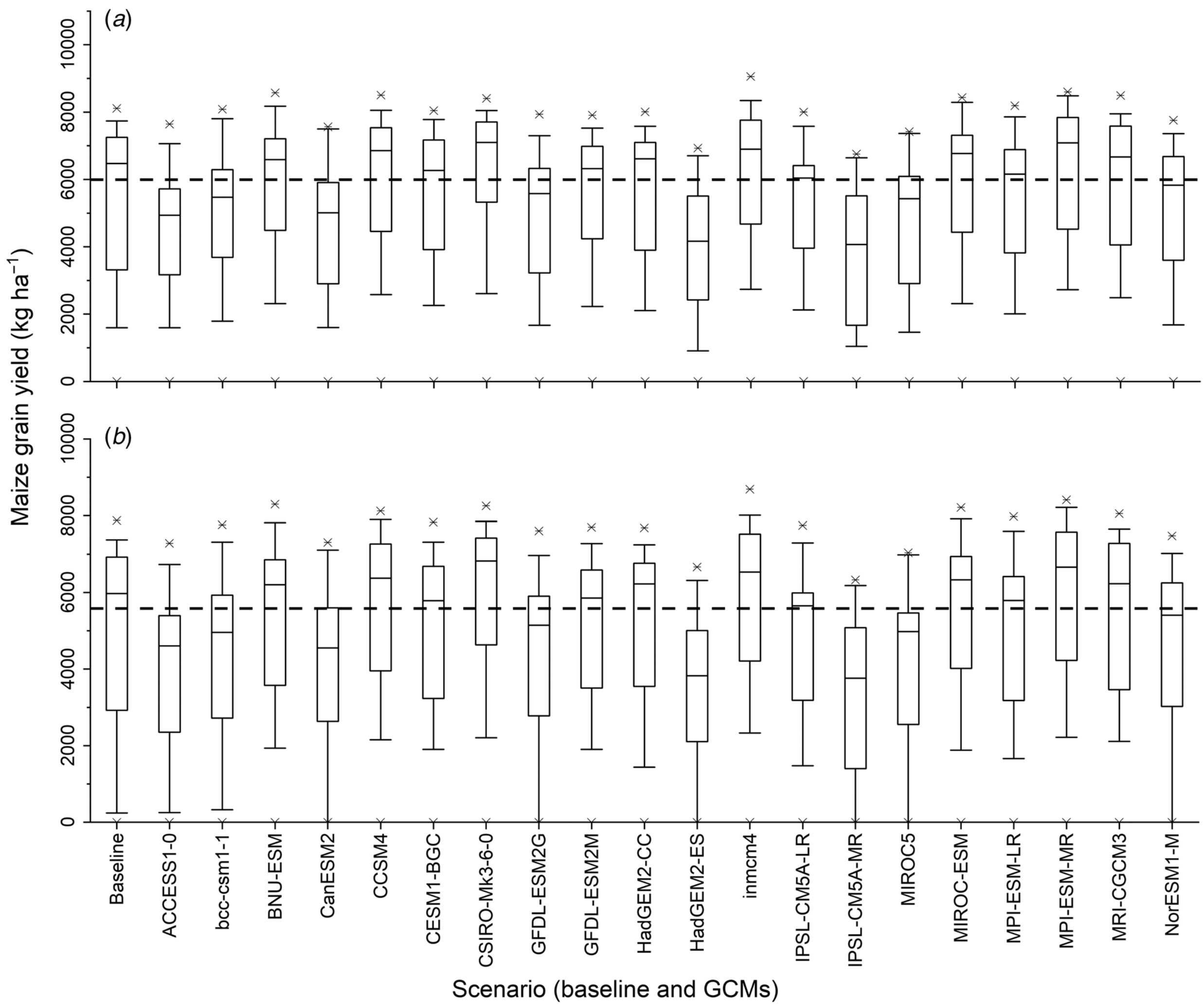

Fig. 4. Boxplots of predicted grain yield of maize under different scenario simulations and soil types. (*a*) Soil type I and (*b*) soil type II). The box boundaries indicate the 75 and 25 percentiles, the whisker caps indicate the 90th and 10th percentiles, the asterisks indicate extreme values, and the solid lines inside the boxes represent medians. The bold dashed line represents the mean medians of multi-GCMs simulation ensemble (20 GCMs, with the mean medians of 5993 and 5584 kg ha^{-1} for soil type I and II, respectively).

study area and high sampling intensity provide an excellent dataset for conducting such kind of modelling study with great control on biases and uncertainties (Dias *et al.* 2019). As indicated in this study, we showed that APSIM could be used as a useful tool for evaluating maize productivity as well as investigating the effects of environmental (e.g. soil) and climatic factor changes on maize growth and development in the ECT region.

APSIM presented only 1.3–10.0% of simulated discrepancies on maize grain yield, indicating excellent reliability and consistency for predicting dryland maize productivity. Generally speaking, however, APSIM over-estimated maize biomass production in most cases in both calibration and validation, especially for the V6 stage – end of juvenile with an over-estimation of 11.4–28.9%. The limited boundary conditions of observation in the field experiment potentially incurred the errors in predicting plant biomass accumulation due to the inconsistent soil water content between simulation and observation. Meanwhile, the soil parameters estimated by Saxton's equations fail to fully represent the actual soil conditions, and lead inaccurate simulations to some extent due to the limitation of equations' own (Saxton and Rawls 2006; Abbasi *et al.* 2011). There might exist another systematic bias of APSIM leading to greater biomass synthesis rate before maize V6 stage: the inaccurate values of RUE or TE for different phenological stages. As indicated by Renton and Chauhan (2017), further research based on crop models should largely focus on incorporating and refining the biotic and abiotic factors (such as APSIM-weed) to improve accuracy.

With identical managerial and climatic conditions, the differences between soil types on maize biomass production

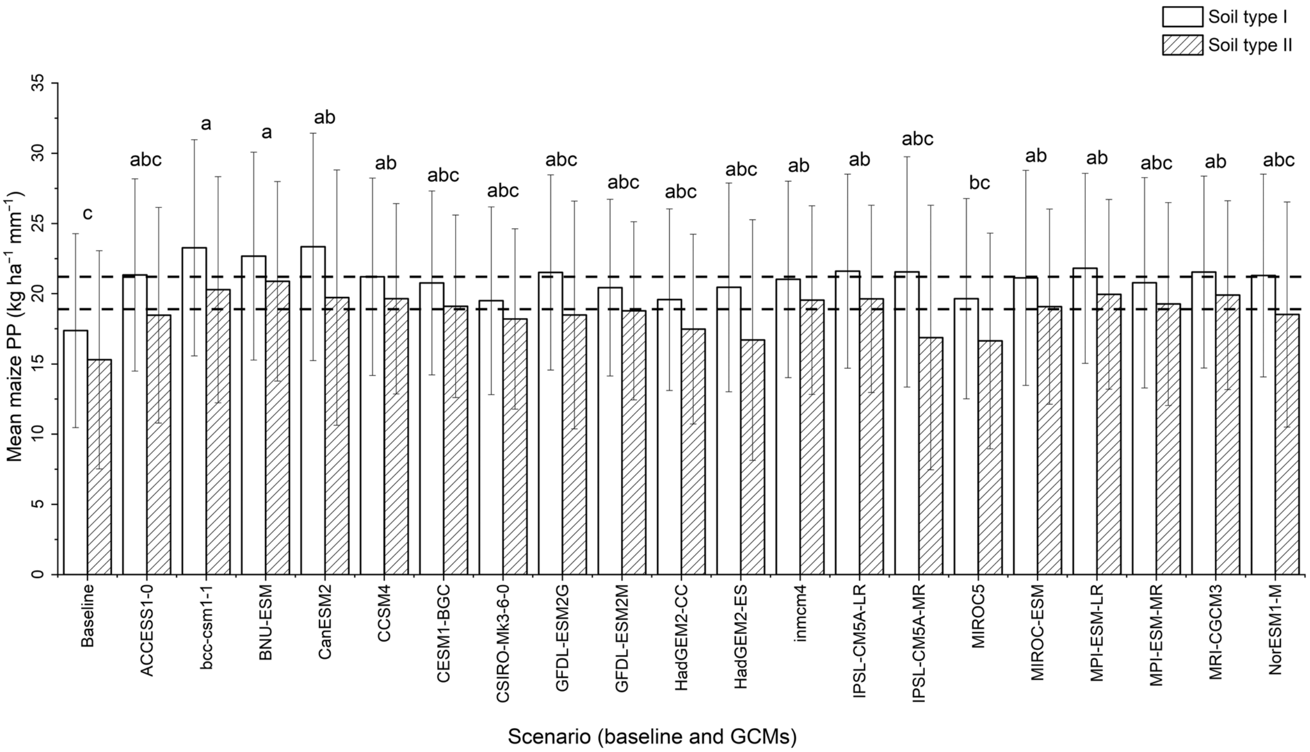

Fig. 5. Mean predicted precipitation productivity (PP) with error bars of maize under different scenario simulations and soil types. The bold dashed line represents the mean grain yield of multi-GCMs simulation ensemble (20 GCMs, with the mean values of 21.2 and 18.9 kg^{-1} mm^{-1} for soil type I and II, respectively). The same lowercase letter indicates insignificant differences of maize PP (both soil type I and II) among different scenarios at level of $P = 0.05$.

and grain yield were reasonably detected in calibration and validation: the different responses were mainly caused by the different parameter values and their interactions under soil property module of APSIM (Table 2). This indicated that APSIM indeed considers the mechanisms of soil hydrological processes and production inputs responses within the simulation process, making it suitable for modelling agronomic production according to local conditions and soil heterogeneity (Archontoulis *et al.* 2014).

The predicted maize phenological stages (end of juvenile, V6; flowering, VT; maturity, R6) of APSIM-Maize in the current study were close to the observed values for both B-H 8845 VTB and Pioneer P1602 AM: the discrepancies of simulating DAS to V6, VT and R6 were less than 4, 3 and 5 day, respectively. The performance statistics of model calibration and validation confirmed the robustness of APSIM-Maize to simulate the developmental stage transition from sowing to V6, VT and R6 (Table 4). APSIM also discriminated the differences of the phenology of maize between two soil types. For example, the relatively lower soil moisture level caused by the property of soil type II would lead to the later plant germination and emergency (https://www.apsim.info/documentation/model-documentation/crop-module-documentation/maize/), resulting in delayed advancement of phenology stages. The small predicted errors of the DAS for different phenological stages could be largely attributed to the inaccuracy associated with historical air temperature data (Ahmed *et al.* 2016), which often received inevitable errors for hourly reaction and record, directly affecting the concise of heat unit accumulation for phenology transition.

Maize grain yield and precipitation productivity (PP) under projected climate scenarios

The warmer climate of future projection identified in this study would result in negative effects on maize grain yield in general. This could be explained by the fact that increasing temperature during maize reproductive stage hastens plant senescence and decreases kernel weight and grain yield potential, affects the rate of plant growth and development, eventually leading to a general decline in yield (Asseng and Pannell 2013; Rose *et al.* 2016; Chen *et al.* 2019). In APSIM framework, once the air temperatures interpolated from daily maximum and minimum temperatures exceeded 35°C (typically emerging in June of future scenarios), the daily thermal time and RUE would pass the threshold and present a decreasing trend, representing slow kernel formation in reproductive development (Wang *et al.* 2018). As we speculated, the formerly mentioned negative consequences caused by

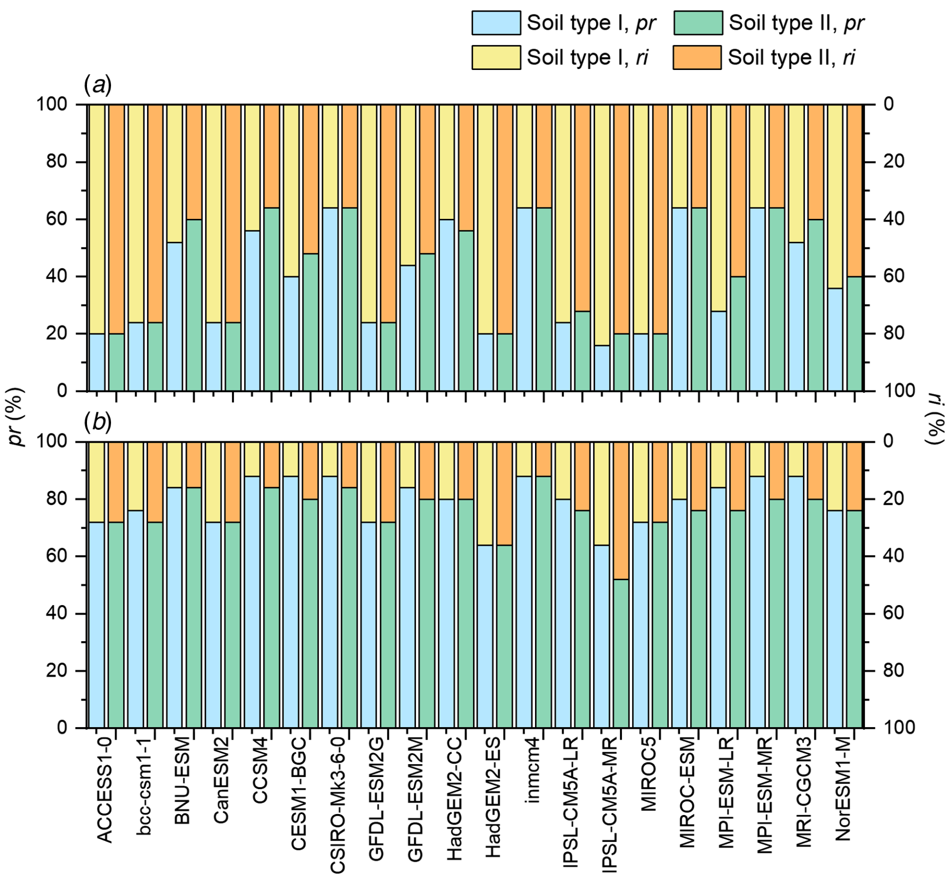

Fig. 6. Guarantee rate (*pr*) and climate risk (*ri*) of maize grain yield under RCP8.5 scenario simulations of 20 GCMs (Global Climate Model) for two key thresholds. (*a*) 50% threshold of baseline scenario (6473 and 5972 kg ha^{-1} for soil type I and II, respectively); (*b*) 75% threshold of baseline scenario (3316 and 2923 kg ha^{-1} for soil type I and II, respectively).

temperature warming could greatly offset the effects of increasing CO_2 concentration on maize as observed in many simulations of the 20 GCMs in our study area.

Overall, the mean annual maize yield for the ensemble of the 20 GCMs was merely lower (0.7–1.0%) than the baseline scenario ($P > 0.05$). Maize, as a C4 crop, is generally positively influenced by higher temperature due to the greater enzyme activity of PEP (phosphoenolpyruvate) carboxylase and increased CO_2 concentration through improved TE to some extent (Kellner *et al.* 2019; also refers to Section *Climate scenarios*). However, this positive temperature response of maize might also be offset by water shortage reflected in reduction of precipitation and soil water reserve. That is why the projected scenarios had not shown great yield improvement in this study, and warm-wet GCMs tended to show higher yields than others, as the similar results reported by Srivastava *et al.* (2018). For PP, different from grain yield, both GCMs showed higher values than the baseline data. Additionally, the warm-dry GCMs indicating high PP values tended to produce relatively low grain yield, such as ACCESS1-0 and CanESM2 (18.5–23.3 kg^{-1} mm^{-1} with grain yield of 4100–4612 kg ha^{-1}). Above results were mainly contributed by the greatly reduced growing season precipitation (GSP) under such scenarios (data not shown). The findings reported here emphasise the importance of identifying management practices that could cope with the high temperature and varied precipitation in the future. Particularly, breeding for drought tolerant maize variety and cropping system practices that could help conserving soil moisture are greatly needed in the future.

Scenario simulations of the current study indicated that soil type I (Ships clay) presented significantly higher maize PP relative to soil type II (Weswood silt loam; $P < 0.001$), as there was a higher trend on grain yield of soil type I than type II ($P > 0.05$). Obviously, APSIM does recognise the physicochemical property differences to a certain extent, judging from the parameter value differences indicated in Table 2. However, the major differences expressed in APSIM framework between soil types were elucidated in the value differences of DUL in soil depth of 0–50 cm due to the higher percentage of sand of soil type II, implying lower water holding capacity. This could cause lower plant available

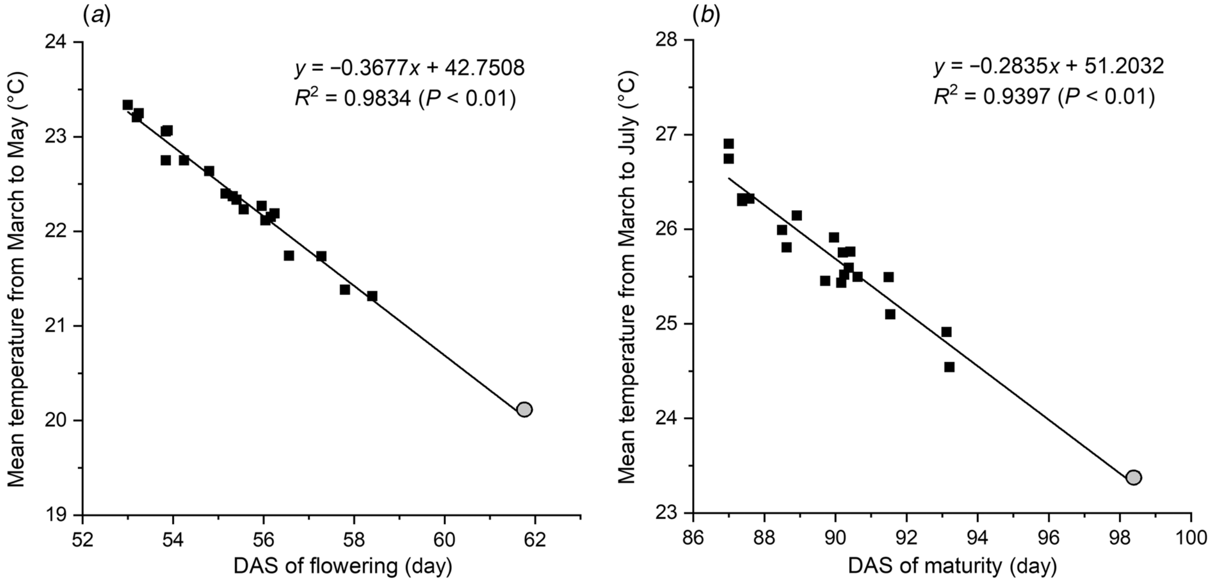

Fig. 7. Simulated DAS (days after sowing) of maize flowering (VT) and maturity (R6) compared with mean temperature from March to May (*a*) or from March to July (*b*) for both GCMs (including baseline). (*a*) flowering; (*b*) maturity. The grey circle points represent the values of baseline scenario.

water under similar precipitation quantity/pattern and eventually translated into lower grain yield as reported by Wu *et al.* (2019). Crop failure differences caused by soil types in APSIM simulations were also presented based on such issues: in the scenario simulations, the crop failures caused by high cumulative phenological water stress factors (for example, 1998 of baseline and 2058 of RCP8.5; https://www.apsim.info/documentation/model-documentation/crop-module-documentation/maize/) in soil type I were less than those in type II due to better soil water holding capacities during critical growth stages of soil type I.

The climate risk of maize production under projected climate scenarios

The results of the climate risks analysis provide more insights for decision makers under future variable climate scenarios. In this study, the distributions of annual maize grain yield were negatively skewed for both the baseline (1981–2005) and future scenarios of RCP8.5 (2041–2065), showing that the median was higher than the mean values of 25-year. Projected future climate change would reduce the climate risk for not passing the 75% threshold of baseline in 13–14 GCMs, but only increase the non-passing of the 50% production threshold of baseline in eighwarm-wet and mitigated GCMs. This implies greater vulnerability and increased erraticism of dryland maize production in 'warm-dry' scenarios (Srivastava *et al.* 2018), particularly for the seasons with relatively higher productivity biologically speaking. Above risks are largely affiliated with production reduction in the future attributed to overall shortened reproductive duration and various phenophase shifts, which potentially make maize plants missing rainfall during critical growth stages, and showed insatiable water demand of higher photosynthetic requirement caused by increasing CO_2 concentration (Mo *et al.* 2016; Castaño-Sánchez *et al.* 2020). Researchers/producers should proceed with caution and adopt appropriate management measures, such as, early sowing for enlarging growing seasons. Implementing irrigations at sowing and VT stages should also be effective but bear higher costs (water and economy) than dryland production. Above practices could potentially become more important governing future maize production in the local environment in the future (Yang *et al.* 2015).

Finally, although the two different soil types did not impose great effects on climate risk of maize production in the future scenarios, both *pr* and *ri* still indicated slightly different patterns in trends between soil type I and II. Particularly, soil type I was appeared to be a more stable soil circumstance in risk evaluation than type II (Fig. 6). These above differences might greater with the time coursing, implicating strategies of low-sand level selection for soil types in the future.

DAS of maize flowering and maturity under projected climate scenarios

Due to the higher temperature predictions of the general maize growing season than those of baseline scenario, RCP8.5 presented faster maize growth/development processes during 2041–2065 (Fig. 7), which agreed with the results reported by Huang *et al.* (2018). The increased advances of maturity and general warmer ambient temperatures of the projected climate conditions of Burleson County, Texas, unfortunately, result in generally negative effects on maize growth and development processes, such as the elevated night-time respiration, especially in the humid subtropical ECT region (Rose et al. 2016). Additionally, shortened growing season and fast senescence process could greatly reduce the overall duration of photosynthesis throughout the growing season. Moreover, IPCC reported that the changes in precipitation in a warming world will not be uniform, the precipitation of April (vegetative production phase for maize) was predicted lower in most GCMs than the baseline scenario (1981–2005), while for May and June (reproductive phase), the different GCMs indicated an inconsistent climate trend compared with the baseline (IPCC 2014). These indicate that in addition to soil water supplementation, shifting sowing to earlier dates would further reduce risks and uncertainties of maize production in the future.

In addition to improvement in crop management practices, breeding more resilient and local-environment based cultivars to cope with climate change should always be an important direction in agricultural research (Traore et al. 2017; Piao et al. 2010). Our climate simulation results suggested that selecting cultivars with early sowing and/or late harvesting capacity could greatly extend reproductive phase of maize to allow greater accumulation of dry matter and nutrient transfer, which is commonly recommended for cereal breeding (Tester and Langridge 2010; Castaño-Sánchez et al. 2020; Xue et al. 2020).

Uncertainty in projections and its implications

Although the results of the current study were obtained from the ensemble of 20 GCMs, there still exists large uncertainty in predicting maize yield and PP across different projected climate scenarios of RCP8.5. This uncertainty was primarily contributed by the differences in the structures, spatial resolutions and model parameterisations of various climate models (Traore et al. 2017). Thus, integrating climate models with crop models based on local field-based data could help control the uncertainty level and provide more reliable results for producers.

Another type of uncertainty was derived from errors/limitations from the experimental parameter collection phase. For example, the soil module in APSIM represents the core mechanics of whole crop production simulation (Holzworth et al. 2014), while the soil data collected for common agronomic studies was usually from relatively shallow profiles. For this study, the standard soil sampling protocol specified by the demonstration project consortium network only includes soil layers of 0–10, 10–30 and 30–50 cm, which might affect the accuracy for setting up APSIM water balance. Measuring the soil parameters at much deeper layers, fully investigating the soil boundary conditions (in particular and the initial condition of crop production) could potentially reduce modelling uncertainty and improve reliability. However, the impact should be limited because few maize roots could be found under the 50 cm layer (mainly within the 0–20 cm layer; Jobbágy and Jackson 2001). For crop parameters, the model calibration was conducted based on data collected from two complete growing seasons based on a large field experiment, which greatly eliminated the biases and inaccuracies caused by small-plot blocked study. The field study area was managed as part of the Texas A&M Producers Management Field Consortium, where participating fields are typically large (>20 ha) and the key management practices (e.g. variety selection) are mainly producer-driven based on product availability and market price. Although different cultivars were selected, both were rated as 'early maturity' type with almost identical relative maturity and similar drought tolerance. Thus, the main between-year variation should be largely contributed by environmental factors than crop genetics, which is common for dryland systems. Finally, sensitivity analysis should be conducted in the future to better evaluate how different initial soil water (and N) contents could affect yield and PP of dryland maize in the ECT area.

Conclusion

To summarise, our results indicated that APSIM is suitable for estimating dryland maize production in ECT, and similar modelling routine might be used on other crops within a specific production region. Our methodology involves output of 20 Global Climate Model (GCMs) for RCP8.5 projecting locally in ECT to predict possible effects of climate change on maize production. In general, the negative effects caused by rising temperature, reduced rainfall quantity, poor rainfall distribution, diminishing soil water storage offset the positive effects on C assimilation of increasing CO_2 concentration on plant growth. Maize grain yield greatly fluctuated across 20 GCMs, while the mean PP (precipitation productivity) tended to improve by 9.2–36.5% in future projections, implying high potential water productivity. Projected future climate change would reduce the climate risk for not passing the 75% threshold of baseline in most cases, but indicated higher risks for the 50% threshold of baseline in the ECT. As ambient temperature increased, the lengths of maize growing seasons were markedly shortened (3–14 day earlier reaching flowering and maturity) compared to the baseline data. The better water holding capacity of soil type I often showed continued advantage on maize productivity compared with type II, implying better management practices on enhancing soil water conservation/retention should be emphasised in the future. Altogether, enhancing water use efficiency through breeding effort (e.g. increase drought tolerance and early mature) and managerial improvement (e.g. early planting and cover cropping) are warranted for moderating risk and even increasing productivity of maize in the future.

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Author affiliations

[A]College of Grassland Science, Shanxi Agricultural University, Taigu, Shanxi 030801, P.R. China.

[B]Grassland Soil and Water Research Laboratory, USDA-ARS, Temple, TX 76502, USA.

[C]School of Agriculture, Middle Tennessee State University, Murfreesboro, TN 37132, USA.

[D]Department of Soil and Crop Sciences, Texas A&M University, College Station, TX 77843, USA.