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RESEARCH

Modelling Maize Yield Sensitivity to Abiotic Stresses in East Africa: Integration of Crop Modelling and Synthetic Climate Change Scenarios

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Abstract

Climate change is expected to significantly affect agricultural production in East Africa (EA). In this study, we synthesized the DSSAT-CERES-Maize model calibrated and evaluated experiments to analyze the sensitivity of climatic variables on maize yield in the region. We used calibrated cultivar coefficients of locally adopted varieties in twelve sites across the region. Consequently, we generated synthetic scenarios of precipitation and temperature changes in line with the plausible projections of the Intergovernmental Panel on Climate Change (IPCC) to characterize the impact of climate change on maize production across the region. Our findings reveal that the impacts of climate change are heterogeneous and vary from location to location. The analysis points to adverse effects in the semi-arid zones, with maize production in Katumani (Kenya), Dodoma (Tanzania), and Ruzizi (Rwanda) expected to decline by -25% to -30% under an extreme temperature rise of +3 °C and a 30% decline in precipitation. The results also reveal that increased precipitation will compensate for yield losses resulting from elevated temperatures in both arid and humid zones. The potential yield gain under increased precipitation and warming is 16%, 18%, and 5% in Katumani, Dodoma, and Morogoro (Tanzania), respectively. The study recommends site-specific soil, water, and land management adaptation strategies. Strategies for soil and water conservation are recommended for dry regions, whereas approaches such as varying sowing dates are recommended for semi-humid to humid zones. Nutrient enhancement and cultivar variation might be feasible in both contexts.

Keywords DSSAT · CERES-Maize · East Africa · Climate change · Sensitivity · Scenarios

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Introduction

The East Africa (EA) region of Sub-Saharan Africa (SSA) is anticipated to experience adverse climatic conditions, such as changes in precipitation and rising temperatures (Haile et al., 2020). As a result, these climatic changes and variations will exacerbate the problem of food security in the region that hosts approximately 40% of the total SSA population (Kaba, 2020). Presently, more than 50% of the population in some countries in the region faces acute food security stemming from poor climatic conditions and perennial droughts, leading to crop failure and livestock sources (WFP, 2022).

Future climate projections show that precipitation and temperatures in the EA region will increase, thus exposing the region to intensified climate extremes such as drought and floods (Gebrechorkos et al., 2023). Climate change impacts will significantly affect agricultural systems, which are dominantly rainfed and highly sensitive to climate extremes (Mugabe et al., 2024). Maize is one of the key staple cereals for the region, and it is expected to be greatly affected by climate change and variability (Davenport et al., 2018). The crop is largely grown in EA, in over 23% of the arable land, and it is largely for human consumption but also used as feed for livestock (De Groote et al., 2013).

Advancements in technology and research have enabled the evaluation of climate change impacts on the yield of main cereal crops, including maize. Among the technologies are crop modelling techniques, which simulate the interactions between soil and the climatic and physiological development of plants to predict crop growth and development (Kasampalis et al., 2018). Crop models integrate climatic variables as inputs, provided as continuous variables, and thus, sensitivities of production across temperature and precipitation ranges can be analysed. Furthermore, various agronomic strategies are embedded within crop models and can be evaluated across different environmental contexts (Kadiyala et al., 2015). However, crop models must be calibrated and evaluated to ensure they mimic crop growth as accurately as possible in the application environment (van Ittersum et al., 2013). Crop models have been increasingly used to address climate change impacts across various regions and climate gradients (Chisanga et al., 2020; Dahri et al., 2024; Faye et al., 2018; Figueiredo Moura da Silva et al., 2021; Kephe et al., 2024; Shawon et al., 2024).

Maize yield response to climate change has been evaluated globally in various maize-cultivated environments. These include studies in Temperate, Mediterranean, Tropical and Subtropical environments (Li et al., 2022; Liu et al., 2021; Ventrella et al., 2012). An ensemble of crop models has been utilized in these studies, with climate change modelling derived from downscaled representative General Circulation Models (GCMs). Despite these efforts, there is still limited knowledge of climate change response to maize in various agroecological zones and environments in EA. Additionally, no study has synthesised long-term experiments conducted in the region to understand yield response in diverse soil and climatic landscapes. We contribute to this gap in the literature by conducting a synthesis analysis of calibrated and evaluated experiments in the region. Furthermore, we evaluate the impacts of climate change on maize as a major cereal crop. The objectives of this study, therefore, are (1) To develop a cultivar coefficient database for the DSSAT-CERES-Maize mode for EA, (2) To evaluate climate change impacts on maize in EA using synthetic climate scenarios, (3) To assess the sensitivities across the region and recommend strategic measures for enhancing production in the faced of climate change.

Materials and Methods

Study Area

The study was conducted in five EA countries where maize is largely grown (Fig. 1). The selection of the regions was also based on past field experiments conducted using the DSSAT-CERES-Maize model (Table 1). The maize-grown areas were obtained from the Spatial Production Allocation Model (SPAM)(Wood-Sichra et al., 2016). In Kenya, the study covered four distinct regions where the DSSAT-CERES-Maize model had been calibrated and evaluated. Four locations in Tanzania were also considered. Three sites in Ethiopia were studied, one site was studied in Uganda, and finally, one site was considered in Rwanda.

Synthesis of Crop Modelling Experiments

We searched scientific databases, including Google Scholar, Scopus, and Web of Knowledge, on past modelling studies that have implemented maize growth simulation using the DSSAT-CERES model. Keywords that were used to search the databases include 'crop modelling', 'climate impacts', 'maize', 'DSSAT', 'CERES Maize' and 'East Africa'. In addition to the scientific databases, we also searched for working papers, reports, theses, and other grey literature covering maize production with cultivar-specific parameters specified.

We then screened the articles and excluded those that did not provide any information relating to cultivar coefficients, which are mandatory to assess the performance of different cultivars in various regions. The remaining articles that provided information on weather variables, soil physicochemical properties, crop management information in the particular region and cultivar coefficients were used to prepare the genotype, Sbuild, Xbuild, and weather files in the DSSAT model. For locations where weather data was unavailable, we used the Climate Hazard Infrared Radiation Station data (CHIRPS) to prepare weather files for the specific locations. The weatherMan module embedded in the DSSAT was used to generate the DSSAT-acceptable weather files. Where soil profile data were missing, we used the grid-based global high-resolution soil profile database for crop modelling applications (Han et al., 2015). The database delivers soil chemical and physical properties used for DSSAT-CERES-Maize simulations.

The sowing dates in the different sites were selected based on the standard local practices or optimal sowing dates with high productivity, as indicated in the studies. The sowing date for Trans Nzoia was selected to be 15 March (Kipkulei et al., 2022). For Ethiopia, the main maize growing season is between June and September. We adopted mid-planting

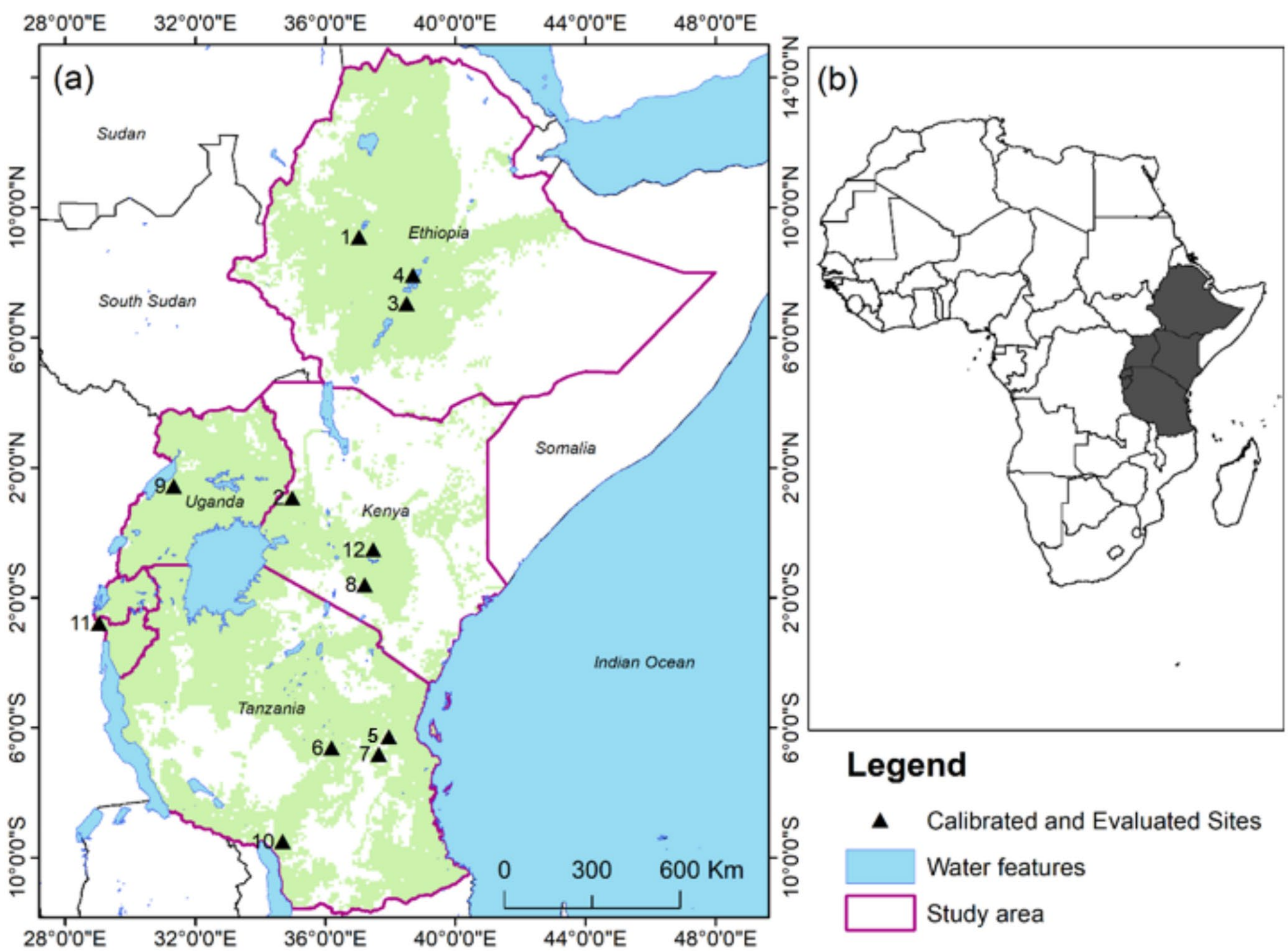

Fig. 1 (**a**) Location of the study area with DSSAT-CERES-Maize model calibrated and evaluated site overlaid on maize harvested areas (in green) from the Spatial Production Allocation Model (SPAM), (**b**) Location of Africa and the context of the study area. Specific sites; 1) Bako (2) Trans Nzoia (3) Hawassa (4) Ziway (5) Wami River Basin (6) Dodoma (7) Morogoro (8) Katumani (9) Hoima (10) Njombe (11) Ruzizi Plain (12) Embu

Table 1 DSSAT-CERES-Maize calibrated cultivars in the EA

Cultivar	Region	Country	Reference
BH-660	Bako National Maize Research Center	Ethiopia	(Araya et al., 2015, 2021)
H614	Trans Nzoia	Kenya	(Kipkulei et al., 2022, 2024)
BH540	Hawassa, Ziway	Ethiopia	(Abera et al., 2018; Falconnier et al., 2020; Kassie et al., 2014)
Melkassa I	Melkassa	Ethiopia	(Abera et al., 2018; Araya et al., 2021; Kassie et al., 2014)
Situka	Dodoma	Tanzania	(Lana et al., 2018)
Situka	Morogoro	Tanzania	(Mourice et al., 2015)
Katumani	Katumani	Kenya	(Grace, 1998)
MH-16	Masindi and Hoima	Uganda	(Grace, 1998)
UH6303, H628	Njombe	Tanzania	(Mtongori et al., 2015)
Ecavel	Ruzizi plains	Rwanda-Burundi	(Bagula et al., 2022)
H511, H513	Embu	Kenya	(Gummadi et al., 2020; Rao et al., 2014)

dates for Ethiopia, which are 15 May, 25 June and 27 May in Bako, Ziway and Hawassa, respectively (Abera et al., 2018). In Morogoro, Tanzania, 10 March was chosen based on the study of Mourice et al. (2014) and 15 December was selected for the Dodoma region as it showed huge yield potential, according to Lana et al. (2018). The same date was adopted for the Wami basin based on its proximity to Dodoma. In Uganda, the sowing date in Hoima was set to 01 March as this was the ideal date for optimal maize yield in the region (Babel & Turyatunga, 2015). The sowing date for the Katumani site was 15 May (Mo et al., 2016), while in Embu, the sowing date was set to 10 April (Gummadi et al., 2020; Kätterer et al., 2022). The sowing date in Njombe, Tanzania, was set to 15 December. No clear planting date was provided in the literature for Ruzizi Plain. However, sowing was set to November, which coincides with the onset of the long rains (Bagula et al., 2022).

For the nitrogen fertilization application, the recommended amounts in the published studies were adopted. The recommended nitrogen fertilizer rate in Kenya is 75 kg N/ha and a similar amount for top dressing. For the Ethiopian context, we adopted the recommended fertiliser rate for 100 kg/ha urea for Hawassa. A 100 kg/ha urea and 100 kg/ ha di-ammonium phosphate (DAP) rate was adopted for Bako stations, and 50 kg/ha urea and 100 kg/ha DAP for Melkassa (Abera et al., 2018). In Morogoro and Wami basin, Tanzania, 40 kg/ha of nitrogen was incorporated during sowing and a similar amount for top dressing (Kadigi et al., 2020). In Njombe, the nitrogen fertilization was 64 kg N/ha and a top dressing amount of 36 Kg N/ha (Mtongori et al., 2015). The amount of nitrogen fertilizer for Embu, Kenya, was 60 kg N/ha (Gummadi et al., 2020; Kätterer et al., 2022). In Hoima, Uganda, the recommended nitrogen fertilizer level of 70 kg/ha was applied at sowing, and an additional 25 kg/ ha was applied 30 days after sowing. We adopted a nitrogen fertilization rate similar to the one for Hoima in Uganda. For all the studied regions a uniform intra/inter row spacing of 25 cm x 75 cm was adopted giving a plant population of 53,333 plants/ha. The planting depth was set to 10 cm.

The DSSAT-CERES-Maize Model

The Decision Support System for Agrotechnology Transfer – DSSAT contains the Crop System Model CERES – Maize model (Jones et al., 2003). The model simulates the development and growth of maize on a daily basis from planting until physiological maturity (Lana et al., 2018). The model calculations are based on environmental and physiological processes that control the phenology and dry matter accumulation in different organs of the plant. The model simulates crop response to various management and can accurately predict the nitrogen, water uptake, nitrogen uptake and crop yield variability. The model requires many inputs with many model parameters, which are not readily available at the farm level. Therefore, robust field experiments and detailed data collection are conducted to adequately mimic plant growth while taking into account environmental processes such as respiration, photosynthesis, soil water uptake, drainage, nutrient assimilation, biomass accumulation and senescence. The model can simulate detailed yield components, leaf numbers, phenological development, biomass and yield at harvest (Chisanga et al., 2021).

Regionally Calibrated Cultivars and Coefficients

The cultivars calibrated in various regions varied from hybrid, long-term to locally adapted cultivars. The calibration was conducted from at least two seasons of data. The calibration process determines the cultivar coefficients that govern the accumulation of temperature heat units and plant development from emergence to physiological maturity (Jones et al., 2003). The parameters are divided into growth (G2, G3, and phyllochron interval) and development (P1, P2, and P5). The parameterization is conducted using the Generalized Likelihood Estimator program in DSSAT software. The articles also documented other protocols, including soil and weather data preparation. The evaluation metrics ranged from good model to excellent model performances, prompting the model to be extended for other assessments. Table 1 presents the corresponding calibrated cultivar coefficients of cultivars. The corresponding cultivar coefficients provided in Table 2 were included in the maize genotype file in the DSSAT installation.

Assessing the Model Sensitivity to Climate Change

The present study assessed climate change influences using the ranges suggested by different regional climate models in the region. Subsequently, the DSSAT-CERES-Maize model was evaluated for plausible changes in temperature and precipitation changes. Eight climate change scenarios were assessed. These included combinations of temperature increments of +1 and +3 °C and precipitation changes of −30% and +30%. Maize yield across the different sites of EA was simulated, and results were presented using boxplots and line graphs analysed using the ggplot package in the R statistical software (R Core Team, 2020). To assess yield change under climate change, simulations were conducted for a baseline period (1981–2010), and the yield averages were compared to those simulated under the synthetic climate change scenarios evaluated in the study. The data for the baseline climate was derived from the AgMERRA Climate Forcing Dataset for Agricultural Modeling. The database contains the Agricultural Model Intercomparison and Improvement Project (AgMIP) climate forcing dataset based on the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Ruane et al., 2015). AgMERRA corrects to gridded temperature and precipitation, incorporates satellite precipitation, and replaces solar radiation with NASA/GEWEX SRB to cover the 1980–2010 period.

Table 2 DSSAT-CERES-Maize genetic coefficients for the calibrated cultivars in EA

Cultivar	P1 (°C day)	P2 (day)	P5 (°C day)	G2 (No. Kernels/ear)	G3 (mg/day)	PHINT (°C day)
BH-660	260	0.75	850	800	8.5	49
BH540	220.1	0.86	840.1	266.2	10.65	38.9
H614	290.8	0.47	921.2	796.8	5.26	39.74
Melkassa 1	101.5	0.75	685	375	11.65	40
Situka	199.5	0.5	672	673	10.03	42.8
MH-16	245.3	0.28	843	417.3	7.87	75
Katumani	172.0	0.50	999.0	398.0	6.27	75.00
UH6303	310	0.5	800	580	6	38
H628	315	0.5	800	470	4.5	38.9
PAN691	330	0.5	800	450	5	50
Ecavel	212	0.75	800	800	8.5	40
H511	190.0	0.600	725.0	550.0	7.90	42
H513	205.0	0.600	760.5	690.0	8.70	40.0

P1 - Thermal time from emergence to end of the juvenile phase (degree days)

P2 - Development delay for each hour increase in photoperiod above a maximum development rate (days)

P5 - Thermal time from silking to physiological maturity (degree days)

G2 - Maximum possible number of kernels per plant

G3 - Kernel optimum filling rate during the linear grain filling stage (mg/day)

PHINT - Phyllochron interval: thermal time between successive leaf tip appearances (degree days)

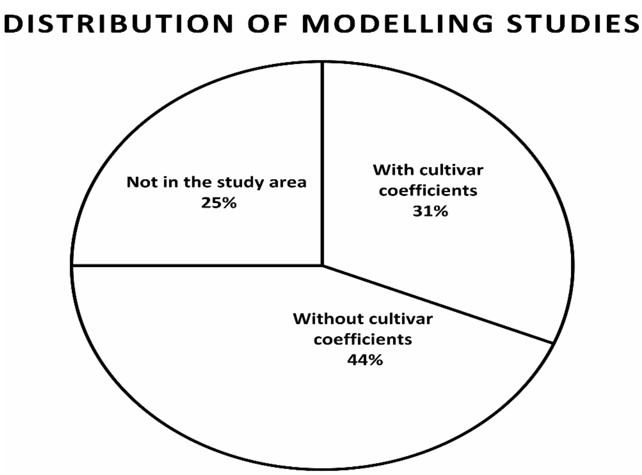

Fig. 2 Crop modelling studies that incorporated the DSSAT-CERES-Maize model in EA

Results

Crop Modelling Studies in the Region

The literature search resulted in 48 articles and other source materials of crop modelling simulations conducted using the DSSAT-CERES-Maize model.

We excluded articles without reported cultivar coefficients in further analysis. Some studies mentioned cultivar coefficients. However, they were not provided in the articles or reports. Fifteen studies in the study area calibrated various cultivars for different applications. Furthermore, information on the field experiments and the model inputs was thoroughly elaborated. Twenty-one studies (31%) used calibrated coefficients from other regional studies, and hence, no cultivar coefficients were directly provided in the studies (Fig. 2). The literature search also resulted in 12 studies conducted outside the study region. These studies made reference to the DSSAT-CERES-Maize modelling practices in the region or simulated the study area cultivars in other regions.

Maize Yield in Different Sites Under the Baseline Period

Maize yield was stimulated for the study sites under the synthetic climate change scenarios. The simulations demonstrated yield differences and variability across the sites (Fig. 3). The results indicate high production in Bako and Hawassa in Ethiopia. Katumani and Embu in Kenya and Ruzizi plain that covers Rwanda-Congo-Burundi and Tanzania show the lowest average production. Wami basin, Njombe, Dodoma, Morogoro in Tanzania, and Hoima in Uganda show moderate to high production. On the yield variability, Morogoro site and Wami basin had the highest yield variability, whereas Hoima, Ruzizi plain, and Hawassa depicted a low variability.

Maize Yield Response Under Synthetic Climatic Scenarios

The DSSAT-CERES-Maize simulations reveal varied yield responses on temperature and precipitation and in their

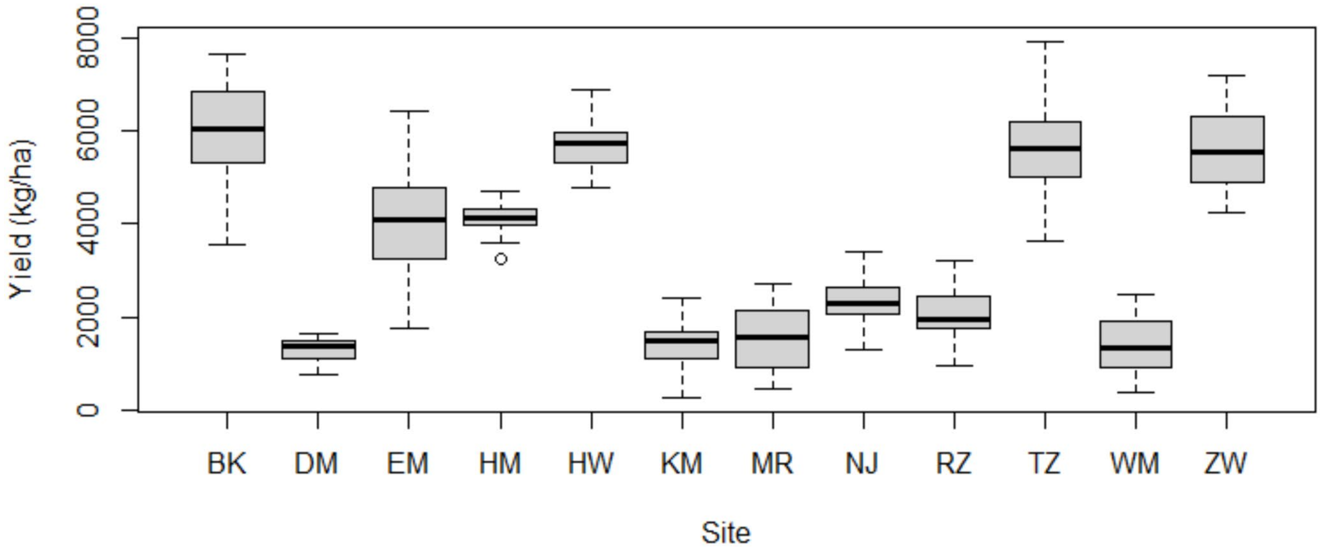

Fig. 3 Maize yield simulations across different sites in EA. BK – Bako, DM- Dodoma, EM-Embu, HM- Hoima, HW- Hawassa, KM-Katumani, MR- Morogoro, NJ- Njombe, RZ- Ruzizi, TZ- Trans Nzoia, WM- Wami, and ZW-Ziway under the baseline period

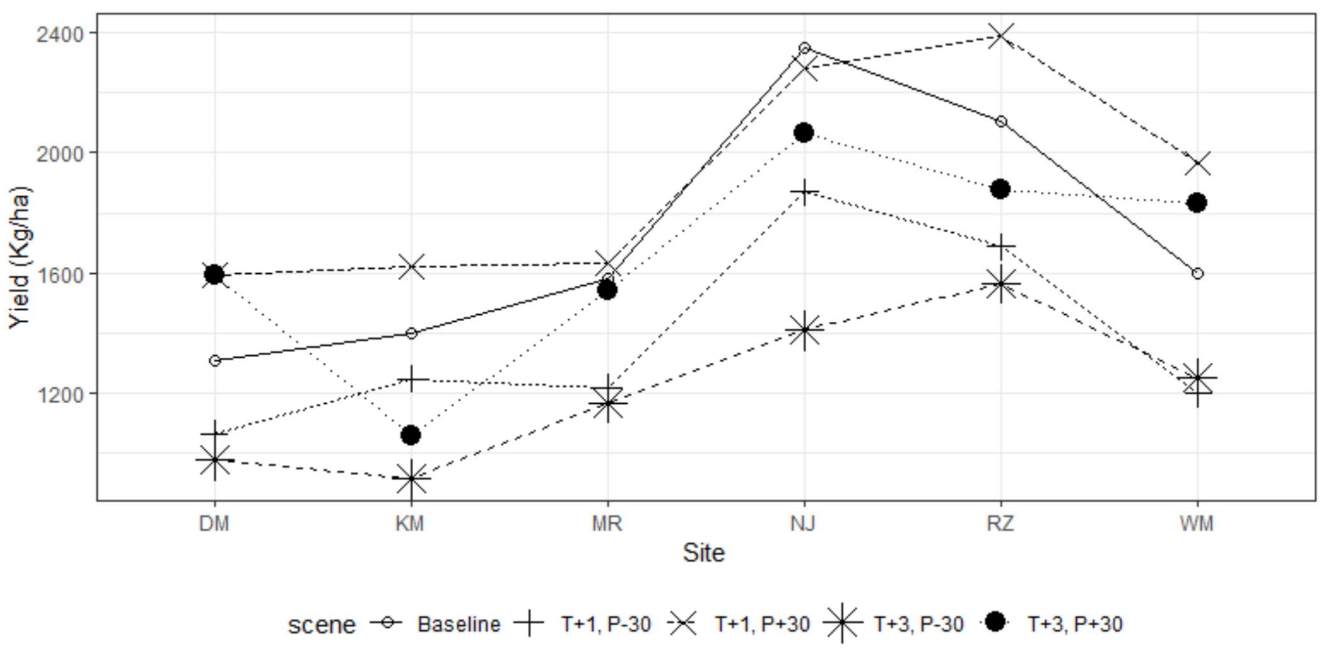

Fig. 4 Maize production based on the baseline mean of 31 crop seasons of locally adopted cultivars in different dry to subhumid sites in EA and under four synthetic climate scenarios with an increment of +1 and +3° C in maximum and minimum temperatures and −30% or +30% precipitation changes

combinations. The various interactions influence maize production across the evaluated sites. Drier regions demonstrate yield decline from the baseline under most projected climatic conditions. Yield in the Njombe region shows a decline under all the assessed scenarios. An exception to negative yield effects is the scenario of an increased temperature of 1 °C and a precipitation increase of 30% from the baseline (Fig. 4). The yield increase under increased precipitation is 21%, 16%, 5%, 13%, and 23% in Dodoma, Katumani, Morogoro, Ruzizi, and Wami, respectively. High variability in climate change sensitivities is observed in Njombe, Ruzizi Plain, and Wami region. This is expected as these regions have moderate climate conditions and, thus, depict high variability under changing climates. The extreme climate scenario (highest temperature increase and highest precipitation decline) reveals a production impact across all the study sites. The model indicates yield decline across all the dry to subhumid sites. The decline range

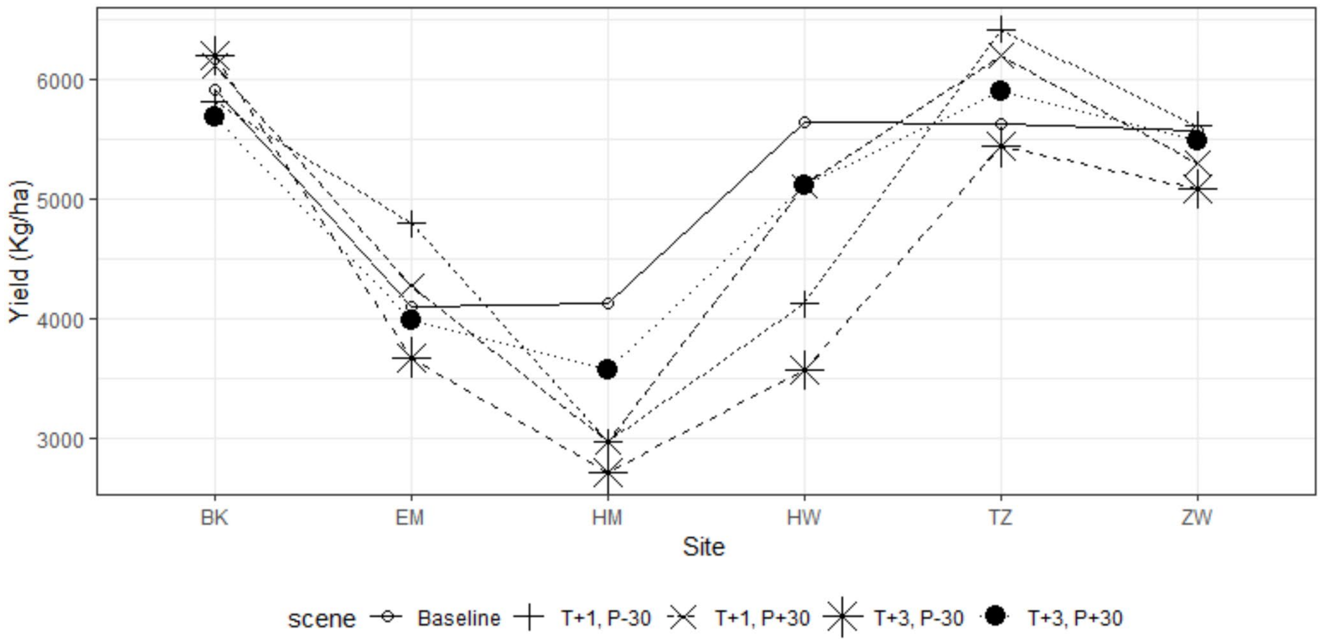

Fig. 5 Maize yields production based on the baseline mean of 31 crop seasons of locally adopted cultivars in different subhumid to humid sites in EA and under four synthetic climate scenarios with an increment of +1 and +3° C in maximum and minimum temperatures and −30% or +30% precipitation changes

between −18% and −26% across all the sites. The effect might be attributable to intensified moisture stress in the regions that are currently experiencing deprived moisture.

Considering the humid areas in the region, the model results indicate high production in Bako and Trans Nzoia under the evaluated synthetic climate scenarios (Fig. 5). Ziway and Hawassa reveal moderate effects of climate sensitivities, whereas Hoima and Embu indicate the lowest yield. The modelling results demonstrate mixed effects, with some regions projecting yield gains from the baseline and others showing a decline. Maize yield in Hawassa and Hoima regions might decline based on the assessed climate change conditions. The two regions also indicate high variability effects on maize yield under the assessed scenarios. Furthermore, the projected decline in the Hoima and Hawassa is 28 and 36%, respectively.

In some scenarios with an increase in temperature and a decline in precipitation, Trans Nzoia and Bako demonstrate yield gains from the baseline. However, in the extreme climate scenario, where temperature increases and precipitation decreases, all the humid areas are likely to be affected except Bako. The projected impact in Bako could be attributed to the increased accumulation of biomass resulting from the increased radiation effect, favouring crop growth in low-temperature zones. Overall, the study findings reveal that climate change might significantly impact maize production across the region, which is currently facing declining agricultural production attributed to climate change, among other biotic influences.

Discussion

Crop Modelling Studies

The present study shows that climate change impacts on maize yield in the region are context-specific and vary from site to site. Nonetheless, crop modelling studies assessed in this study are few and comprehensive studies are needed to assess the yield stability and susceptibility to abiotic stresses in other areas of the region. Although the study sites calibrated and evaluated for yield response cover main maize growing areas, our study reveals that a considerable coverage of the current growing areas is yet to be covered. In Ethiopia, for example, the model has been evaluated in Hawassa and Bako regions, which are situated in the Central and Western parts of the country. Modelling studies have not covered much of the Northern and Eastern areas. These regions need to be evaluated as they have been found to have a higher risk of climate change effects (Gebrehiwot & van der Veen, 2013).

In Kenya, the studies are also sparse, with only three studies in Mt Kenya and the Western region. Many other maize-growing areas have not been covered in modelling studies. The evaluated studies are majorly in humid zones, with one study in an arid area. Therefore, it is imperative to conduct more modelling studies in the arid regions as these areas are expected to be greatly affected by climate change. In Tanzania, the modelling studies are concentrated in the semiarid areas and plateau zones, which are at higher risk of climate change effects. A single study utilizing the DSSAT-CERES-Maize model has been conducted in both Uganda and Rwanda. Therefore, more studies are needed to assess and address climate change impacts on maize production.

Maize Yield Variation Under the Baseline Period

The DSSAT-CERES-Maize model was applied to simulate long-term (1980–2010) maize yield in twelve sites across the EA region. The sites were chosen because experiments have been conducted in these areas. Additionally, the locally adopted cultivars have been calibrated and evaluated satisfactorily. The results indicate variability in simulated yields across the region. Generally, a favourable climate for crop production revealed high production and less yield variation. Therefore, the results showed the DSSAT-CERES-Maize model's reliability in representing conditions in varied soil and climatic contexts. Under the baseline period, Bako, Hawassa, Ziway, Trans Nzoia, Embu, and Njombe revealed a high potential for maize production. These regions have a climate that ranges from cool sub-humid to humid agro-ecologies with extended rainfall seasons (Mugalavai et al., 2008; Seyoum et al., 2018). Moderate to low yields were observed in Wami, Morogoro, and Dodoma regions. However, the model simulated low yield in the Ruzizi Plain and Katumani areas of Kenya. The literature assessment indicated that these regions receive high seasonal and inter-annual rainfall variability (Bagula et al., 2022; Recha et al., 2016). In the past years, the areas have also shown an increased frequency of dry seasons (Recha et al., 2016).

Maize Yield Response Under Synthetic Climatic Scenarios

The synthetic climate change scenarios assessed in the present study show varied effects across the study sites. Combined effects of temperature and precipitation have a significant influence on yield. The results show that warming accompanied by a decrease in precipitation might favour the highland areas, whereas the drought-prone regions might be severely affected. Increased warming and elevated temperatures depict negative yield effects in almost all the sites in the region. The influence is greater in the dry areas, where crop production is already affected by severe water stress. Our results show that some sites in the region could record yield losses of up to 30% under the extreme scenario of precipitation and temperature. This finding aligns with other climate projections in the area that show a decrease in maize production by up to 45% under future warming and reduced precipitation (Adhikari et al., 2015). Similarly, previous studies point out that maize yield in the study areas will record yield losses greater than 20% in some areas, which reinforces our analysis (Thornton et al., 2009; Waha et al., 2013).

Furthermore, the present results indicate that excessive precipitation could result in a yield decline in high-rainfall zones in the region. This finding corroborates other studies that reveal the negative influence of yield due to increased precipitation (Li et al., 2019). Some regional studies have also established the heterogeneous effects of precipitation and temperature. Mubenga-Tshitaka et al. (2023) found that temperature and precipitation variation have a detrimental impact on yield in the study region.

Moreover, our study found that yield might increase in some areas relative to the baseline. This concurs with previous studies conducted in the same region (Luhunga et al., 2016). One such observation was noted in the Wami River basin. Wami River basin is characterized by soils rich in nutrient deposits resulting from sediment transport from upstream areas. Therefore, soil nutrients compounded with less effect of climate change in this region could be a possible attribution to the projected yield increase under climate change (Madulu, 2005).

Implications for Crop Management and Adaptation Practices

Crop modelling applications and climate change impact assessment have many implications for agricultural productivity in climate-risk regions. Our results showed that the effects of climate change on maize yield are highly impactful in the region. Even with increased precipitation, most sites in the region are likely to experience low crop yields from the current production due to increased warming (Thornton et al., 2009). The compounding climate effects and low soil fertility will worsen crop conditions in dry areas.

Adaptation through soil and water management practices is imperative in these regions. Techniques such as tied gauge ridges, micro-dosing, and mulching might positively affect yield production in drier areas (Rotich et al., 2024). Also, small-scale irrigation systems and water harvesting structures are potential measures for improving maize yield, especially in smallholder agriculture contexts.

Conclusions

The present study synthesised calibrated, and evaluated experiments in East Africa (EA) and assessed climate change sensitivities on maize yield using synthetic climatic scenarios. Therefore, the study developed the first database of cultivar coefficients, which can be used to evaluate maize production.

The study revealed that climate change has heterogeneous impacts on maize crop productivity across the region. Notably, extreme precipitation and temperature are likely to severely impact dry regions of Kenya and Tanzania. Although Global Climate Models (GCMs) and climate projections in the region demonstrate large levels of uncertainties, with temporal and spatial shifts in rainfall events, crop modelling simulations can provide an understanding of the likely impacts of climate change.

We recommend that crop modelling techniques be harnessed to assess climate change impacts, and additional multi-locational trials across maize-growing regions can be supplemented with modelling studies. Various agronomic practices can be tested in different environments to design site-specific strategies for yield enhancement. Additionally, we recommend assessing climate-proof strategies under an array of plausible cropping systems in the future. As such, crop models can provide continuous decision support tools to enable farmers and agricultural planners to adapt production to changing climatic conditions.

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Data Availability The AgMERRA climate forcing dataset is freely available from the https://data.giss.nasa.gov/impacts/agmipcf/agmerra/. The calibrated and evaluated coefficients are available from the crop modelling references in the article. The soil physical and chemical characteristics for the region are available from the global high-resolution soil profile database for crop modelling applications https://dataverse.harvard.edu/dataset.xhtml? persistentId=doi:https://doi.org/10.7910/DVN/1PEEY0.

Declarations

Conflict of Interest The authors declare no conflict of interest.

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