frontiers | Frontiers in Climate

ORIGINAL RESEARCH
published: 01 July 2022
doi: 10.3389/fclim.2022.890210

Changes in Climate Extremes and Their Effect on Maize (*Zea mays* L.) Suitability Over Southern Africa

Abel Chemura[1], Shingirai S. Nangombe[2], Stephanie Gleixner[1], Sinclair Chinyoka[3] and Christoph Gornott[1,4]*

[1] Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Potsdam, Germany, [2] Climate and Air Quality Modelling, Council for Scientific and Industrial Research, Pretoria, South Africa, [3] Meteorology and Air Quality Section, Wageningen University, Wageningen, Netherlands, [4] Agroecosystem Analysis and Modelling, Faculty of Organic Agricultural Sciences, University of Kassel, Kassel, Germany

OPEN ACCESS

Edited by:
Mphethe Tongwane, Zutari, South Africa

Reviewed by:
Samiha Abu El-Fetouh Ouda, Agricultural Research Center, Egypt
Vimbayi Grace Petrova Chimonyo, International Maize and Wheat Improvement Centre (CIMMYT), Zimbabwe

***Correspondence:**
Abel Chemura
chemura@pik-potsdam.de

Specialty section:
This article was submitted to Climate Services, a section of the journal Frontiers in Climate

Received: 05 March 2022
Accepted: 07 June 2022
Published: 01 July 2022

Citation:
Chemura A, Nangombe SS, Gleixner S, Chinyoka S and Gornott C (2022) Changes in Climate Extremes and Their Effect on Maize (Zea mays L.) Suitability Over Southern Africa. Front. Clim. 4:890210. doi: 10.3389/fclim.2022.890210

Southern Africa has been identified as one of the hotspot areas of climate extremes increasing, at the same time many communities in the region are dependent on rain-fed agriculture, which is vulnerable to these rainfall and temperature extremes. The aim of this study is to understand changes in extreme indices during the agricultural season under climate change and how that affect the modeling of maize suitability in Southern Africa. We analyze the changes in rainfall and its extreme indices (consecutive dry days, heavy rain events and prolonged rainfall events), and temperature and its extreme indices (hot night temperatures, hot day temperatures and frequency of very hot days) from the past (1986–2014) to the future (2036–2064) and integrate these into a maize suitability model. Temperature extremes are projected to increase in both duration and intensity, particularly in the eastern parts of the region. Also, consecutive dry days are projected to increase over larger areas during the agricultural season, while rainfall will be less in sums, heavier in intensity and less prolonged in duration. Including extreme climate indices in maize suitability modeling improves the efficiency of the maize suitability model and shows more severe changes in maize suitability over Southern Africa than using season-long climatic variables. We conclude that changes in climate extremes will increase and complicate the livelihood-climate nexus in Southern Africa in the future, and therefore, a set of comprehensive adaptation options for the agricultural sector are needed. These include the use of heat, drought and high-intensity rainfall tolerant maize varieties, irrigation and/or soil water conservation techniques, and in some cases switching from maize to other crops.

Keywords: climate extremes, suitability, maize, climate–change, Southern Africa

INTRODUCTION

Maize (*Zea mays* L.) is one of the most important agricultural commodities globally by area under cultivation (over 150 million hectares annually), production volume (around 1 billion metric tons) and calorie contribution for humans (∼20%) (Nuss and Tanumihardjo, 2010; Bassu et al., 2014; Dowswell et al., 2019). It is the most preferred food source in Southern and Eastern Africa, where it accounts for 73% of the total food demand, in addition to its use as feed (Shiferaw et al., 2011).

Maize contains abundant phenotypic and genotypic diversity, which explains its wide distribution across tropical and temperate regions (Liu et al., 2021). However, maize is highly sensitive to weather preferring a set of conditions, outside of which marked yield decreases occur (Holzkämper et al., 2013; Lobell et al., 2014; Meng et al., 2016). Temperature and rainfall variability during the growing season are therefore important for successful maize production, especially under rainfed conditions. Abiotic stress weakens the metabolic processes of maize by decreasing the photosynthetic rates, which results in reduced nutrient assimilation and biomass accumulation, resulting in morphological, physiological and biochemical changes that culminate in decreases in yield, and in severe cases result in plant death (Zhang et al., 2009; Song et al., 2019). However, it is not just the amount of water that is important for maize but its distribution during critical phenological stages (Omoyo et al., 2015; Krell et al., 2021). Water is the most limiting factor to maize production in many areas (Hossain, 2020) and the effects of water deficit are also mediated through temperature or soil conditions.

Temperature effects on the maize plant are multi-faceted. On one hand, increases in temperatures cause greater water loss from the soil due to increased evapotranspiration, thus reducing plant water supply. On the other hand, increases in temperature increase plant transpiration and photosynthesis, which concurrently increase plant water demand which can be up to a point of plant desiccation (Lobell et al., 2014). High temperatures also have the effect of reducing maize pollen fertility, hastening grain filling, and increasing wasteful respiration, resulting in a yield decrease of about 7% for every degree of warming (Sánchez et al., 2014; Hatfield, 2016; Zhao et al., 2017). The lethal temperature limits for maize are comparatively high to be achieved in the surface air (46°C) but those for plant growth and reproductive processes such as shoot development (38.9°C), tassel initiation (39.2°C), anthesis (37.3°C) and grain filling (36°C) are much lower (Sánchez et al., 2014). In addition, and most importantly, global change will alter the satisfaction of the required growing degree days, the phenoclimatic temperature conditions needed for different phases of plant development (Grigorieva, 2020). In many tropical areas, water deficit and temperature effects on the maize crop can also occur at the same time with interactive effects on growth and development of the plant. Thus, there is a risk that global warming will push many maize growing areas outside thresholds for the crop, with this having significant impacts on food security, livelihoods and economies.

There is substantial evidence on crop-climate interactions and climate change impact assessments for maize as expected for such as important crop. This evidence is premised on countless experimental studies on maize responses to various conditions and perturbations [for example Song et al. (2019) and Ge et al. (2012)]. Statistical models fitting local, regional or national yields to weather parameters and other variables have also been used to elucidate crop-climate responses over time and area [for example, Lobell et al. (2011), Laudien et al. (2020)]. While both experimental studies and statistical models provide valuable information on crop-climate relationships and climate change impacts, they are difficult to use for adaptation planning over large heterogeneous countries or regions such as Southern Africa (Silva and Giller, 2020).

Crop suitability models are used to identify where and which crops can be grown, and in providing quantitative, spatially explicit, large-scale and time-bound estimates of the impacts of climate change on the agriculture sector. They are based on the understanding that weather and climate still play a significant role in crop production, despite the developments in agricultural technology (Iizumi and Ramankutty, 2015; Ray et al., 2015). As such, maize will grow within a specific climatic envelope – with strong indications that climate change will alter the conditions and subsequently change the geography of crop suitability (Travis, 2016). For example, Ramirez-Villegas et al. (2013) has shown that suitable areas for sorghum could be reduced by 20% over Southern Africa in the next decade. Similar suitability changes have been reported for cassava (Heumann et al., 2011; Jarvis et al., 2012), maize (Nabout et al., 2012; Estes et al., 2013; Holzkämper et al., 2013) and common beans (Ramirez-Cabral et al., 2016; Taba-Morales et al., 2020). Multiple crop suitability under climate change has also been evaluated with these models (Jarvis et al., 2012; Chemura et al., 2020).

Crop modeling in general and suitability modeling in particular, have rarely captured the influence of extreme climate variables in determining crop growth, yields and other production outcomes (Vogel et al., 2019). This is despite the fact that climate change will further make extreme weather more common in future periods than in the past and current periods (Nangombe et al., 2019). Extreme weather events are conditions that are unusual, severe, and/or infrequent and fall at the tails of the historical distribution for a particular place or time (Stephenson et al., 2008; Bouwer, 2019; Kusangaya et al., 2021). The high importance of extreme weather events for crop production requires a better consideration of these events in crop impact studies (Lobell et al., 2012; Lesk et al., 2016; Beillouin et al., 2020). This is especially so in regions such as Southern Africa for which experimental data for process-based modeling is limited while yield and other data for statistical models is not available, inconsistent or uncertain.

Here, we analyzed changes in temperature and rainfall extreme indicators over Southern Africa, and how these changes in extreme climate indices affect maize suitability. We analyzed the past and future distribution of extreme indices over the agricultural season (October to April) and used these to calibrate a suitability model to show their influence on maize suitability. Adding climate extreme indices to the modeling and using agricultural season-specific metrics rather than annual values advances current climate crop impact studies. Such assessments help not only in identifying impact hotspots but also in targeted adaptation planning in the light of National Adaptation Plans (NAPs) and investment under Nationally Determined Contributions (NDCs). Results of these studies are important in assessing the shifts in crop potential under different climate scenarios, and identify the areas where and which adaptation measures are required for building agricultural resilience (Ramirez-Cabral et al., 2016; Jayasinghe and Kumar, 2019).

DATA AND METHODS

Location Data for Maize Suitability Modeling

To run suitability models, knowledge on the location of current maize growing areas is required. This information was obtained from the Global Biodiversity Information Facility (GBIF, www.gbif.org) and secondary sources (**Supplementary Information 1**). The GBIF was established in 2001 to publish primary biodiversity data using community-driven and agreed standards and tools. It facilitates open access to biodiversity data worldwide for scientific research, conservation and sustainable development with over one billion occurrence records of species. In order to supplement the presence points obtained from the databases, especially for countries where GBIF entries were few, maize location points were also digitized from scientific publications. These were for South Africa (Bradley et al., 2012; Estes et al., 2013), Namibia (De Waele et al., 1998) and for Botswana (Chipanshi et al., 2003; Chimbari et al., 2009; Legwaila et al., 2012). The maize location points were cleaned by removing records with incorrect geographic coordinates, and where two points or more existed in the same grid (∼55 km), only one was randomly retained to avoid extracting the same pixels with multiple points. After these steps of data cleaning, a total of 146 valid geographic points were obtained and used for the modeling (**Supplementary Informations 2, 3**).

Agro-Climatic Indices for Maize Modeling

Six agro-climatic indices were used in modeling the climatic suitability of maize over Southern Africa for the baseline and future climatic conditions. These indices were selected as they have a major agronomic influence on maize over Southern Africa obtained from literature and expert knowledge (Du Plessis, 2003; Nagy, 2006; Rivas et al., 2011; Adisa et al., 2018; Hossain, 2020). The indices utilized are based on rainfall and temperature during the maize sowing period, maize growing season and the whole season. These indices are described in full in **Table 1**. The sowing period ranges from October to December, growing period from December to March and the whole season is from October to April according to the FAO GIEWS (2020) maize crop calendars summarized for each country in **Supplementary Information 4**. Since the periods transcend the calendar year, the months were coded according to harvest year and then processed. Although there is an overlap in some of the indices, we considered that the lengths of the periods are very different and therefore the variables are independent of each other. In addition to the base model, which is the model with the six agro-climatic indices, further models were created by adding, for each model, the extreme index for the sowing period and season. The climate data used for model fitting was the W5E5 data (Lange et al., 2021). This observational dataset was chosen due to its compatibility with the model data for future climate (see Climate Change Impact Assessment).

TABLE 1 | Indices used for maize crop suitability modeling and their descriptions and units.

Basis	Index	Description in day of year (DOY)
Base indices	Sowing rainfall sum (mm)	Sum of rainfall between 1 October (DOY = 274) and 31 December (DOY = 365) = 92
	Growing season rainfall sum (mm)	Sum of rainfall between 1 December (DOY = 335) and 28 February (DOY = 59) = 90
	Seasonal sum rainfall (mm)	Sum of rainfall between 1 October (DOY =274) and 30 April (DOY = 120) = 212
	Mean temperature of sowing period (°C)	Mean temperature between 1 October (DOY=274) and 31 December (DOY = 365) = 92
	Mean temperature of growing season (°C)	Mean temperature between 1 December (DOY= 335) and 28 February (DOY = 59) = 89
	Mean seasonal temperature (°C)	Mean temperature between 1 October (DOY=274) and 30 April (DOY = 120) = 212
Extreme weather indices	Consecutive Dry Days (CDD)	Maximum length of dry spell defined as number of consecutive days with rainfall < 1mm.
	Very heavy rain events (R20 mm)	Annual count of days when rainfall ≥ 20 mm.
	Prolonged rainfall amount (Rx5Day) (mm)	Maximum consecutive 5-day rainfall
	Hot night temperatures (°C) periods (TNx)	Maximum value of daily minimum temperature
	Hot day temperatures (TXx) (°C)	Maximum value of daily maximum temperature
	Very hot days (TXge30)	Days when average temperature is at least 30 °C

Climate Change Impact Assessment

To determine climate change impacts for the base model and the models with extreme indices, we replaced the baseline climate data with climate projections and compared the results to indicate the impact of climate change on crop suitability (Ramirez-Cabral et al., 2016; Jayasinghe and Kumar, 2019; Chapman et al., 2020). We chose the benchmark period around 2050 (2036–2064) in line with Paris Agreement targets for climate action against a baseline period around 2000 (1986–2014) climatic conditions for the impact assessment. For climate data, we used the bias-adjusted projections from 10 General Circulation Models (GCMs) from the Coupled Model Inter-comparison Project Phase 6 (CMIP6). These models were used for historical simulations and future projections: CAN-ESM5, CNRM-CM6-1, CNRM-ESM2-1, EC-EARTH3, MIROC6, GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1, MRI-ESM2-0, and UKESM1-0-LL. Their bias-adjusted simulations are provided by Inter-Sectorial Impact Model Inter-comparison Project (ISIMIP) ensemble (Lange et al., 2021) with full names and origins of each GCM given in **Supplementary Information 5**.

As the bias-adjustment is based on the W5E5 observational dataset (see Agro-climatic Indices for Maize Modeling), the past and future climate data of our study forms one comprehensive dataset. The selected GCM models cover a range of model uncertainty and are also widely used in climate change impact studies in Africa because they feature as reliable for the region in model evaluation studies (Aloysius et al., 2016; Klutse et al., 2016; Ongoma et al., 2019). For the assessment of future suitability, we used the GCM simulations under the scenario without climate policy, i.e., representative concentration pathway (RCP) 8.5 under shared socioeconomic pathway (SSP) 5 known as SSP5-8.5. The SSP5-8.5 emission scenario represents no effective mitigation policies put in place to change the current emission trajectory, resulting in high population but relatively slow income growth with modest rates of technological change and energy intensity improvements (Rao et al., 2019). Here, we chose the lowest mitigation scenario only because previous studies have shown that significant changes in shorter duration (3–5 day) extreme indices such as used in this study by 2050 would occur mostly under this scenario especially over Southern Africa (Nangombe et al., 2018; Tebaldi and Wehner, 2018). Therefore, the results of our study are only limited to the context of this scenario without climate policy, while also accepting that other climate trajectories are possible.

Maize Suitability Modeling Approach

In our study we applied the Maximum Entropy (MaxEnt) approach to maize suitability modeling. MaxEnt is an environmental niche modeling approach that is capable of making reliable predictions using information from sites where the modeled species is known to occur (Phillips et al., 2006). MaxEnt uses crop location data and a set of predictors (agroclimatic and extreme climate indices in our case) across a defined landscape to compute the probability of target distribution by finding the possibility of maximum entropy. Unlike other modeling approaches, MaxEnt is a learning model and data is fit using linear and non-linear functions and different functions can be hinged together (Heumann et al., 2011). The model is described in full by Elith et al. (2011). MaxEnt is highly regarded due to its superlative analytical capacity, it is more accurate when applied to "presence only" data than other approaches and is capable of providing reliable distribution from relatively smaller sets of data (Hernandez et al., 2006; Elith et al., 2011; Stokland et al., 2011). Based on these characteristics, MaxEnt was chosen as the best fitting modeling approach to perform maize suitability assessments under past and future climatic conditions with and without extreme indices. In total, seven models were run as base model with only the six agro-climatic variables without any precipitation/temperature extreme indices, then six other models with the added season and sowing period extreme indices (Base + CDD, Base + R20 mm, Base + Rx5Day, Base + TNx, Base + TXx and Base + TXge30).

Model Settings, Evaluation, and Data Analysis

MaxEnt version 3.3.3k was used for the modeling (Phillips and Dudík, 2008). We controlled the complexity of the MaxEnt model by selecting input parameters and model settings to reduce model overfitting. Model calibration is required to deal with issues of geographic sampling bias, small sample sizes, model overfitting due to bias and/or noise characteristic of input datasets. This calibration is therefore critical where models are transferred across space and time as in large scale climate impact studies of this nature (Merow et al., 2013). The model calibration, evaluation and selection was done using the "ENMeval" R package (Muscarella et al., 2014), and the "rMaxEnt" library. The regularization multiplier was applied to control the model complexity by assigning a penalty for each additional term included in the model (Anderson and Gonzalez Jr, 2011; Warren and Seifert, 2011). The optimal model complexity was determined from combinations of five values for the MaxEnt regularization parameter from 0.5 to 4 at intervals of 0.5 and six different individual and combined feature classes (L, LQ, H, LQH, LQHP, LQHPT; where L=linear, Q=quadratic, H=hinge, P=product and T=threshold) (Merow et al., 2013; Muscarella et al., 2014; Cuervo et al., 2020). These. The optimal model complexity was evaluated and together with the optimization of regularization gain resulted in 336 models.

The best model from these was selected as the one with statistical significance (partial Receiver Operating Characteristic (ROC) tests), high performance (omission rate), and smaller Akaike Information Criterion. The settings of the best model were then used to run 10 bootstrap replicates, with no clamping or extrapolation while retaining a random partition of 30% of the points from each run. To evaluate the model performance of the extreme variables against a base model without these, we compared the area under the receiver ROC curves (AUC) on 30% of the independent sample data set aside for this purpose. The AUC measures overall discrimination capacity independent of any thresholds (Allouche et al., 2006). A perfect model would have an AUC of 1, while a threshold of 0.75 is considered as threshold for accepting a model (Chang and Bourque, 2020). Comparison of the modeled maize suitability area for each country with the reported maize average area for the period 2001 and 2019 and for each country from FAOSTAT (2021) was conducted to evaluate the model (**Supplementary Information 4**). The relative contribution of each variable to maize suitability was calculated from median estimates across replicates of percent contribution. The sensitivity-specificity equality approach, which minimizes the absolute value of the difference between sensitivity and specificity to ensure that the model performs well for both presences and absences, was used to select the threshold for determining suitable and unsuitable areas to calculate area. This method was selected because it seeks to achieve a balance of accuracy for areas modeled for presence and absence of the species and is the recommended approach for presence only suitability models where prevalence is usually low (Cantor et al., 1999; Hernandez et al., 2006; Bean et al., 2012).

RESULTS

Baseline and Future Changes of Agro-Climatic Variables and Extreme Indices

The spatial distribution of surface air temperature averages and related extreme indices over Southern Africa under the baseline and changes under future conditions are shown in **Figure 1**.

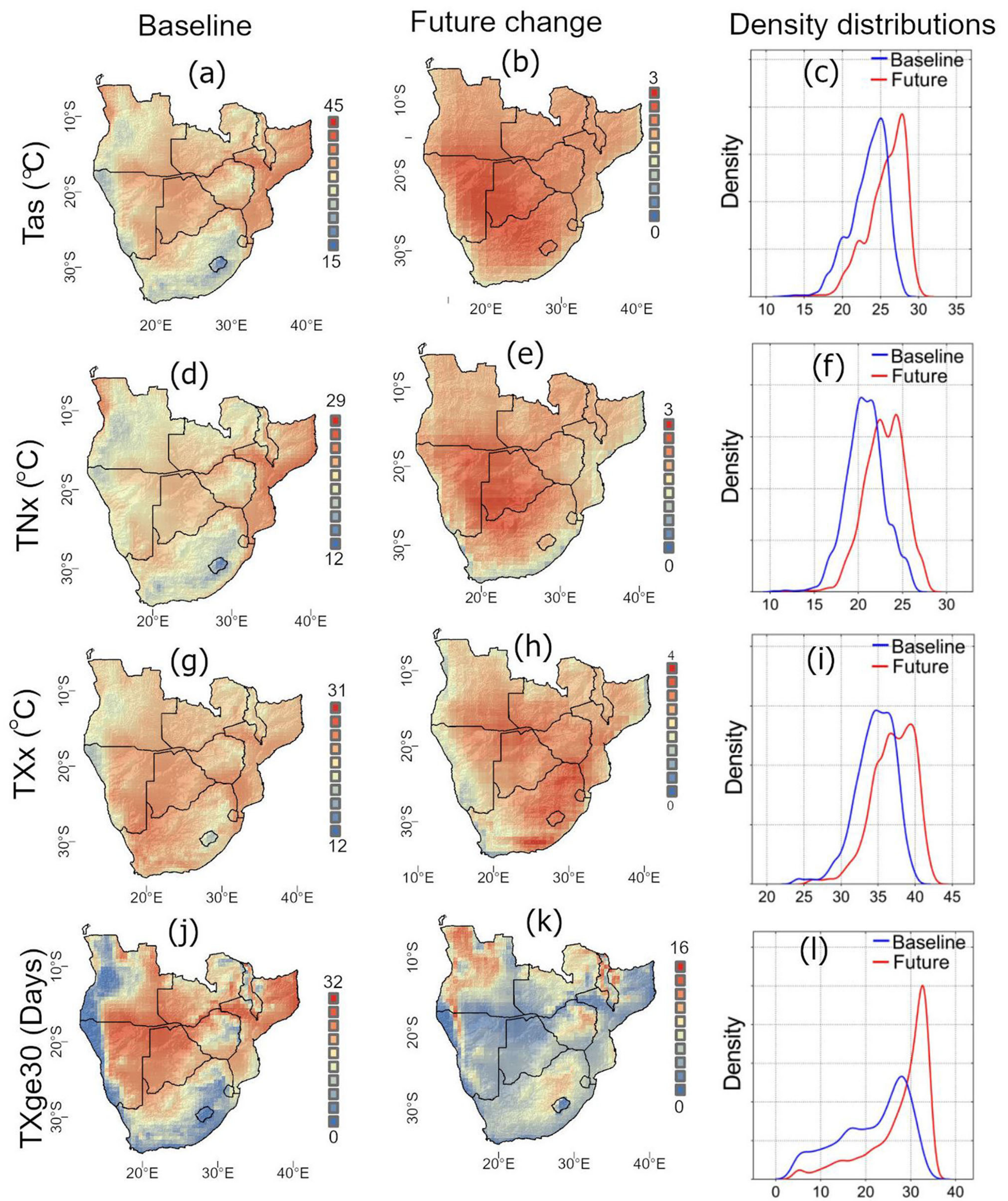

FIGURE 1 | The distribution of mean temperature and temperature indices under baseline and projected climate conditions for the agricultural season (October to April) over Southern Africa. First, second, third and fourth row show assessment of mean temperatures (Tas), maximum value of daily minimum temperature (TNx), maximum value of daily maximum temperature (TXx) and number of days when TX ≥ 30°C (TXge30), respectively. The first and second columns present the baseline (1986–2014) and the changes in the future (2036–2064) relative to the baseline, respectively. The third column show the area density plots to indicate the changes in area between the two climate periods.

These show that the greater part of the region experiences on average warm temperatures (mean temperature above 15°C) within the agricultural season. Exception to this are Lesotho, due to its elevation, and southern parts of South Africa and western Namibia, due to elevation and coastal upwelling (**Figure 1**). The Karoo region covering Botswana, Namibia, southern Angola, south-western Zambia and western Zimbabwe experienced up to 32 hot days with temperatures above 30°C within the agricultural season, which is over a fifth of the period (**Figure 1J**).

Projections show a warming trend for all pixels over the whole region by mid-century and there are no negative changes across the region. These changes are reflected in daily minimum as well as maximum temperatures in many parts of Southern Africa, especially in Botswana and Namibia. Warming of the agricultural season over Southern Africa is also confirmed by the area density plots that show movement of projected temperatures to the right (**Figure 2**). This also applies in terms of the extreme temperature indices where the future values move to the right by up to 3°C under this scenario for the Karoo region (**Figures 1B,E,H**). The maize production regions will warm by up to 2°C under climate change. Maximum values of minimum and maximum temperatures show similar trends for most regions, except that the maximum temperatures are projected to increase by as much as 4°C (**Figure 1H**) compared to 3°C for average (**Figure 1B**) and minimum (**Figure 1E**) temperatures by mid-century (**Supplementary Information 5**). The number of days with temperature above 30°C within the agricultural season will increase by up to 16 days compared to the baseline period for some areas in Angola, South Africa, Malawi and Zimbabwe (**Figures 1K,L**). The distribution curve shows also a strong increase for temperature above 35°C (a much steeper tail of the curve).

The baseline and projected future changes in rainfall and extreme rainfall indices over the agricultural season over Southern Africa are shown in **Figure 2**. Northern parts of Angola, Zambia and eastern parts of Zimbabwe and parts of Mozambique have received the most rainfall (more than 1,000 mm) in the agricultural season in the baseline period (**Figure 2A**). Areas that receive over 1,200 mm during the agricultural season in the baseline period will largely be unchanged but those between 300 and 1,300 mm are projected to have reduced rainfall amounts by the mid-century. Over Mozambique, parts of Zimbabwe and Angola, these decreases will be up to 150 mm of rainfall in the agricultural season.

Consecutive dry days (CDD) during the agricultural season are projected to increase over Southern Africa particularly in areas where they are between 20 and 60 days in the agricultural season, with no changes above that (**Figures 2E,F**). These changes in CDD are mainly projected to change over Mozambique, Angola, parts of South Africa and Zimbabwe (**Figure 2**). The number of heavy precipitation events of days with rainfall above 20 mm is projected to increase over Southern Africa (**Figures 2H,I**) despite the decrease in total seasonal rainfall (**Figures 2B,C**) and the increasing dry days (**Figures 2E,F**, **3**). This indicates that the reduced rainfall amounts over the season will come in higher intensity than during the baseline period especially for areas where days with heavy rainfall are between 5 and 20 days in the baseline period (**Figure 2I**). The contribution of prolonged rainfall to the total rainfall in the season will decrease in many areas in the future. Specifically, by the 2050s, many of the rainfall events will become shorter (<5 days) and of high intensity (over 20 mm per day) then in the baseline period (**Supplementary Informations 5, 6**). This pattern is especially clear in the northern countries of Southern Africa like Angola, Zambia, and Mozambique (**Figure 2**). Rainfall events above 20 mm correlate positively with sum rainfall and prolonged rainfall amounts over the season but negatively with CDD and all the temperature-based indices (**Figures 2E,G,J**, **Supplementary information 6**).

Variable Selection for Modeling

After the model optimization to determine the best parameters for the model, ten replicates of the model for sampling training and test data were implemented with different sets of variables. The mean AUC values on independent 30% of the data are shown in **Table 2**. In all cases rainfall and temperature extreme indices are included, the model performance was better than the base model with mean climatic indices only. The best model fit was obtained from inclusion of CDD (AUC= 0.91 for tuned model) followed by TXx (AUC = 0.88 for tuned model). In all cases, model optimization improved the modeling accuracy compared to the raw model across all model settings (**Table 2**). Overall, the results indicate that including extreme variables improved the modeling accuracy for maize suitability together with model optimization routines.

The most important variable driving maize suitability over Southern Africa for most models was the rainfall of the growing season (**Figure 3**). This variable was the most important variable across models in explaining maize suitability except for the model with Txge30 (33%), where it was ranked as the second most important variable (27%). This result underscores the importance of rainfall distribution on maize suitability in comparison to the rainfall sum. Growing season temperatures and rainfall during the sowing period are also important variables while the least important was mean temperature of the agricultural season, which explained <2% for all models (**Figure 3**).

When rainfall and temperature indices were introduced to the modeling, season CDD (23%), season TNx (20%) and sowing period TXx (28%) were ranked second after growing season rainfall, while season Txge30 (33%) was the most important variable for that model explaining about a third of maize suitability over Southern Africa (**Figure 3**). R20 mm and Rx5day were variables with low importance, falling below most of the base agro-cimatic variables in explaining maize suitability. Based on the model accuracy results and the variable importance assessments, five maize suitability models were developed as the Base, Base + CDD, Base + TNx, Base + TXx and TXge30, with R20 mm and Rx5Day models excluded as they are not improving the accuracy over the base models nor contributed inexplaining maize suitability over Southern Africa.

Baseline Distribution of Maize Suitability

The general distribution of maize suitability across Southern Africa under baseline climatic conditions with and without

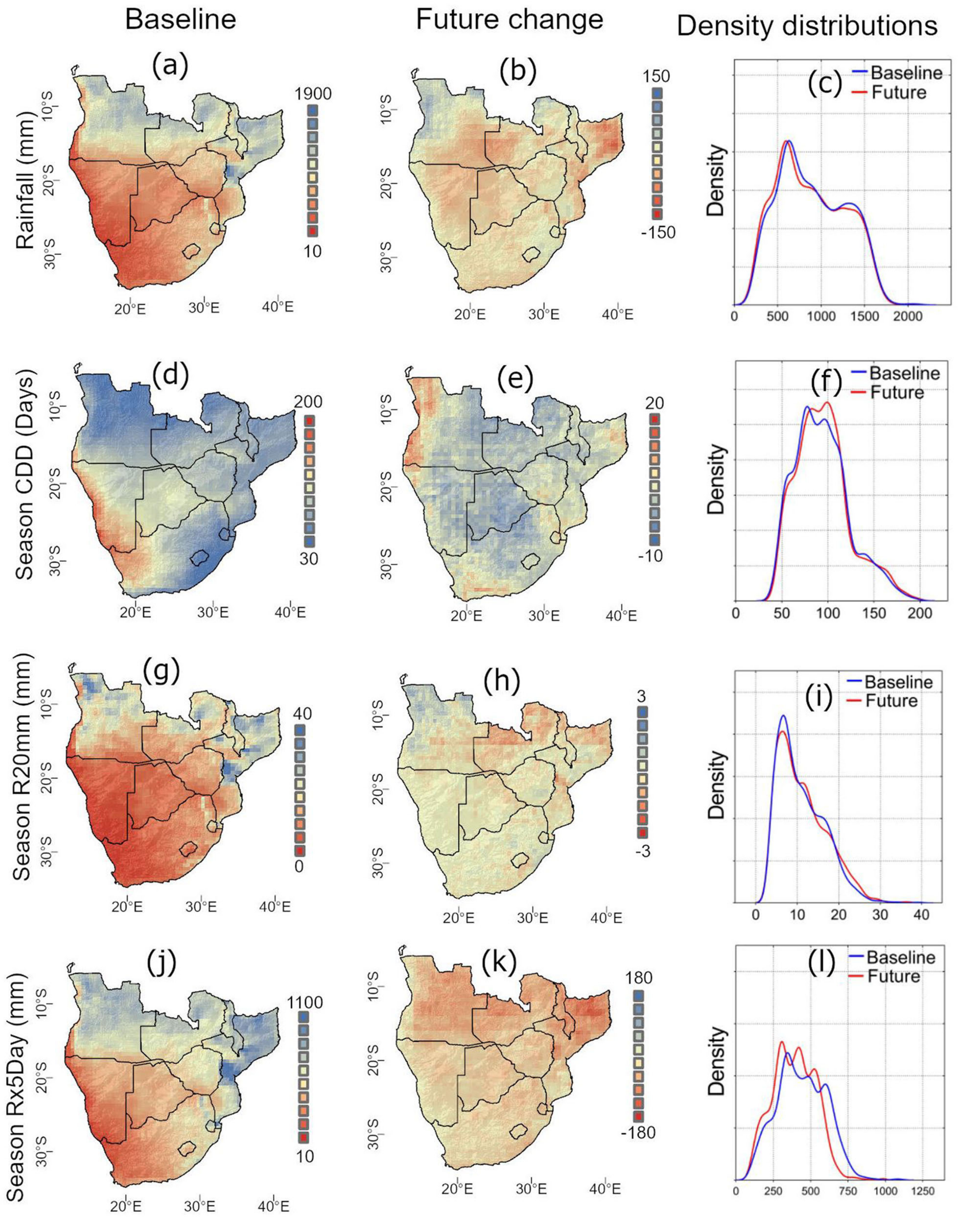

FIGURE 2 | The distribution of precipitation and precipitation indices under baseline and projected climate conditions for the agricultural season (October to April) over Southern Africa. First, second, third and fourth row show total precipitation, consecutive dry days (CDD), count of days when rainfall ≥ 20 mm (R20 mm), and maximum consecutive 5-day precipitation (Rx5Day), respectively. The first column present the baseline period (1986–2014) and the second column show the changes in the future period (2036–2064) relative to the baseline. The third column show the area density plots to indicate the changes in area between the two climate periods.

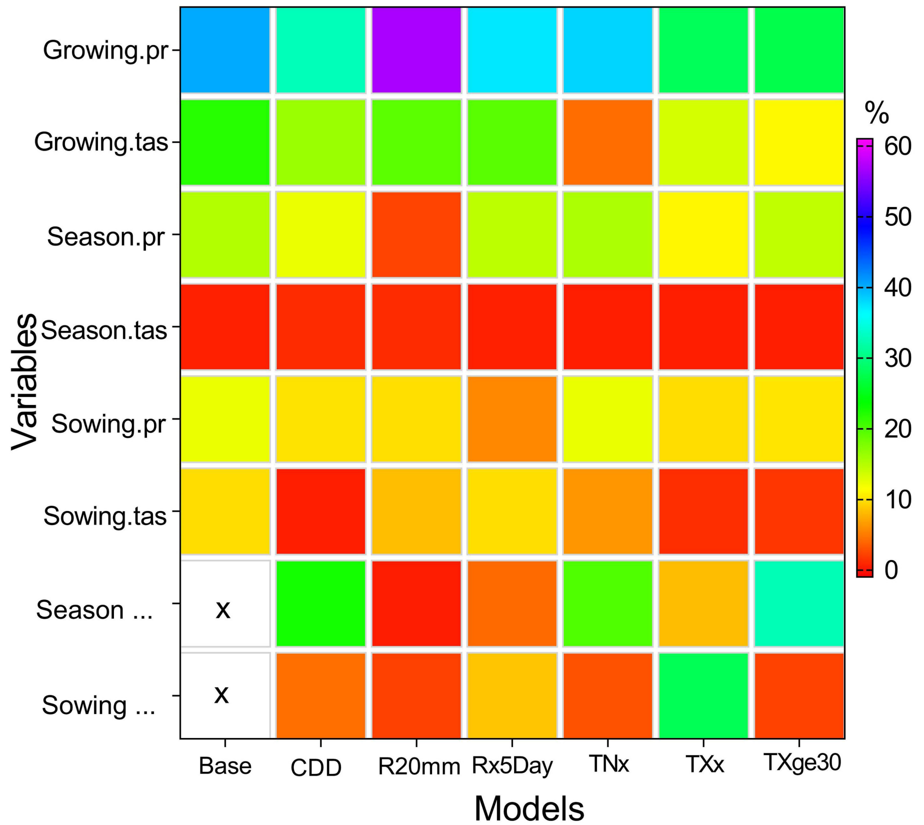

FIGURE 3 | Percent contribution of variables used in maize suitability modeling from the model variable importance. The Y axis shows first the six variables used and then the seasonal and sowing period importance values for each of the rainfall and temperature indices used, with the x showing that no other indices were used for the base model. In all cases the column values add to 100% with the green and blue shades showing more important variables for maize suitability for each model compared to the red shades which indicate non low importance of a variable.

TABLE 2 | Accuracy assessment of the crop suitability modeling using AUC values obtained from base variables and extreme variables from independent test data.

Model	Raw	Tuned
Base	0.817	0.840
Base + CDD	0.863	0.914
Base + R20 mm	0.835	0.844
Base + Rx5Day	0.859	0.876
Base + TNx	0.821	0.856
Base + TXx	0.868	0.881
Base + TXge30	0.868	0.872

(Base) extreme indices included in the modeling is shown in **Figures 4A–E**. About 32% of the region is suitable for maize in the baseline period, with Zambia and South Africa having the largest areas (**Figure 4A**). Under baseline climatic conditions, suitability is higher over Angola, Zambia and Zimbabwe, and markedly decreases when indices are introduced to the model. The model shows that maize is suitable extensively across Zambia (88% with Base + CDD model), in central parts of Angola (32% with Base + CDD model), central to northern Zimbabwe (86% with Base + CDD model), central-eastern South Africa (28% with Base + CDD model), central to northern parts of Mozambique (19% with Base +CDD model) and across Malawi (39% with Base + CDD model) under baseline climatic conditions (**Supplementary Information 7**). Marginal areas for maize are identified over the Karoo region covering the desert areas on western to southern parts of the region. Eastern coastal areas in Mozambique also show lower suitability for maize under baseline climatic conditions (**Figures 4A–E**).

We find that under baseline climatic conditions, higher mean temperatures and temperature indices (Tas, TNx, TXx and TXge30) are negatively correlated to maize suitability over southern Africa (**Supplementary Materials 8, 9**). On the other hand, maize suitability is positively correlated with rainfall variables and indices (rainfall sum, R20 mm, and Rx5Day), except CDD, which has a strong negative correlation (**Supplementary Material 6**). There is a general correlation, however, within rainfall and temperature variables but not between them, with the strongest correlation being between rainfall sum and prolonged rainfall (Rx5Day). It therefore follows that over Southern Africa, maize suitability is generally higher over wetter and cooler areas, although no individual

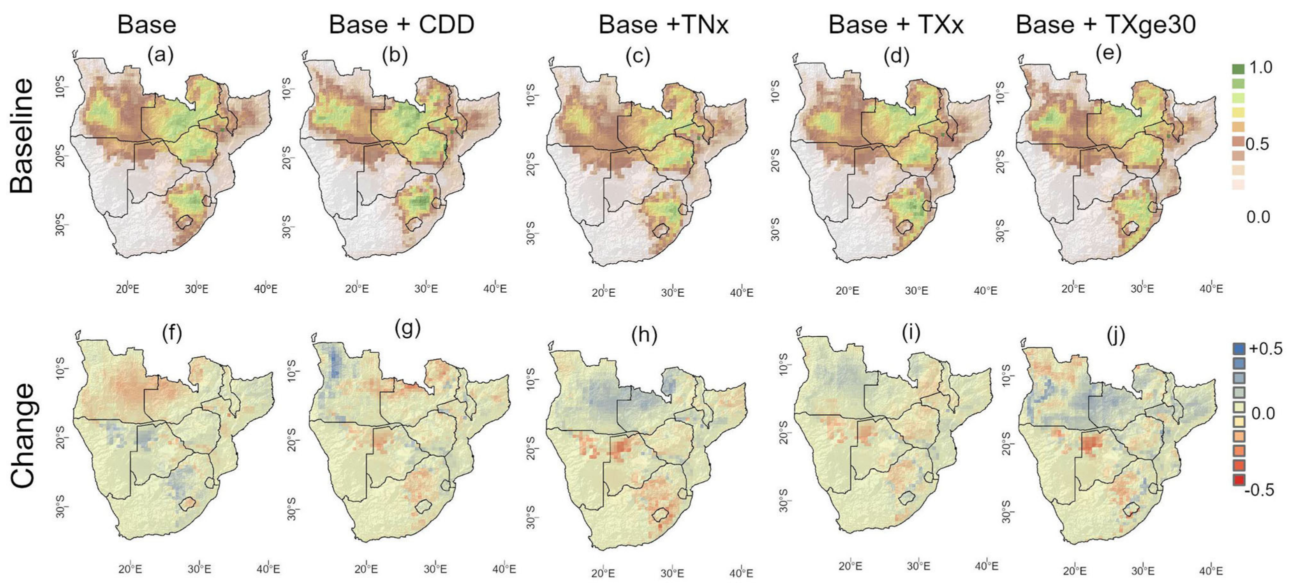

FIGURE 4 | Maps showing maize suitability under baseline (1986–2014) and future changes (2036–2064) in maize suitability for the base model (first column), and adding CDD (second column), TNx (third column), TXx (fourth column) and TXge30 (fifth column) indices to the modeling. A suitability of 1 can be interpreted as highly suitable, while 0 means not suitable. The changes (lower row) are calculated as future suitability minus baseline suitability with positive values showing improved suitability and negative values showing decreases in maize suitability.

parameter has absolute individual influence over the suitability (**Figures 2**, **4**).

Maize Suitability Under Future Climatic Conditions

The changes in maize suitability under projected climate change conditions with and without indices are shown in second row of **Figure 4** and the area changes in **Figure 5**. Using the base model without extreme climate indices projects a net loss in area suitable for maize by the mid-century for most of the countries (Botswana, Malawi, Mozambique, Namibia, South Africa, Zambia and Zimbabwe) in the region. Although maize suitability over the whole region is projected to remain stable (+1.2 to +4.4% change), a northward shift in maize suitable areas is apparent with losses in the central parts of the regions and gains in the northern parts under most models (**Figures 4F–J**). Overall, our results show that the maize suitability changes are variable among countries and also influenced by GCMs. Positive maize suitability changes are projected over Angola, Lesotho (except for Base + TNx model) and parts of Mozambique (**Figure 5**, **Supplementary Information 10**).

The results for Malawi and Lesotho show high GCM uncertainty by the large variance in projected changes for all variables (**Figure 5**). In addition, and more importantly, the inclusion of temperature indices to the model reduces positive suitability changes where they were projected (Angola and Lesotho) and increases the suitability losses (Zimbabwe and Botswana). A positive suitability change is projected for Zambia in the Base model but this diminishes when TXx and Txge30 are added to the model resulting in maize suitability losses. The projected westward extension of maize suitability under climate change in South Africa using the base model clearly diminishes when rainfall and temperature indices are included in the modeling, while for Lesotho the opposite is true (**Figures 4F–J**, **5** and **Supplementary Information 10**).

DISCUSSION

Climate extremes will further increase with climate change and will have severe impacts on agricultural production. However, these are not often captured in crop modeling studies that rely on either continuous weather time steps or seasonal agro-climatic indices. In this study, we therefore assessed the changes in extreme temperature and rainfall indices and then integrated them in modeling the suitability of maize over the whole of Southern Africa. In addition, instead of using the annual values, we calculated our climate input variables over the agricultural season (October - April) and not apply annual variables that are tangent to the growing season. For Southern Africa, this is more relevant for agricultural production impact assessments and associated food security studies as the agricultural season is split between two calendar years. Thus, restricting the analysis to the agricultural season only produce results that are directly linked to livelihoods and the economy compared to using the whole year. In addition, we also provide a multi-country assessment that compares the changes in distribution of extreme indices and maize suitability rather than a country or sub-country assessment. Our study

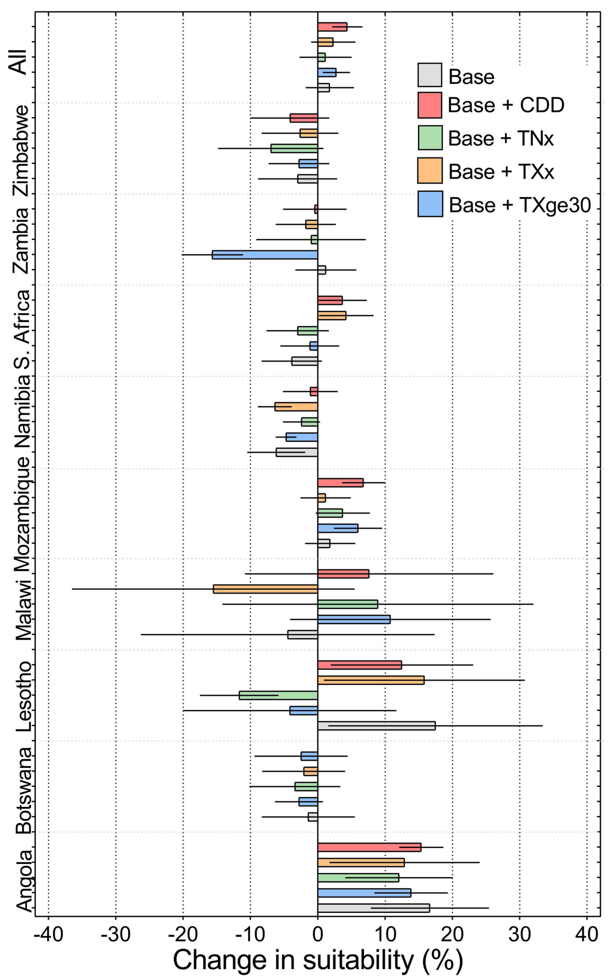

FIGURE 5 | Changes in maize suitability by around mid-century in individual countries and overall over Southern Africa from running the base models and including temperature and rainfall indices to the model. The base model has six agro-climatic indices while the other models have eight variables from adding the temperature sowing period and seasonal indices to the base variables. Eswatini was excluded as it had <10 pixels. The error bars sow the results according to the 10 GCMs used. The changes are calculated as future suitability minus baseline suitability with positive values showing improved suitability and negative values showing decreases in maize suitability as averaged over the whole country.

therefore provides, in combination, an assessment of climate variables in the agricultural season and their associated impacts on agriculture, as an important sector for livelihoods of a large part of the population.

Our analysis confirmed the projected warming trend over Southern Africa is reaching up to 3°C by the mid-century in many areas. In the present-day maize production areas, the projected increase in temperature of 1 or 2 degrees Celsius affects crop production in general and maize in particular (Lesk et al., 2016). In addition, our results indicate increases in the extreme temperature indices such as hot night temperatures, hot day temperatures and number of very hot days above 30°C. These results confirm reported increases in temperature and extreme temperature indices over the whole year reported in literature (Nangombe et al., 2019; Kusangaya et al., 2021), even though our results are over the agricultural season, which is more meaningful for crop impact assessments.

The magnitudes of changes in extreme temperature indices (TNx, TXx and TXge30) projected is higher than those projected for extreme rainfall indices (CDD, R20 mm and Rx5day). While much climate change focus in agricultural impact studies have focused on rainfall decreases and variability, temperature effects seem more important and substantial in their signal than those of rainfall. This means that even if rainfall parameters remain the same or even increase under climate change, the changes in temperature will still result in decreases in crop suitability and thus lower production. Decreases in rainfall variability and resulting changes in available soil moisture affect crop potential (Krell et al., 2021), but temperature impacts are both direct on the crop and also indirect through effects on water supply and demand through altering vapor pressure deficit (Lobell et al., 2011; Sánchez et al., 2014; Hatfield, 2016). As such, the negative effects of future warming is expected to outweigh those of precipitation changes, as shown in our study. This concurs with findings by Nangombe et al. (2019) who reported that the magnitude of heat extreme events is projected to be significantly more across Africa under a 2°C global warming world.

Our analysis of model parameterization showed that (1) accuracy of the suitability models increases when temperature and rainfall extreme indices are included in the modeling and (2) the suitability of maize is affected more by most extreme indices than by average precipitation and temperature. This suggest that reliability of models increases with inclusion of extreme climate indices as they are more related to observed spatial and temporal distribution of maize, which provides more confidence in the application of the model for climate impact studies. Moreover, and perhaps more interestingly, we observe that including climate extremes reduces projected positive changes and magnifies negative impacts on climate suitability for maize over the region. Therefore, reported suitability changes in maize that did not incorporate extreme indices may have over-estimated positive changes and underestimated negative climate change impacts over Southern Africa and elsewhere. For example, Ojara et al. (2021) projected that area highly suitable for maize in Eastern Africa will decrease by more than 50% under the RCP8.5 scenario by the mid-century but if extreme indices were included, the decreases could be worse. Many studies have projected maize suitability changes without incorporating extreme variables (Holzkämper et al., 2013; Adisa et al., 2018; Lopez-Blanco et al., 2018; Kogo et al., 2019; Mumo et al., 2021; Yang et al., 2021), and the reported changes may need to be revisited in light of our findings.

Projected temperature impacts explain the observed changes in maize suitability over Southern Africa through a number of pathways. The higher magnitude effects of temperature extreme indices during the growing season on crop suitability correspond to the known effects of high temperatures on crop growth and yield. For example, high temperatures reduce absorption and subsequent assimilation of nutrients, reduce the shoot and root growth, and lead to under-development of anthers and loss of viability of pollen and pollen abortion in maize (Sánchez et al., 2014; Hatfield, 2016; Lesk et al., 2016; Zhao et al., 2017). Further, increases in temperature presents a double-edged sword effect on maize production. On one hand, it is responsible for heat stress on the plants and its associated biochemical and biophysical processes, while on the other hand, it mediates water supply through controlling evaporation and water demand through controlling canopy evapotranspiration (Zhang et al., 2009; Ge et al., 2012; Meng et al., 2016; Krell et al., 2021). It is not surprising that all the temperature extreme indices made it to the final modeling while for rainfall variables only CDD, which is positively correlated to temperature, remained.

As response to the projected climate changes, we suggest that technical (short-term), operational (medium term) and strategic (long-term) adaptation strategies for maize production systems should be implemented in many parts of Botswana, Namibia, South Africa Zambia, and Zimbabwe to avert or reduce negative climate impacts on the maize production. Supplementary irrigation, mulching or other water conservation techniques are recommended as technical adaptation strategies because CDD and TNx are projected to increase in many maize-producing areas. As our results also indicate that temperature extreme factors and CDD are the most important determinants of maize suitability over Southern Africa, agroforestry, with its potential canopy cooling and micro-climate regulation effects for maize systems, agronomic optimization and variety switching to more heat and drought tolerant varieties can be adopted as an operational strategies (Fisher et al., 2015; Cairns and Prasanna, 2018; Chemura et al., 2021). In addition, we project some positive changes in maize suitability over Angola, Lesotho and Mozambique that may provide socio-economic opportunities not just for the country but for the entire region.

Some potential limitations of our modeling should be considered in the interpretation of our results. The area suitability calculations include other land that may not be available for agricultural production because of the relatively course horizontal resolution of the data (∼50 km) used in the modeling. These other land areas are, for instance, urban areas, protected areas and riparian zones, which cannot be removed at the spatial resolution of the datasets used. The ten GCMs may also represent a subset of climate data as more models are more likely to capture a bigger range of climate model uncertainty. It is suggested that these GCMs can be selected for specific study areas based on their ability to reproduce past climate or on range of projected means (Lutz et al., 2016; Mendlik and Gobiet, 2016), but this analysis was beyond the scope of the current study. Although the modeling captures the conditions required for specific stages of the crop, it does not quantitatively simulate transitions in growth and reproductive stages, and therefore also misses on plant–climate relationship as influenced by for example increased CO_2 under climate change (Estes et al., 2013).

CONCLUSIONS

The trans-national assessments of climate change impacts on agricultural potential is needed to support vulnerable regions in increasing their climate resilience, especially where extreme climate events increase due to climate change. In this study, we tested the integration of extreme climate events in assessing future maize suitability over Southern Africa. We observe that hot night temperatures, hot day temperatures, very hot days, heavy rainfall events and consecutive dry days will increase by the 2050's while average rainfall and prolonged rainfall will decrease over the agricultural season in Southern Africa. Including these extremes in a maize suitability model improved the model robustness and resulted in a higher share of areas affected negatively by climate change. This underlines the need for tailoring the planning of adaptation strategies for specific areas facing losses, while also adjusting the agricultural system in regions which may have more favorable conditions to cultivate maize.

DATA AVAILABILITY STATEMENT

The datasets for this study can be found in manuscript and in the **Supplementary Materials** with all data sources mentioned available in the public repositories. Code and produced graphics are available at a reasonable request from the corresponding author.

AUTHOR CONTRIBUTIONS

AC, SC, CG, and SN designed the research. AC, SG, and SN planned the research activities, collected, analyzed, and curated data. AC ran the models. AC and SN wrote draft manuscript. SG, SC, and CG reviewed and fine-tuned the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

This work was funded by the German Ministry for Economic Cooperation and Development (BMZ) in close collaboration with the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH as part of the project AGRICA – Climate risk analyses for identifying and weighing adaptation strategies in sub-Saharan Africa.

ACKNOWLEDGMENTS

We are also grateful to the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) team in producing, coordinating, and making available the ISIMIP input data.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fclim.2022.890210/full#supplementary-material

REFERENCES

Adisa, O. M., Botai, C. M., Botai, J. O., Hassen, A., Darkey, D., Tesfamariam, E., et al. (2018). Analysis of agro-climatic parameters and their influence on maize production in South Africa. *Theor. Appl. Climatol.* 134, 991–1004. doi: 10.1007/s00704-017-2327-y

Allouche, O., Tsoar, A., and Kadmon, R. (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol.* 43, 1223–1232. doi: 10.1111/j.1365-2664.2006.01214.x

Aloysius, N. R., Sheffield, J., Saiers, J. E., Li, H., and Wood, E. F. (2016). Evaluation of historical and future simulations of precipitation and temperature in central Africa from CMIP5 climate models. *J. Geophys. Res. Atmos.* 121, 130–152. doi: 10.1002/2015JD023656

Anderson, R. P., and Gonzalez Jr, I. (2011). Species-specific tuning increases robustness to sampling bias in models of species distributions: an implementation with Maxent. *Ecol. Model.* 222, 2796–2811. doi: 10.1016/j.ecolmodel.2011.04.011

Bassu, S., Brisson, N., Durand, J. L., Boote, K., Lizaso, J., Jones, J. W., et al. (2014). How do various maize crop models vary in their responses to climate change factors? *Glob. Change Biol.* 20, 2301–2320. doi: 10.1111/gcb.12520

Bean, W. T., Stafford, R., and Brashares, J. S. (2012). The effects of small sample size and sample bias on threshold selection and accuracy assessment of species distribution models. *Ecography* 35, 250–258. doi: 10.1111/j.1600-0587.2011.06545.x

Beillouin, D., Schauberger, B., Bastos, A., Ciais, P., and Makowski, D. (2020). Impact of extreme weather conditions on European crop production in 2018. *Philos. Trans. Royal Soc. B* 375, 20190510. doi: 10.1098/rstb.2019.0510

Bouwer, L. M. (2019). "Observed and projected impacts from extreme weather events: implications for loss and damage," in *Loss and damage from climate change.* (Springer), 63–82.

Bradley, B. A., Estes, L. D., Hole, D. G., Holness, S., Oppenheimer, M., Turner, W. R., et al. (2012). Predicting how adaptation to climate change could affect ecological conservation: secondary impacts of shifting agricultural suitability. *Divers. Distrib.* 18, 425–437. doi: 10.1111/j.1472-4642.2011.00875.x

Cairns, J. E., and Prasanna, B. M. (2018). Developing and deploying climate-resilient maize varieties in the developing world. *Curr. Opin. Plant Biol.* 45, 226–230. doi: 10.1016/j.pbi.2018.05.004

Cantor, S. B., Sun, C. C., Tortolero-Luna, G., Richards-Kortum, R., and Follen, M. (1999). A comparison of C/B ratios from studies using receiver operating characteristic curve analysis. *J. Clin. Epidemiol.* 52, 885–892. doi: 10.1016/S0895-4356(99)00075-X

Chang, Y., and Bourque, C. P.-A. (2020). Relating modelled habitat suitability for Abies balsamea to on-the-ground species structural characteristics in naturally growing forests. *Ecol. Indic.* 111, 105981. doi: 10.1016/j.ecolind.2019.105981

Chapman, S., Birch, C. E., Pope, E., Sallu, S., Bradshaw, C., Davie, J., et al. (2020). Impact of climate change on crop suitability in sub-Saharan Africa in parameterized and convection-permitting regional climate models. *Environ. Res. Lett.* 15, 094086. doi: 10.1088/1748-9326/ab9daf

Chemura, A., Schauberger, B., and Gornott, C. (2020). Impacts of climate change on agro-climatic suitability of major food crops in Ghana. *PloS ONE* 15, e0229881. doi: 10.1371/journal.pone.0229881

Chemura, A., Yalew, A. W., and Gornott, C. (2021). Quantifying agroforestry yield buffering potential under climate change in the smallholder maize farming systems of Ethiopia. *Fronti. Agron.* 3, 609536. doi: 10.3389/fagro.2021.609536

Chimbari, M., Magole, L., Wiles, G., Dikgola, K., Kurugundla, N., Teketay, D., et al. (2009). *Application of the Ecohealth Approach to Understand Flood-Recession (Molapo) Farming in the Context of Hydro-Climate Variability and Hydro-Climate Change in the Okavango Delta, Botswana*. Maun: University of Botswana, Harry Oppenheimer Okavango Research Centre.

Chipanshi, A., Chanda, R., and Totolo, O. (2003). Vulnerability assessment of the maize and sorghum crops to climate change in Botswana. *Clim. Change* 61, 339–360. doi: 10.1023/B:CLIM.0000004551.55871.eb

Cuervo, P., Percara, A., Monje, L., Beldomenico, P., and Quiroga, M. (2020). Environmental variables determining the distribution of an avian parasite: the case of the Philornis torquans complex in South America. *Med. Vet. Entomol.* 35, 284–292. doi: 10.1101/839589

De Waele, D., McDonald, A. H., Jordaan, E. M., Orion, D., Van den Berg, E., and Loots, G. (1998). Plant-parasitic nematodes associated with maize and pearl millet in Namibia. *Afr. Plant Prot.* 4, 113–117.

Dowswell, C. R., Paliwal, R. L., and Cantrell, R. P. (2019). *Maize in the Third World.* Boulder, CO: CRC Press.

Du Plessis, J. (2003). *Maize Production*. Department of Agriculture Pretoria, South Africa, ARC-Grain Crops Institute, p38.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., and Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Divers. Distrib.* 17, 43–57. doi: 10.1111/j.1472-4642.2010.00725.x

Estes, L., Bradley, B., Beukes, H., Hole, D., Lau, M., Oppenheimer, M., et al. (2013). Comparing mechanistic and empirical model projections of crop suitability and productivity: implications for ecological forecasting. *Glob. Ecol. Biogeogr.* 22, 1007–1018. doi: 10.1111/geb.12034

FAO GIEWS (2020). *Global Information and Early Warning System; Food Price Data and Analysis Tool. Rome: FAO.*

FAOSTAT (2021). *Production of Crops and Livestock in Africa*. Food and Agriculture Organization of the United Nations (FAO), Rome (Italy).

Fisher, M., Abate, T., Lunduka, R. W., Asnake, W., Alemayehu, Y., and Madulu, R. B. (2015). Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Clim. Change* 133, 283–299. doi: 10.1007/s10584-015-1459-2

Ge, T., Sui, F., Bai, L., Tong, C., and Sun, N. (2012). Effects of water stress on growth, biomass partitioning, and water-use efficiency in summer maize (Zea mays L.) throughout the growth cycle. *Acta Physiol. Plant.* 34, 1043–1053. doi: 10.1007/s11738-011-0901-y

Grigorieva, E. (2020). Evaluating the sensitivity of growing degree days as an agro-climatic indicator of the climate change impact: a case study of the Russian Far East. *Atmosphere* 11, 404. doi: 10.3390/atmos11040404

Hatfield, J. L. (2016). Increased temperatures have dramatic effects on growth and grain yield of three maize hybrids. *Agric. Environ. Lett/* 1, 150006. doi: 10.2134/ael2015.10.0006

Hernandez, P. A., Graham, C. H., Master, L. L., and Albert, D. L. (2006). The effect of sample size and species characteristics on performance of different species distribution modeling methods. *Ecography* 29, 773–785. doi: 10.1111/j.0906-7590.2006.04700.x

Heumann, B. W., Walsh, S. J., and McDaniel, P. M. (2011). Assessing the application of a geographic presence-only model for land suitability mapping. *Ecol. Inf.* 6, 257–269. doi: 10.1016/j.ecoinf.2011.04.004

Holzkämper, A., Calanca, P., and Fuhrer, J. (2013). Identifying climatic limitations to grain maize yield potentials using a suitability evaluation approach. *Agric. For. Meteorol.* 168, 149–159. doi: 10.1016/j.agrformet.2012.09.004

Hossain, A. (2020). *Maize: Production and Use.* BoD–Books on Demand, IntechOpen, London, p. 144.

Iizumi, T., and Ramankutty, N. (2015). How do weather and climate influence cropping area and intensity? *Glob. Food Secur*. 4, 46–50. doi: 10.1016/j.gfs.2014.11.003

Jarvis, A., Ramirez-Villegas, J., Campo, B. V. H., and Navarro-Racines, C. (2012). Is cassava the answer to African climate change adaptation? *Trop. Plant Biol.* 5, 9–29. doi: 10.1007/s12042-012-9096-7

Jayasinghe, S. L., and Kumar, L. (2019). Modeling the climate suitability of tea [Camellia sinensis (L.) O. Kuntze] in Sri Lanka in response to current and future climate change scenarios. *Agric. For. Meteorol.* 272, 102–117. doi: 10.1016/j.agrformet.2019.03.025

Klutse, N. A. B., Abiodun, B. J., Hewitson, B. C., Gutowski, W. J., and Tadross, M. A. (2016). Evaluation of two GCMs in simulating rainfall inter-annual variability over Southern Africa. *Theor. Appl. Clim.* 123, 415–436. doi: 10.1007/s00704-014-1356-z

Kogo, B. K., Kumar, L., Koech, R., and Kariyawasam, C. S. (2019). Modelling climate suitability for rainfed Maize cultivation in Kenya using a Maximum Entropy (MaxENT) approach. *Agronomy* 9, 727. doi: 10.3390/agronomy9110727

Krell, N., Morgan, B., Gower, D., and Caylor, K. (2021). Consequences of dryland maize planting decisions under increased seasonal rainfall variability. *Water Resour. Res.* 57, e2020WR029362. doi: 10.1029/2020WR029362

Kusangaya, S., Mazvimavi, D., Shekede, M. D., Masunga, B., Kunedzimwe, F., and Manatsa, D. (2021). "Climate change impact on hydrological regimes and extreme events in southern Africa," in *Climate Change and Water Resources in Africa*, eds S. Diop, P. Scheren, and A. Niang (Cham: Springer), 87–129. doi: 10.1007/978-3-030-61225-2_5

Lange, S., Menz, C., Gleixner, S., Cucchi, M., Weedon, G. P., Amici, A., et al. (2021). *WFDE5 Over Land Merged With ERA5 Over the Ocean (W5E5 v2.0)*. ISIMIP Repository. doi: 10.48364/ISIMIP.342217

Laudien, R., Schauberger, B., Gleixner, S., and Gornott, C. (2020). Assessment of weather-yield relations of starchy maize at different scales in Peru to support the NDC implementation. *Agric. For. Meteorol.* 295, 108154. doi: 10.1016/j.agrformet.2020.108154

Legwaila, G., Marokane, T., and Mojeremane, W. (2012). Effects of intercropping on the performance of maize and cowpeas in Botswana. *Int. J. Agric. For.* 2, 307–310. doi: 10.5923/j.ijaf.20120206.07

Lesk, C., Rowhani, P., and Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature* 529, 84–87. doi: 10.1038/nature16467

Liu, N., Du, Y., Warburton, M. L., Xiao, Y., and Yan, J. (2021). Phenotypic plasticity contributes to maize adaptation and heterosis. *Mol. Biol. Evol.* 38, 1262–1275. doi: 10.1093/molbev/msaa283

Lobell, D. B., Bänziger, M., Magorokosho, C., and Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nat. Clim. Change* 1, 42–45. doi: 10.1038/nclimate1043

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., et al. (2014). Greater sensitivity to drought accompanies maize yield increase in the US Midwest. *Science* 344, 516–519. doi: 10.1126/science.1251423

Lobell, D. B., Sibley, A., and Ortiz-Monasterio, J. I. (2012). Extreme heat effects on wheat senescence in India. *Nat. Clim. Change* 2, 186–189. doi: 10.1038/nclimate1356

Lopez-Blanco, J., Pérez-Damián, J. L., Conde-Álvarez, A. C., Gómez-Díaz, J. D., and Monterroso-Rivas, A. I. (2018). Land suitability levels for rainfed maize under current conditions and climate change projections in Mexico. *Outlook Agric.* 47, 181–191. doi: 10.1177/0030727018794973

Lutz, A. F., ter Maat, H. W., Biemans, H., Shrestha, A. B., Wester, P., and Immerzeel, W. W. (2016). Selecting representative climate models for climate change impact studies: an advanced envelope-based selection approach. *International Journal of Climatology* 36, 3988–4005. doi: 10.1002/joc.4608

Mendlik, T., and Gobiet, A. (2016). Selecting climate simulations for impact studies based on multivariate patterns of climate change. *Climatic Change* 135, 381–393. doi: 10.1007/s10584-015-1582-0

Meng, Q., Chen, X., Lobell, D. B., Cui, Z., Zhang, Y., Yang, H., et al. (2016). Growing sensitivity of maize to water scarcity under climate change. *Sci. Rep.* 6, 1–7. doi: 10.1038/srep19605

Merow, C., Smith, M. J., and Silander Jr, J. A. (2013). A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography* 36, 1058–1069. doi: 10.1111/j.1600-0587.2013.07872.x

Mumo, L., Yu, J., Ojara, M., Lukorito, C., and Kerandi, N. (2021). Assessing changes in climate suitability and yields of maize and sorghum crops over Kenya in the twenty-first century. *Theor. Appl. Climatol.* 146, 381–394. doi: 10.1007/s00704-021-03718-6

Muscarella, R., Galante, P. J., Soley-Guardia, M., Boria, R. A., Kass, J. M., Uriarte, M., et al. (2014). ENM eval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. *Methods Ecol. Evol.* 5, 1198–1205. doi: 10.1111/2041-210X.12261

Nabout, J. C., Caetano, J. M., Ferreira, R. B., Teixeira, I. R., and Alves, S.,d.F. (2012). Using correlative, mechanistic and hybrid niche models to predict the productivity and impact of global climate change on maize crop in Brazil. *Nat. Conserv.* 10, 177–183. doi: 10.4322/natcon.2012.034

Nagy, J. (2006). *Maize Production*. Akadémiai Kiadó, Budapest, p. 391.

Nangombe, S., Zhou, T., Zhang, W., Wu, B., Hu, S., Zou, L., et al. (2018). Record-breaking climate extremes in Africa under stabilized 1.5 C and 2 C global warming scenarios. *Nat. Clim. Change* 8, 375–380. doi: 10.1038/s41558-018-0145-6

Nangombe, S. S., Zhou, T., Zhang, W., Zou, L., and Li, D. (2019). High-temperature extreme events over Africa under 1.5 and 2 C of global warming. *J. Geophys. Res. Atmos.* 124, 4413–4428. doi: 10.1029/2018JD029747

Nuss, E. T., and Tanumihardjo, S. A. (2010). Maize: a paramount staple crop in the context of global nutrition. *Compr. Rev. Food Sci. Food Saf.* 9, 417–436. doi: 10.1111/j.1541-4337.2010.00117.x

Ojara, M. A., Yunsheng, L., Ongoma, V., Mumo, L., Akodi, D., Ayugi, B., et al. (2021). Projected changes in East African climate and its impacts on climatic suitability of maize production areas by the mid-twenty-first century. *Environ. Monit. Assess.* 193, 1–24. doi: 10.1007/s10661-021-09547-4

Omoyo, N. N., Wakhungu, J., and Oteng'i, S. (2015). Effects of climate variability on maize yield in the arid and semi arid lands of lower eastern Kenya. *Agric. Food Sec.* 4, 1–13. doi: 10.1186/s40066-015-0028-2

Ongoma, V., Chen, H., and Gao, C. (2019). Evaluation of CMIP5 twentieth century rainfall simulation over the equatorial East Africa. *Theor. Appl. Climatol.* 135, 893–910. doi: 10.1007/s00704-018-2392-x

Phillips, S. J., Anderson, R. P., and Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecol. Model.* 190, 231–259. doi: 10.1016/j.ecolmodel.2005.03.026

Phillips, S. J., and Dudík, M. (2008). Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography* 31, 161–175. doi: 10.1111/j.0906-7590.2008.5203.x

Ramirez-Cabral, N. Y. Z., Kumar, L., and Taylor, S. (2016). Crop niche modeling projects major shifts in common bean growing areas. *Agric. For. Meteorol.* 218, 102–113. doi: 10.1016/j.agrformet.2015.12.002

Ramirez-Villegas, J., Jarvis, A., and Läderach, P. (2013). Empirical approaches for assessing impacts of climate change on agriculture: the EcoCrop model and a case study with grain sorghum. *Agric. For. Meteorol.* 170, 67–78. doi: 10.1016/j.agrformet.2011.09.005

Rao, N. D., Sauer, P., Gidden, M., and Riahi, K. (2019). Income inequality projections for the shared socioeconomic pathways (SSPs). *Futures* 105, 27–39. doi: 10.1016/j.futures.2018.07.001

Ray, D. K., Gerber, J. S., MacDonald, G. K., and West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nat. Commun.* 6, 5989. doi: 10.1038/ncomms6989

Rivas, M. A. I., Conde Álvarez, C., Rosales Dorantes, G., Gómez Díaz, J. D., and Gay García, C. (2011). Assessing current and potential rainfed maize suitability under climate change scenarios in México. *Atmósfera* 24, 53–67.

Sánchez, B., Rasmussen, A., and Porter, J. R. (2014). Temperatures and the growth and development of maize and rice: a review. *Glob. Change Biol.* 20, 408–417. doi: 10.1111/gcb.12389

Shiferaw, B., Prasanna, B. M., Hellin, J., and Bänziger, M. (2011). Crops that feed the world 6. Past successes and future challenges to the role played by maize in global food security. *Food Secur.* 3, 307–327. doi: 10.1007/s12571-011-0140-5

Silva, J. V., and Giller, K. E. (2020). Grand challenges for the 21st century: what crop models can and can't (yet) do. *J. Agric. Sci.* 158, 794–805. doi: 10.1017/S0021859621000150

Song, L., Jin, J., and He, J. (2019). Effects of severe water stress on maize growth processes in the field. *Sustainability* 11, 5086. doi: 10.3390/su11185086

Stephenson, D. B., Diaz, H., and Murnane, R. (2008). Definition, diagnosis, and origin of extreme weather and climate events. *Clim. Extremes Soc.* 340, 11–23. doi: 10.1017/CBO9780511535840.004

Stokland, J. N., Halvorsen, R., and Støa, B. (2011). Species distribution modelling—Effect of design and sample size of pseudo-absence observations. *Ecol. Model.* 222, 1800–1809. doi: 10.1016/j.ecolmodel.2011.02.025

Taba-Morales, G., Hyman, G., Mejía, J. R., Castro-Llanos, F., Beebe, S., Rubyogo, J. C., et al. (2020). Improving African bean productivity in a changing global environment. *Mitig. Adap. Strateg. Glob. Change* 25, 1013–1029. doi: 10.1007/s11027-019-09910-4

Tebaldi, C., and Wehner, M. F. (2018). Benefits of mitigation for future heat extremes under RCP4. 5 compared to RCP8. 5. *Clim. Change* 146, 349–361. doi: 10.1007/s10584-016-1605-5

Travis, W. R. (2016). Agricultural impacts: Mapping future crop geographies. *Nat. Clim. Change* 6, 544. doi: 10.1038/nclimate2965

Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., et al. (2019). The effects of climate extremes on global agricultural yields. *Environ. Res. Lett.* 14, 054010. doi: 10.1088/1748-9326/ab154b

Warren, D. L., and Seifert, S. N. (2011). Ecological niche modeling in Maxent: the importance of model complexity and the performance of model selection criteria. *Ecol. Appl.* 21, 335–342. doi: 10.1890/10-1171.1

Yang, X., Sun, J., Gao, J., Qiao, S., Zhang, B., Bao, H., et al. (2021). Effects of climate change on cultivation patterns and climate suitability of spring maize in Inner Mongolia. *Sustainability* 13, 8072. doi: 10.3390/su13148072

Zhang, Z., Hua, Q., Zhang, Y., Sun, S., and Yang, G. (2009). Effects of water stress on photosynthetic rate and water use efficiency of maize. *Acta Agric. Boreali. Sin.* 24, 155–158. doi: 10.7668/hbnxb.2009.S1.037

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proc. Natl. Acad. Sci.* 114, 9326–9331. doi: 10.1073/pnas.1701762114

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.