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Key Points:

- Maize yield would decrease more under 2.0 than 1.5°C warming scenario
- Under a reasonable logarithmic technology development scenario, maize security would become worse in most of the countries in Africa
- Technology development and adaptation strategies are essential to meet the challenges of food security in the vulnerable regions

Supporting Information:

- Supporting Information S1

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Africa Would Need to Import More Maize in the Future Even Under 1.5°C Warming Scenario

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Abstract Producing enough food to feed a growing population is a great future challenge, especially for vulnerable areas in Africa. There is limited understanding of food security under future climate conditions, particularly under the warming target stipulated in the Paris Agreement. Maize is the most widely cultivated crop in Africa. Taking maize as an example, we present an integrated assessment of maize supply and demand under 1.5°C and 2.0°C warming scenarios, considering the combined impacts of climate change, technology development and population increase. We find that global warming of 1.5°C or 2.0°C would shorten maize growth duration, aggravate droughts, and consequently reduce yield with a spatially explicit pattern. Maize yield would decrease more under global warming of 2.0°C versus 1.5°C. Benefit of rising CO_2 concentration could not fully offset the yield loss due to climate change under global warming of 1.5°C. Technology development can significantly improve the ratio of maize supply to demand, which is however subject to future projections on population and technology development. Under a reasonable logarithmic technology development scenario, maize security would become worse in most of the countries in Africa. Our findings highlight the importance of technology development and adaptation strategies to meet the challenges of food security in the vulnerable regions.

1. Introduction

Ensuring food security is one of the greatest challenges facing the world community (Beddington et al., 2012), particularly in low-income and food-deficit regions such as Africa (Nuss & Tanumihardjo, 2010; Tefera, 2012). Global climate change may have a major impact on the spatial-temporal patterns of temperature and precipitation, and subsequently pose challenges or opportunities for agricultural production and food security over the world (Lobell et al., 2011; Tao et al., 2014). Different methods including field experiments (Cai et al., 2018), statistical analyses based on long-term historical data (Lobell & Field, 2007), and crop model simulations (Falconnier et al., 2020; Rosenzweig et al., 2014), have been applied to investigate the impacts of climate change on various crops at various spatial scales. However, previous studies have mainly focused on the impacts of climate change and extreme climate events on crop yield (Asseng et al., 2015; Y. Chen et al., 2018; Deryng et al., 2014; Liu et al., 2019). The balance between food supply and demand or food security has rarely been investigated (Tao et al., 2009; van Ittersum et al., 2016). Furthermore, climate impact assessments have only considered a limited range of potential agricultural technology development (Rippke et al., 2016). Impacts of climate change and extreme climate events on food security will have important implications for food trade, food price, hunger, poverty, and food policy (Schmidhuber & Tubiello, 2007). It is essential to have an integrated assessment of future food security taking into account climate change, technology and socio-economic developments (Tao et al., 2009).

The Paris Agreement set a long-term target of holding the global average temperature increase well below 2.0°C and make efforts to limit the global average temperature increase less than 1.5°C above pre-industrial levels (Schleussner et al., 2016). This calls for more efforts to investigate the responses of agricultural production and food security under 1.5°C and 2.0°C warming scenarios, especially for the vulnerable areas such as Africa (Müller et al., 2011). Although a few studies have investigated crop response to the global warming target of Paris Agreement in several countries in Africa (e.g., Faye et al., 2018), a key question is whether Africa can feed itself under 1.5°C and 2.0°C warming scenarios in the future.

Maize (*Zea mays*) is the most widely cultivated crop in Africa relative to other cereal crops and is therefore important regarding future food security (Nuss & Tanumihardjo, 2010). In Africa, maize is mostly grown in small-holder farming systems under rainfed conditions with low input and poor technology (Falconnier et al., 2020). Therefore, maize yields in Africa, especially in Sub-Saharan Africa, are much lower than those in the top five maize producing countries in the world, including USA, China, Brazil, Mexico, and Indonesia (Cairns et al., 2013). Among other things, future maize security will be subject to the integrated impacts of climate change, atmospheric CO_2 concentration, technology development, and population change. Elevated CO_2 directly increases photosynthesis and benefits C_3 plants such as wheat and rice by improving the carboxylation rate of Rubisco (Ainsworth & Long, 2005). Unlike C_3 crops, elevated CO_2 has limited effect on C_4 plants such as maize (Berg et al., 2013; Parkes et al., 2018), because photosynthesis is saturated at current CO_2 concentrations for C_4 plants (Hussain et al., 2013). Nevertheless, maize could benefit from elevated CO_2 concentration which will cause partial closure of stomata and reduce evapotranspiration (Cairns et al., 2013). The beneficial effects could be spatially and temporally different depending on soil moisture and crop growth conditions (Deryng et al., 2016).

In this study, taking maize as an example, for the first time, we present a comprehensive analysis on the impacts of global warming of 1.5°C and 2.0°C on the balance between maize supply and demand in Africa. We aim to (1) investigate the projected changes in key climate variables, maize growth duration, droughts, and yield at a 0.5° resolution grid scale across Africa; (2) investigate the balance between maize supply and demand with different technology developments and national population projections under the global warming of 1.5°C and 2.0°C relative to the pre-industrial condition.

2. Materials and Methods

2.1. Maize Production in Africa

Maize (*Zea mays*) is a major crop in terms of production and cultivated area in Africa. Harvest area for rainfed and irrigated maize is about 26.7 and 1.2 million hectares, respectively, in Africa according to the Spatial Production Allocation Model (SPAM) 2005 (IFPRI, 2016). Maize usually has low inputs and rainfed maize is highly dependent on rainfall, therefore maize production in Africa is vulnerable to climate change/variability (Cairns et al., 2013; Shi & Tao, 2014). Rainfed maize is mainly cultivated in Western Africa, Eastern Africa, and the east part of Southern Africa (Figure S1a), while irrigated maize is mainly cultivated in the above-mentioned areas, as well as Egypt (Figure S1b).

2.2. Model Description

Maize growth and yield are simulated at a 0.5° resolution for Africa using the Crop Estimation through Resources and Environmental Synthesis maize (CERES-Maize) model in the version 4.6 of the Decision Support System for Agrotechnology Transfer (DSSAT) (J. W. Jones et al., 2003), through the parallel System for Integrating Impact Models and Sectors (pSIMS) (Elliott et al., 2014). DSSAT is a process-based model which has been used to simulate soil and crop processes for various crops in a number of studies over the world (Faye et al., 2018; P. G. Jones & Thornton, 2003; Palosuo et al., 2011; Rötter et al., 2012; Tubiello et al., 2002). However, DSSAT has been used widely at sites instead of grids at a large scale. The pSIMS is designed to support high-resolution application of any site-based climate impact model that can be compiled in a Unix environment, currently including DSSAT and Agricultural Production Systems Simulator (APSIM, Keating et al., 2003). This system could substantially decrease the labor-intensive data converting processes, and allows researchers to use high-performance computing to run substantial simulations simultaneously on clusters. Parallel DSSAT (pDSSAT) implemented in the pSIMS has been successfully applied in several recent studies (Elliott et al., 2018; M. Glotter & Elliott, 2017; M. J. Glotter et al., 2016; Schiferl et al., 2018).

2.3. pDSSAT Model Calibration

The pDSSAT model is calibrated using observed data obtained from Food and Agriculture Organization of the United Nations (FAO) during a period from 1980 to 2010 after removing a linear trend which represents drivers of yield change not associated with changes in weather, such as technology development, while preserving mean yield in each country. We simulate rainfed maize and irrigated maize separately from 1980 to 2010 in each 0.5 × 0.5° grid, therefore total yield in each grid x is calculated through the following formulation,

$$\mathrm{Yield}_x = \frac{\left(A_x^{\mathrm{rf}} \cdot Y_x^{\mathrm{rf}} + A_x^{\mathrm{ir}} \cdot Y_x^{\mathrm{ir}}\right)}{\left(A_x^{\mathrm{rf}} + A_x^{\mathrm{ir}}\right)}, \quad (1)$$

Y_x^{rf} and Y_x^{ir} represent rainfed yield (kg/ha) and irrigated yield (kg/ha) in grid x. A_x^{rf} and A_x^{ir} represent rainfed area (ha) and irrigated area (ha) in grid x from the SPAM 2005 data set. A_x^{rf} and A_x^{ir} are assumed to remain unchanged in this research. In some grids where the harvest date is around 31 December, there is a probability that double harvests happen in a year and no harvest happens in the following year. Thus, adjustments are made in these grids to make sure each year has one harvest. We calculate the harvest dates from 1980 to 2010 according to the output of the pDSSAT model at grid scale. If harvest happened more frequently in the year of sowing, maize is assumed to be harvested in the year of sowing for the whole calibration period, otherwise, it is assumed to be harvested in the following year of sowing for the whole calibration period. This adjustment ensures that each year has only one harvest for maize. We use the AgMERRA climate forcing data set (Ruane et al., 2015) at a 0.5° resolution to drive the pDSSAT model. This data set is constructed by the Modern-Era Retrospective Analysis for Research and Applications (MERRA) data and several other data sets including global gridded observational data sets provided by the Climate Research Unit TS 3.1, the University of Delaware, and the Global Precipitation Climatology Centre Full Data Product version 6. The AgMERRA climate forcing data set provides daily high-resolution data for evaluating the agricultural impacts of climate variability and climate change (Ruane et al., 2015). The climate variables required for driving pDSSAT include daily maximum temperature (°C), daily minimum temperature (°C), daily average downward shortwave radiation flux (W/m^2), and daily precipitation (mm). Agronomic management practices are fixed to isolate the impact of climate change on maize growth, so temporally homogeneous (but spatially heterogeneous) cultivar parameters, planting windows, and fertilizer applications are assumed (M. J. Glotter et al., 2016). Fertilizer data and growing season data are obtained from Global Gridded Crop Model Intercomparison (GGCMI) data for Phase 1 (Elliott et al., 2015). Each grid cell's growing season aims to represent the practice of the majority of farming system even though many regions include a wide diversity in sowing dates. Monthly CO_2 concentration for historical period (1980–2010) is from the reference data in the DSSAT model. Soil data used in this study are from gridded Global Soil Dataset for use in Earth System Models (GSDE) (Shangguan et al., 2014). Model parameter calibration is conducted at country level. Cultivars' potential kernel number and soil fertility factor are calibrated to make the bias in percentage (i.e., PBIAS) between the simulated yield and observed yield less than |20|% in each country. The uncalibrated model overestimated yields significantly because the cultivars are generally poor and have open pollination in Africa. In some grids, maize is harvested in the next year after sowing, so PBIAS is calculated from 1981 to 2009. PBIAS is calculated using the following formulation,

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n} x_{\mathrm{sim},i} - \sum_{i=1}^{n} x_{\mathrm{obs},i}}{\sum_{i=1}^{n} x_{\mathrm{obs},i}} \times 100\%, \quad (2)$$

where $x_{\mathrm{sim},i}$, $x_{\mathrm{obs},i}$ represent simulated yield (kg/ha) and observed yield (kg/ha) in year i respectively, n represents the total number of years used for calibration.

2.4. Global Circulation Model (GCM) Simulations

Simulations for baseline scenario (2006–2015) and future 1.5 and 2.0°C warming scenarios (2106–2115), relative to pre-industrial period, are forced by climate input data from the "Half a degree Additional warming, Prognosis and Projected Impacts" (HAPPI) project (Mitchell et al., 2017). There are four GCMs (ECHAM6-3-LR, MIROC5, NorESM1-HAPPI, CAM4-2 degree) and 20 ensembles in each GCM after bias-correction through the method described in the Inter-Sectoral Impact Model Inter-comparison Project 2b (ISIMIP2b, Frieler et al., 2017). Large ensembles of GCM simulations aim to reduce the uncertainties in climate change impact assessment, but it is challenging to run all the ensembles because of high computation cost. The Katsavounidis-Kuo-Zhang (KKZ) method is designed to solve this problem for covering the ensembles' range of change in variables as much as possible (Cannon, 2015; J. Chen et al., 2016; Wang et al., 2018). Five representative ensembles are selected for each of the four GCMs through KKZ method in this study. The input data for the KKZ method include four variables: daily maximum temperature (Tmax;°C), daily minimum temperature (Tmin;°C), daily average downward shortwave radiation flux (Rsds; W/m^2), daily precipitation (Pr; mm). Since daily maximum temperature has strong correlation with daily minimum temperature, maximum and minimum temperatures are combined to select the representative ensembles. First, changes in precipitation (ΔPr/Pr), temperature (ΔTmax+ΔTmin) and downward shortwave radiation flux (ΔRsds/Rsds) are calculated for each ensemble under 1.5°C and 2.0°C warming scenarios, relative to the baseline period. Then, the changes are standardized to zero mean and unit standard deviation for selection of the representative ensembles under 1.5°C and 2.0°C warming scenarios, respectively. The procedure of the KKZ method is as follows. In a certain GCM, the first representative ensemble is the ensemble closest to the centroid of all ensembles, and the second representative ensemble is the ensemble farthest to the first ensemble. The next three ensembles are selected according to their distances to the previously selected representative ensembles. The nearest distance of every remaining ensemble to the previously selected ensembles is calculated, and the ensemble with the largest calculated distance is selected as the next representative ensemble.

2.5. Simulation Protocol

We run the simulations for irrigated and rainfed maize at grid scale with and without taking CO_2 effect into account, respectively. We have two simulation settings for each ensemble under baseline period (2006–2015) and four simulation settings for each ensemble under 1.5°C and 2.0°C warming scenarios, respectively. They include rainfed and irrigated maize with CO_2 effect in the baseline period (2006–2015), and rainfed and irrigated maize with and without CO_2 effect in the future (2106–2115). The simulations with and without CO_2 effect aim to disentangle the impacts of elevated CO_2 on yield change. For simulating rainfed and irrigated maize growth with CO_2 effect, CO_2 concentration is set to be 390, 423, and 487 ppm for baseline period (2006–2015), 1.5°C and 2.0°C warming scenarios (2106–2115), respectively (Ruane et al., 2018). For simulating rainfed and irrigated maize growth without CO_2 effect under 1.5°C and 2.0°C warming scenarios, CO_2 concentration is set to be 390 ppm which is the same as CO_2 concentration for the baseline period. The average yield for each grid is calculated according to Equation 1. Except climate forcing data and CO_2 concentration, all other input data under baseline, 1.5°C and 2.0°C warming scenarios are fixed as in the calibration period for each grid.

2.6. Estimating Maize Yield Accounting for the Impacts of Future Technology Development

Agronomic management practices such as cultivars, irrigation and fertilization are assumed to be constant in the simulations, so the differences between simulated yields in 2106–2115 and 2006–2015 are ascribed to climate change. In fact, the development of technology will lead to yield increase to some extent in the future (Huang et al., 2002; Müller et al., 2011; Tao et al., 2009). Thus, we analyze maize security in Africa with and without taking into account the impacts of technology development on maize yield. We define the yield trend due to technology development by linear fitting (Equation 3) and logarithmic fitting (Equation 4) of the observed yields at country level from 1961 to 2017 with time (years, Table S1), and assume these trends would continue until 2115 under 1.5°C and 2.0°C warming scenarios. The fitting starts from 1961.

$$y = ax + b \tag{3}$$

$$y = a\ln(x) + b \tag{4}$$

Then, mean yields for 1980–2010 ($\bar{y}_{1980-2010}$), 2006–2015 ($\bar{y}_{2006\text{-}2015}$), and 2106–2115 ($\bar{y}_{2106\text{-}2115}$) in each country are calculated for the linear and logarithmic trend assumptions using the Equations 3 and 4, respectively. The period of 1980–2010 is included because model parameters are calibrated using this period. The difference ($m_{2006-2015}$) between $\bar{y}_{2006-2015}$ and $\bar{y}_{1980-2010}$, and the difference ($m_{2106-2115}$) between $\bar{y}_{2106-2115}$ and $\bar{y}_{1980-2010}$ are used to represent the impacts of technology development on maize yield between the two time periods in each country. In each country, the simulated yields in 2006–2015 plus $m_{2006-2015}$ are used to represent the yields including the contribution of technology development in 2006–2015, for each ensemble in the four GCMs. Likewise, the simulated yields under 1.5°C and 2.0°C warming scenarios in 2106–2115 plus $m_{2106-2115}$ are used to represent the yields accounting for technology development in 2106–2115. Projected yields without accounting for technology development, represented by the pDSSAT simulated yields under 1.5°C and 2.0°C warming scenarios (2106–2115), are also used to analyze maize security in Africa for comparison. Then, the median mean yields among all the ensembles in the four GCMs under baseline period, 1.5°C and 2.0°C warming scenarios in 2106–2115 are used to represent the projected yields accounting for technology development in a linear trend, logarithmic trend, and remaining unchanged. In this study, total maize production at country level is estimated by calculating area-weighted production using the projected yields and planting areas from SPAM 2005. And the planting areas are kept constant under the baseline period, 1.5°C and 2.0°C warming scenarios.

2.7. Statistical Analyses on Climate Change, Climate Change Impacts, and Maize Supply and Demand

Changes in mean of daily maximum temperature (°C), daily minimum temperature (°C), daily precipitation (%), and daily downward shortwave radiation flux (%) in each grid are calculated for each ensemble over 2106–2115 under 1.5°C and 2.0°C warming scenarios, respectively, relative to the baseline period (2006–2015). Because maize would be harvested in the next year after sowing in some grids, maize growth duration, drought stress, and yield in the first nine growing seasons are analyzed in each grid during each simulation period. Changes in maize growth duration (%), drought stress, and yield (%) in each grid are calculated for each ensemble in the nine growing seasons under 1.5°C and 2.0°C warming scenarios, relative to the baseline period. Median changes among all ensembles for a GCM and for the four GCMs are used to represent the changes in every variable. Maize demand for food consumption is assumed to be the same as the mean value from 2006 to 2013 obtained from the FAO food balance sheet in each country per capita per year under baseline, 1.5°C and 2.0°C warming scenarios. The total amount of annual maize consumption for food is the product of maize consumption per capita per year and the total number of population. Maize demand except for food consumption including feed, seed, and losses, processed and other uses is assumed to account for the same proportion to food consumption from 2006 to 2013 under baseline period, 1.5°C and 2.0°C warming scenarios. The mean population number between 2006 and 2013 obtained from FAO food balance sheet is used to represent the population number under baseline period for countries across Africa. The population number obtained from Shared Socioeconomic Pathway 1 (SSP1) and Pathway 2 (SSP2) population projections (Lutz et al., 2018) in 2100 is used to represent the population number under 1.5°C and 2.0°C warming scenarios in each country. Eritrea was separated from Ethiopia in 1993, and South Sudan gained independence from Sudan in 2011. In this study, when the pDSSAT model parameters are calibrated at country level from 1980 to 2010, the average yield of Ethiopia and Eritrea is estimated by calculating area-weighted average of yield after 1993. In investigating maize demand of Africa, only Ethiopia (except Eritrea), Sudan and South Sudan are considered, so available data for Ethiopia (2006–2013) and Sudan (former) (2006–2011) are used. Linear fitting and logarithmic fitting are done using the yield data of People's Democratic Republic of Ethiopia from 1961 to 1992 and that of Ethiopia from 1993 to 2017 for Ethiopia (except Eritrea). For Sudan and South Sudan as a whole, yield data of Sudan (former) from 1961 to 2011 and that of Sudan from 2012 to 2017 are used.

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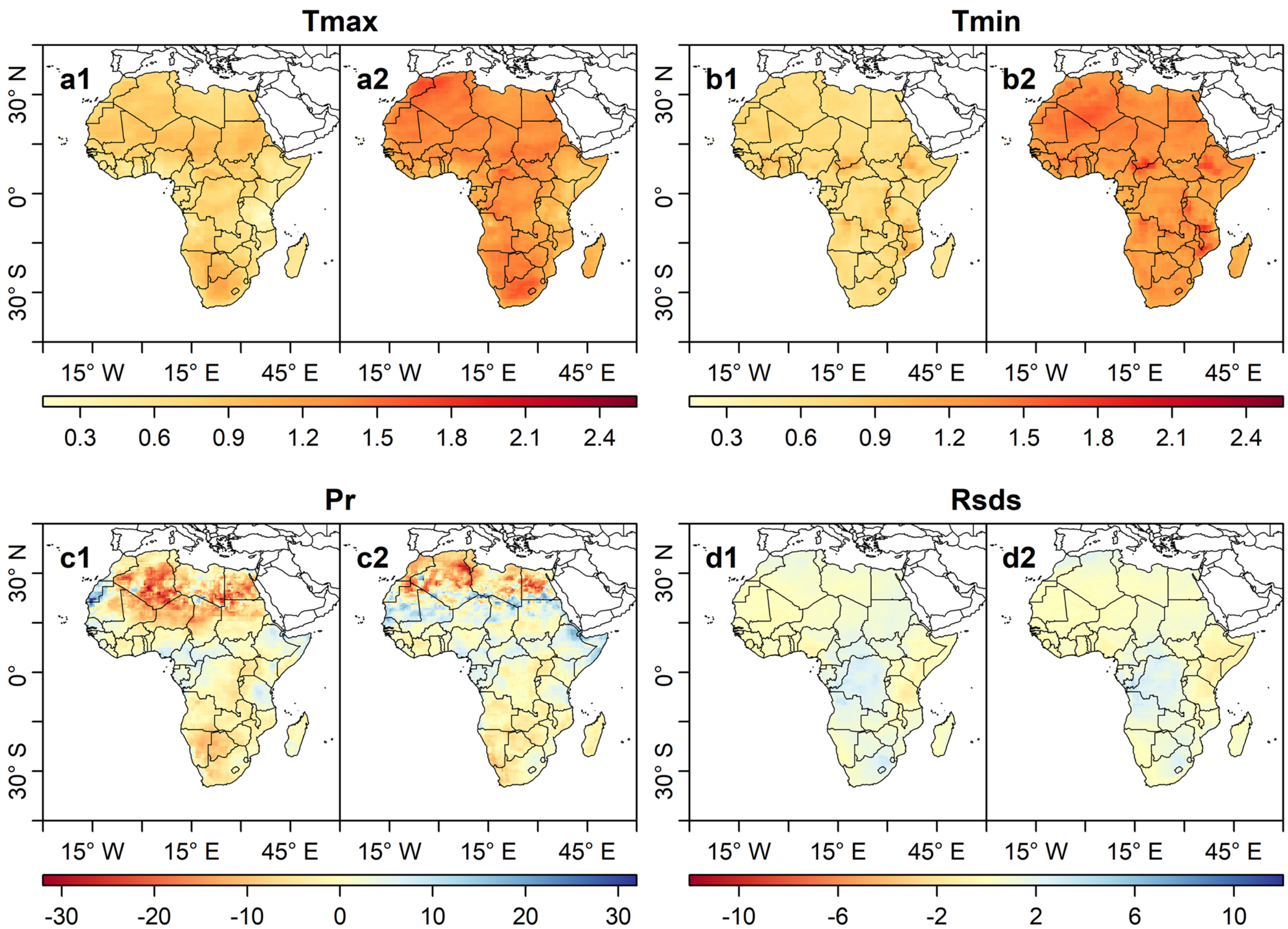

Figure 1. Predicted changes in critical climate variables. Projected median changes in daily maximum temperature (Tmax, °C, a1 and a2), minimum temperature (Tmin, °C, b1 and b2), precipitation (Pr, %, c1 and c2), downward shortwave radiation flux (Rsds, %, d1 and d2), under 1.5 (a1, b1, c1, and d1) and 2.0°C (a2, b2, c2, and d2) warming scenarios (2106–2115), relative to the baseline period (2006–2015), respectively, across all 20 ensembles (4 GCMs × 5 ensembles) in each scenario.

3. Results

3.1. Projected Changes in Climate, Maize Growth and Productivity under 1.5°C and 2.0°C Warming Scenarios

The pDSSAT model is calibrated at country level against de-trended yearly maize yields from FAO during 1980 to 2010 (Figure S2). The PBIAS between the simulated and observed yields are within 20% (±) in different countries. Then, the calibrated model is forced by 20 representative ensemble projections of future climate change from four GCMs including ECHAM6-3-LR, MIROC5, NorESM1-HAPPI, and CAM4-2 degree to simulate rainfed maize and irrigated maize growth and yield, respectively, at a spatial resolution of 0.5°.

The projected median changes in critical climate variables including daily maximum temperature, minimum temperature, precipitation, and downward shortwave radiation flux are investigated (Figures 1, S3–S6). Among all the ensembles from the four GCMs, at grid scale, the 5th to 95th percentiles of median changes range from 0.5°C to 1.0°C (0.9°C–1.5°C) for daily maximum temperature (Figures 1a1 and 1a2) and from 0.6°C to 0.9°C (1.1°C–1.5°C) for daily minimum temperature (Figures 1b1 and 1b2), under 1.5°C (2.0°C) warming scenarios. Among all the ensembles from the four GCMs, at grid scale, median changes in precipitation are projected to decrease by up to ~37% in about 68% of areas across Africa under 1.5°C warming scenario, especially in the Northern Africa and the Southern Africa (Figure 1c1). And they are projected to decrease by up to ~29% in about 48% of areas under 2.0°C warming scenario (Figure 1c2). The

5th to 95th percentiles of median changes in daily precipitation range from −16% to 6% (−12% to 10%) under 1.5°C (2.0°C) warming scenario (Figures 1c1 and 1c2). Downward shortwave radiation flux is projected to change little under 1.5°C and 2.0°C warming scenarios with similar spatial patterns (Figures 1d1 and 1d2). It is projected to increase slightly in the Central Africa and Southern Africa, but decrease slightly in the Eastern Africa.

Taking CO_2 effect into account, an increase in temperature would shorten maize growth duration ubiquitously across Africa (Figures 2a–2e), because warming would accelerate crop development rate (Zhao et al., 2017). Growth duration is projected to reduce more significantly for rainfed maize in South Africa and Ethiopia under 1.5°C warming scenario (Figures 2a1, 2b1, 2c1, 2d1, and 2e1). Under 2.0°C warming scenario, the areas with growth duration decrease are projected to extend to the Southern Africa and Eastern Africa (Figures 2a2, 2b2, 2c2, 2d2, and 2e2). The case is also true for irrigated maize (Figure S7). Growth duration is projected to decrease significantly in South Africa under 1.5°C and 2.0°C warming scenarios for irrigated maize. Among all the ensembles from the four GCMs, the fifth percentile and 95th percentile of median changes in growth durations at grid scale range from −6.3% to −2.0% (−9.6% to −3.4%) for rainfed maize, and from −8.5% to −2.2% (−13.2% to −3.7%) for irrigated maize, under 1.5°C (2.0°C) warming scenarios. Under combined impacts of multiple factors, including temperature, precipitation and solar radiation, the drought stress on rainfed maize productivity, represented by the ratio of actual evapotranspiration (AET) to potential evapotranspiration (PET), would aggravate in most areas across Africa under 1.5°C and 2.0°C warming scenarios (Figures 2f–2j), even taking CO_2 effect into account. However, the aggravation would be less significant in the Eastern Africa than other areas. And drought stress would decrease in the United Republic of Tanzania under the two warming scenarios (Figures 2f–2j).

Owing to the shorter growth duration and increased drought stress, maize yields are projected to decrease in most areas across Africa (Figures 3 and S8). Median changes in yields among all the ensembles from each GCM and all the four GCMs have similar spatial patterns. Under 1.5°C warming scenario, yields in the southern Democratic Republic of the Congo, southern Angola, and Western Africa are projected to decrease more significantly than other areas (Figures 3a1, 3b1, 3c1, 3d1, and 3e1). Yields are projected to decrease more, and the spatial heterogeneity of yield change is projected to become more obvious, under 2.0°C than 1.5°C warming (Figure 3). Under 2.0°C warming scenario, yields in the Western Africa, Central Africa and Northern Africa are projected to decrease more than those in other areas (Figures 3a2, 3b2, 3c2, 3d2, and 3e2). Changes in median yields among all the ensembles at grid level ranged from −21.6% (5th percentile) to 3.3% (95th percentile) and from −31.1% (5th percentile) to 2.2% (95th percentile) under 1.5°C and 2.0°C warming scenarios, respectively. The projected climate change impacts on maize yields with (Figures 3a–3e) and without (Figure S8) taking CO_2 effect into account are also investigated. Maize will benefit from elevated CO_2 to some extent, which suggests that elevated CO_2 should offset yield loss due to climate change to some extent. Changes in maize yields at country level are also investigated (Figure 3f). The 16 countries with average maize productions more than 500 thousand tons from 1961 to 2017 are selected for illustration, including Cameroon (CMR), Democratic Republic of the Congo (COD) in the Central Africa, Ethiopia (ETH), Kenya (KEN), United Republic of Tanzania (TZA), Uganda (UGA) in the Eastern Africa, Egypt (EGY) in the Northern Africa, Angola (AGO), Malawi (MWI), Mozambique (MOZ), South Africa (ZAF), Zambia (ZMB), Zimbabwe (ZWE) in the Southern Africa, Benin (BEN), Ghana (GHA), Nigeria (NGA) in the Western Africa. Generally, the changes in maize yield at country level are similar to those at grid level. The differences between the projected changes in maize yields among different countries under 1.5°C warming scenario are less than those under 2.0°C warming scenario (Figure 3f). Maize yields would decrease by less than 15% in all countries under 1.5°C warming scenario with and without CO_2 effect into account, however would decrease by more than 15% in COD, EGY, AGO, MWI, BEN, GHA, and NGA under 2.0°C warming scenario even with CO_2 effect into account. The impacts of different warming scenarios on maize yields would be more significant than those of different CO_2 concentrations.

3.2. Changes in Maize Productivity due to Technology Development

Future technology development for maize production could have large uncertainties in the next 100 years in different countries in Africa. We assume the technology development for maize production would change

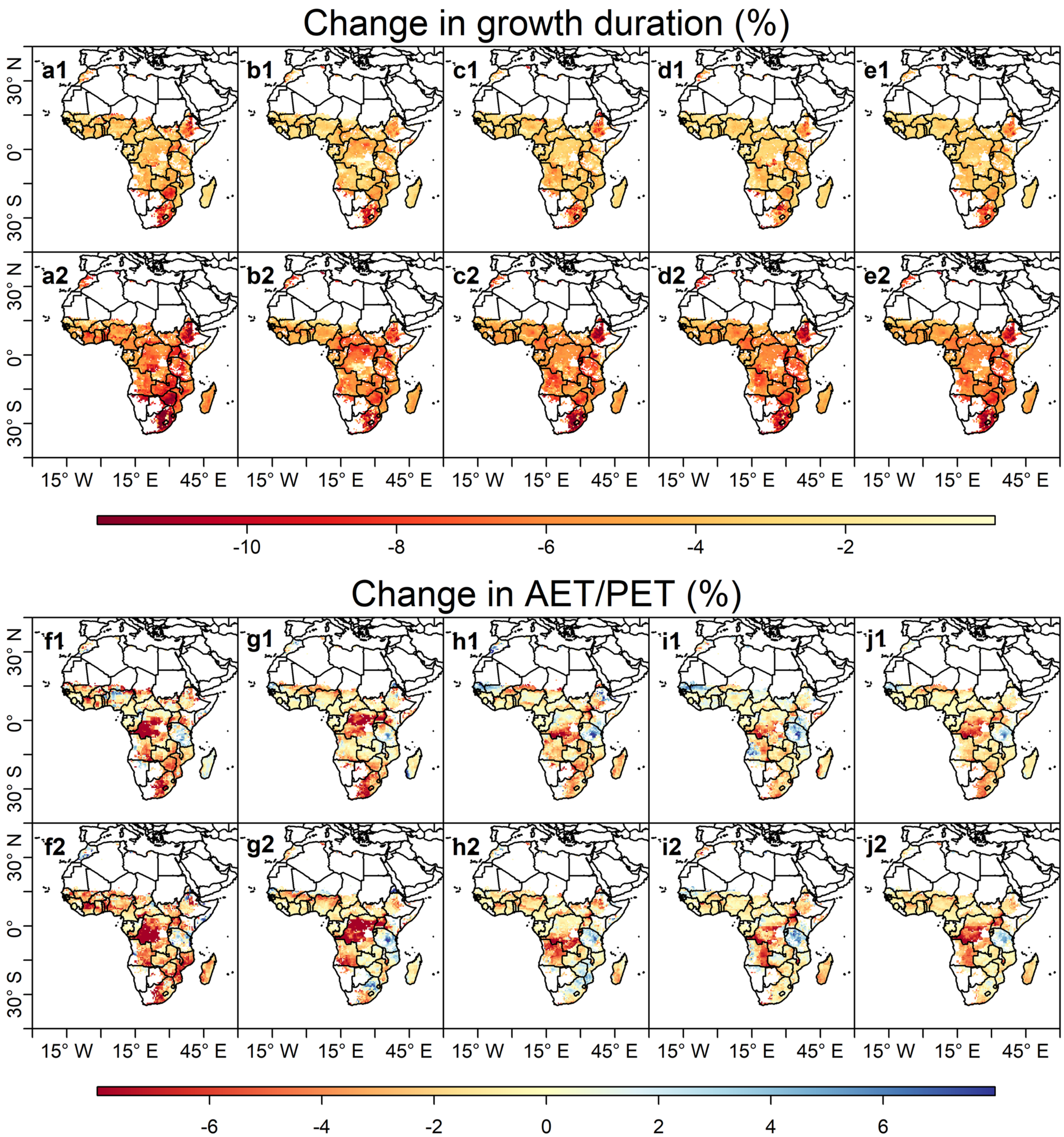

Figure 2. Predicted changes in growth duration (%) and AET/PET (Actual evapotranspiration/Potential evapotranspiration) for rainfed maize, taking CO_2 effect into account. Predicted median change in growth duration (%) for rainfed maize during 2106–2115 under 1.5 (a1–e1) and 2.0°C (a2–e2) warming scenarios by ECHAM6-3-LR (a1 and a2), MIROC5 (b1 and b2), NorESM1-HAPPI (c1 and c2), CAM4-2degree (d1 and d2), and all the four GCMs (e1 and e2), relative to 2006–2015. Predicted median change in AET/PET for rainfed maize during 2106–2115 under 1.5 (f1–j1) and 2.0°C (f2–j2) warming scenarios by ECHAM6-3-LR (f1 and f2), MIROC5 (g1, g2), NorESM1-HAPPI (h1 and h2), CAM4-2degree (i1 and i2), and all the four GCMs (j1 and j2), relative to 2006–2015.

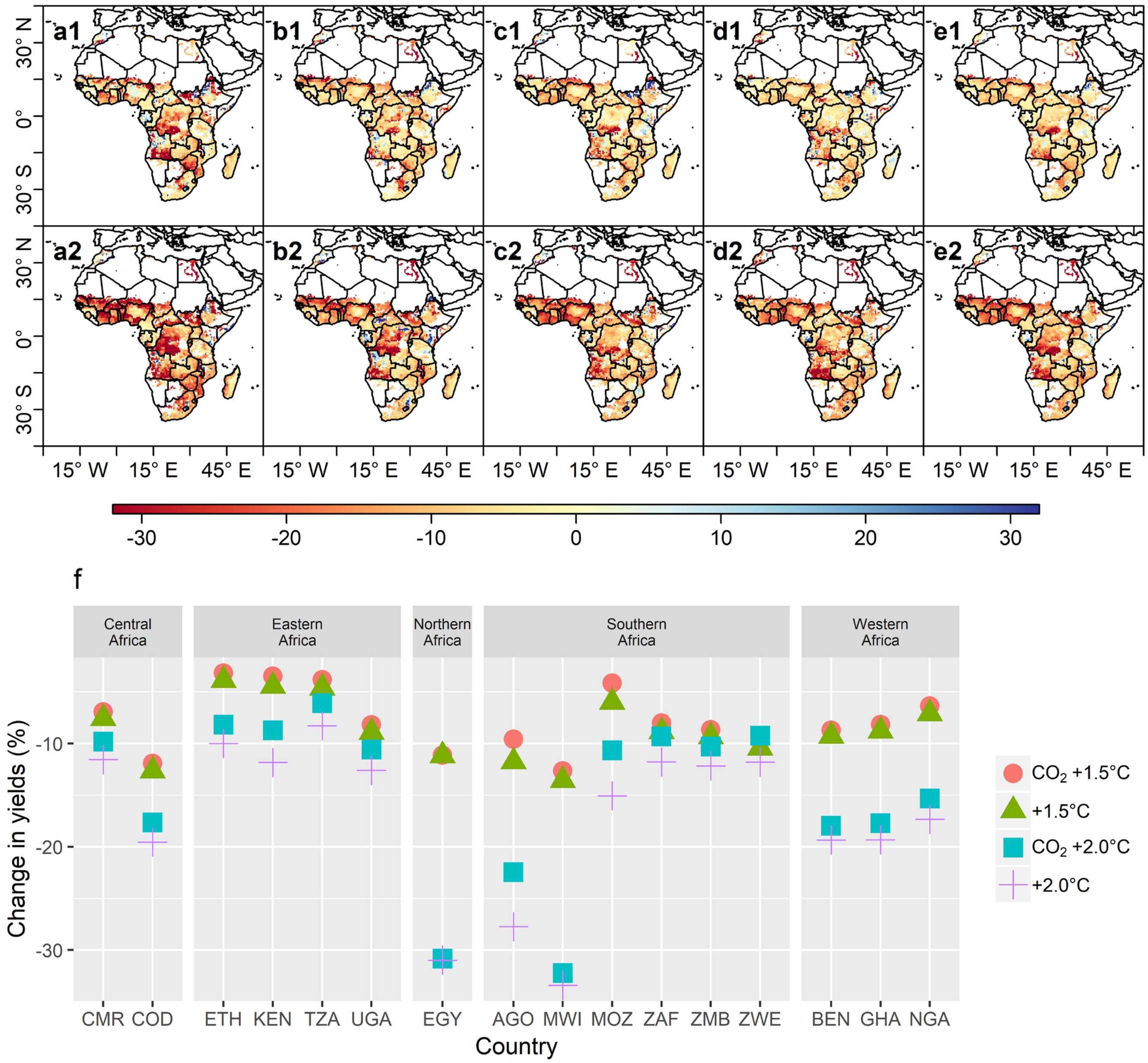

Figure 3. Predicted change in maize yield (%), taking the CO_2 effect into account. Median changes (%) in projected yield for maize during 2106–2115 under 1.5 (a1–e1) and 2.0°C (a2–e2) warming scenarios by ECHAM6-3-LR (a1 and a2), MIROC5 (b1 and b2), NorESM1-HAPPI (c1 and c2), CAM4-2degree (d1 and d2), and all the four GCMs (e1 and e2), relative to 2006–2015. As well as median changes in yields at country level in 16 major maize producing countries (f) under 1.5°C warming scenario with taking CO_2 effect into account (CO_2 +1.5°C), 1.5°C warming scenario without taking CO_2 effect into account (+1.5°C), 2.0°C warming scenario with taking CO_2 effect into account (CO_2 +2.0°C), 2.0°C warming scenario without taking CO_2 effect into account (+2.0°C).

in a linear or a logarithmic trend until 2106, comparing with the technology for maize production during the calibration period (1980–2010) at country scale. Linear fitting and logarithmic fitting of maize yields against time (years) are done in all available Africa countries during 1961–2017, the coefficients of determination (R^2) are larger than 0.2 in 28 countries for linear fitting, and in 24 countries for logarithmic fitting (Table S1). In most countries, R^2 of linear fitting is larger than that of logarithmic fitting (Table S1), which indicates that linear fitting performed better than logarithmic fitting for most Africa countries from 1961 to 2017, but logarithmic fitting could be more reasonable for the trends in the future. The linear fitting curve and logarithmic fitting curve are shown in Figure S9 for every country in each part of Africa from 1961 to 2017.

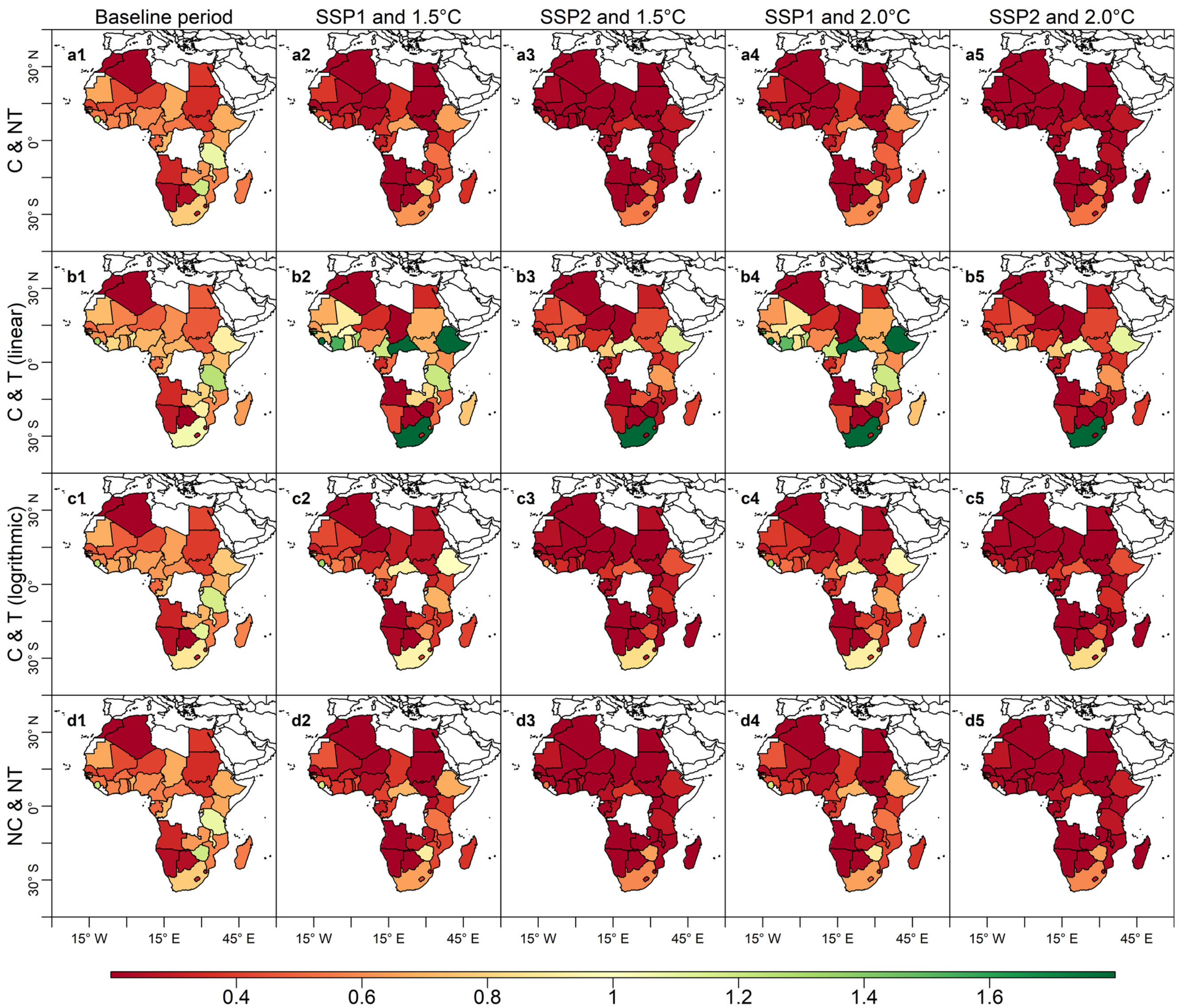

Figure 4. Predicted R_{msd} at country level in Africa. R_{msd} under constant (a1–a5, C & NT), linear (b1–b5, C & T [linear]) and logarithmic (c1–c5, C & T [logarithmic]) technology development with climate change, and without technology development and climate change (d1–d5, NC & NT), is presented. Panels (a1, b1, c1, and d1) represent the ratio under baseline period, (a2, b2, c2, and d2) represent the ratio under 1.5°C warming and SSP1 population growth scenario. Panels (a3, b3, c3, and d3) represent the ratio under 1.5°C warming and SSP2 population growth scenario. Panels (a4, b4, c4, and d4) represent the ratio under 2.0°C warming and SSP1 population growth scenario. Panels (a5, b5, c5, and d5) represent the ratio under 2.0°C warming and SSP2 population growth scenario.

3.3. Balance Between Maize Supply and Demand Under 1.5°C and 2.0°C Warming Scenarios

Thirty-nine African countries have maize demand data in the FAO food balance sheet, so only these 39 countries are investigated on maize security. Taking into account the impacts of climate change, rising CO_2 concentration, and (or) technology development, the ratio of maize supply to demand (R_{msd}) at country level in Africa is investigated under 1.5°C and 2.0°C warming scenarios with national SSP1 and SSP2 population projections (Lutz et al., 2018). As a control, R_{msd} is discussed without the impacts of climate change and technology development, but with population growth as the SSP1 and SSP2 projections. African population is projected to reach 1,725 and 2,919 million in 2100 according to SSP1 and SSP2 population projections from 921 million during 2006–2013 based on FAO data. Based on the SSP1 population projection, under 1.5°C and 2.0°C warming scenarios, food security for maize would become worse in most countries if the technology remains at the same level as the calibration period from 1980 to 2010 (Figures 4a1–4a5) or the

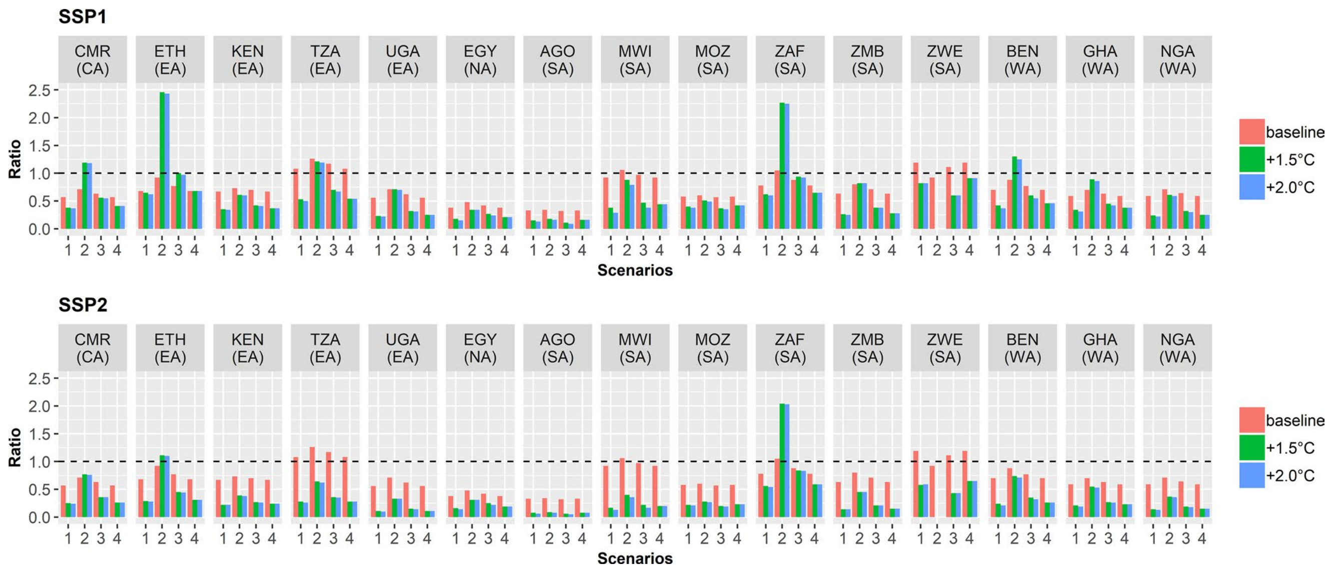

Figure 5. Predicted R_{msd} in the major maize producing countries. R_{msd} in the major maize producing countries under baseline period (2006–2015), 1.5°C and 2.0°C warming scenarios (2106–2115) in SSP1 (top row) and SSP2 (bottom row) national population growth projections scenarios, in which maize production technology remains constant as calibration period with climate change (1), develops in a linear trend with climate change (2), develops in a logarithmic trend with climate change (3), and remains constant without climate change (4).

technology develops in a logarithmic trend (Figures 4c1–4c5). However, when the technology develops in a linear trend, the threat of maize deficiency would be reduced at some countries (Figures 4b1–4b5). Based on the SSP2 population projection, maize security in more countries would become worse compared with SSP1 population projection, because of increasing population and maize demand (Figure 4, Tables S2–S4). The median R_{msd} for the whole Africa will increase to 0.87 (0.85) with SSP1 population projection under 1.5°C (2.0°C) warming scenario from 0.72 under baseline period with linear technology development trend, while the threat of maize deficiency will increase with other scenarios. R_{msd} will increase slightly if there is no climate change or technology development compared with if there is no technology development but climate change, however, adverse effect of climate change could be compensated by technology development (Table S2). R_{msd} is further analyzed for the major maize producing countries mentioned in Section 3.1 except for Democratic Republic of the Congo because of lacking maize demand data (Tables S3 and S4). The trend of change (increase or decrease) in R_{msd} for each country under 1.5°C is the same as that under 2.0°C warming scenario, relative to the baseline period, except Uganda with consideration of linear technology development and climate change, which indicates that the two warming targets stipulated by Paris Agreement could not be distinguished significantly with each other regarding maize supply and demand. R_{msd} is projected to decrease in all major maize producing countries with constant technology and SSP1 and SSP2 population projections taking climate change into account or not in 2106–2115, relative to the baseline period (Figures 4a1–4a5, 4d1–4d5, Tables S3 and S4). In contrast, R_{msd} is projected to increase in many major maize producing countries when the technology for maize production could keep the linear development trend until the end of century. For example, R_{msd} is projected to increase in Benin, Cameroon, Ethiopia, Ghana, South Africa, Uganda and Zambia under 1.5°C warming scenario with SSP1 population projection, more details could be found in Tables S3 and S4, Figures 4b1–4b5 and Figure 5. If maize production technology develops in a logarithmic trend, most of the major maize producing countries would need to import more maize to feed itself in Africa under 1.5°C and 2.0°C warming scenarios, relative to the baseline period, except Ethiopia, South Africa for SSP1 population growth projection (Tables S3 and S4, Figures 4c1–4c5, 5). Maize security is influenced more by technology development (Figure 4a vs. Figure 4b and Figure 4a vs. Figure 4c) than climate change (Figures 4a vs Figure 4d) when global warming of 1.5°C and 2.0°C. Both under 1.5°C and 2.0°C warming scenarios, in the major maize producing countries, R_{msd} is always projected to decrease to less than 1.0 in Kenya, Egypt, Angola, Malawi, Mozambique, Zimbabwe and Nigeria even with linear technology development and SSP1 population projection (Figure 5, Tables S3 and S4). This calls for more attentions to the shortage of maize in these countries. Overall, maize security situation for the whole Africa will become worse under 1.5°C and 2.0°C warming scenarios, relative to the baseline period (Table S2), except with linear technology development and SSP1 population projection. Our results indicate that keeping the global average temperature increase below 1.5°C relative to pre-industrial levels alone will not enable Africa to maintain maize security due to rising population. Development in technology of maize production will minimize or even reverse the adverse effects of global warming of 1.5°C and 2.0°C in Africa significantly, so future studies should put more efforts to develop technology of maize production in Africa.

4. Discussion

The results show that Africa would become warmer and drier under 1.5°C and 2.0°C warming scenarios, which could reduce growth duration, aggravate drought stress, and consequently reduce maize yields in most areas across Africa. The results are supported by previous studies (e.g., Challinor et al., 2014; Faye et al., 2018; Rosenzweig et al., 2014). The increase of CO_2 does not directly stimulate photosynthesis, but can indirectly stimulate carbon gain under drought condition, for C_4 plants such as maize (Leakey et al., 2009). Under 1.5°C and 2.0°C warming scenarios, drought stress is projected to increase in most areas (Figures 2f–2j), so elevated CO_2 can offset partly yield losses due to climate change in Africa, especially in Angola and Mozambique in the Southern Africa (Figure 3f). Since drought stress is projected to increase in most grids under 2.0°C than 1.5°C warming scenario (Figures 2f–2j), elevated CO_2 can offset yield loss more under 2.0°C than 1.5°C warming scenario (Figure 3f). In addition, nitrogen fertilization could improve crop performance under stress conditions. With low nitrogen fertilizer input, maize could benefit less from elevated CO_2 (Falconnier et al., 2020).

Besides climate change impacts, maize productivity has been and will be affected by agricultural technology development including agronomic management and breeding technologies (Huang et al., 2002; Müller et al., 2011). The yield of maize in Africa is lower than other areas (Shiferaw et al., 2011) although maize yield has steadily increased in the past decades in many countries in Africa according to FAO. Smallholder farmers in Sub-Saharan Africa currently grow rainfed maize with limited inputs including fertilizer. Adaptation strategies should be taken, including breeding crop cultivars with long growth duration and strong drought resistance, and improving agricultural inputs and agronomic management. Food security in Africa can be improved by sustainable agricultural intensification to close yield gap, which, however, requires a large, abrupt acceleration in rate of yield increase (van Ittersum et al., 2016). This seems unlikely given the trends showed in this study are all linear or logarithmic not exponential.

The real trend in maize production caused by technology development is hard to predict. Large uncertainties exist in whether the linear technology development can be maintained until 2115 and if the increase of maize yield is at the early stages of logarithmic technology development. More attention should be focused on technology development of dryland crops traditionally cultivated in Africa. Linear and logarithmic fitting are reasonable for the yield series data, although the coefficients of determination are low for some countries, partly due to the large number of samples from 1961 to 2017. In linear fitting, the trend is negative for Botswana, Chad, Lesotho, and Zimbabwe. In logarithmic fitting, the trend is negative for Angola, Botswana, Chad, Lesotho, Mozambique, and Zimbabwe (Table S1). The negative trends may indicate negative technology development in maize production in these countries because of poor cultivars and agronomic management. In these countries, R_{msd} would decrease more under 1.5°C and 2.0°C warming scenarios (2106–2115), relative to the baseline period (2006–2015), because of increase in maize demand due to population increase, and decrease in maize supply.

The processes and methods used to simulate crop growth, development and yield formation vary among different crop models, so crop model selection could be another source of uncertainties (Tao et al., 2018). Although climate change impact assessment can be more robust with multiple models, some studies have indicated that the simulation of DSSAT model is close to the median value among multiple crop models (Palosuo et al., 2011; Rosenzweig et al., 2014). On one hand, our results may be more negative than the actual scenario because of higher mortality and migration driven by decreasing R_{msd}, which are not taken into account in the population projections (Lutz et al., 2018). On the other hand, consumption patterns may increase over time with regional development and higher income. The supply of maize in the future is also estimated based on the planting area provided by SPAM 2005 (IFPRI et al., 2016), although the planting area of maize may extend to more dry areas because of the high risks of hunger or transit into other crops in the future (Rippke et al., 2016). However, massive cropland expansion will lead to biodiversity loss and greenhouse gas emissions (Molotoks et al., 2018), and therefore, should be cautious.

5. Conclusions

In this study, we conduct an integrated assessment on maize production and security in Africa under 1.5°C and 2.0°C warming scenarios, considering the combined impacts of climate change, technology development and population increase. The results show that maize yield in Africa would overall decrease due to shorter growth duration and more severe drought stress. The threat of maize security will likely increase in the future, so timely countermeasures should be taken to mitigate maize deficit risks in Africa, especially in Kenya, Egypt, Angola, Malawi, Mozambique, Zimbabwe, and Nigeria. The results highlight the importance of technology development and adaptation strategies including sustainable agricultural intensification, cultivars breeding technologies, agronomic inputs and management technologies such as irrigation and fertilization to meet the challenges of maize deficit in the vulnerable regions. In particular, more attention should be focused on technology development of dryland crops traditionally grown in Africa in the future.

Data Availability Statement

The DSSAT (version 4.6) source code is on github.com and the repository is private. Request from the DSSAT group is necessary for access (https://github.com/DSSAT). Harvested area data for rainfed and irrigated maize at a 0.5° resolution grid scale is obtained from SPAM 2005 V3.2 global data (http://mapspam.info/data/). We applied fertilizer data and growing season data at a 0.5° resolution grid scale from the Global Gridded Crop Model Intercomparison (GGCMI) phase 1 project. Historical maize yield data in each Africa country is from FAO (http://www.fao.org/faostat/en/#data/QC). Historical AgMERRA climate data and GSDE soil data are download through the guide in https://github.com/RDCEP/psims/blob/release-2.0/quickstart.txt. 1.5 and 2.0°C warming climate data are obtained from HAPPI project (https://portal.nersc.gov/c20c/data/ClimateAnalytics/). Maize demand for food, feed, seed, losses, processed and other uses, as well as population number from 2006 to 2013 are all from FAO food balance sheet. Population data obtained from SSP1 and SSP2 population projections in 2100 are used to represent population number under 1.5 and 2.0°C warming scenarios in each Africa country (http://dataexplorer.wittgensteincentre.org/wcde-v2/). The data that support the findings of this study will be openly available at National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdc.ac.cn) within 3 months after this paper has been published.

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