



Near-term climate change impacts on food crops productivity in East Africa

Yeon-Woo Choi¹ · Elfatih A. B. Eltahir¹

Received: 9 September 2022 / Accepted: 20 February 2023
© The Author(s) 2023

Abstract

Crop production in East Africa (i.e., Sudan and Ethiopia), where economy relies largely on rainfed agriculture, is facing significant challenges due to climate change, population growth, and the slow adoption rate of agricultural technology. However, a lack of consensus exists on how near-term climate change may affect food crop productivity in the region through changes in temperature and precipitation. Here, we empirically estimate optimal-growing temperature and precipitation for a select group of food crops using historical observations. We then project climate change impacts on crop yields based on a non-parametric empirical crop model using, as input, results from high-resolution (20 km) regional climate model driven by CMIP5/CMIP6 global climate models. Our projections consistently show increases in growing season temperature and precipitation during 2021–2050 under RCP8.5 and SSP5-8.5 scenarios, relative to 1976–2000. However, the projected climate change will exert dramatically different impacts on the agricultural sectors across the region. That is, the significant warming would likely cause overall negative impacts on agriculture in Sudan and mixed impacts on agriculture in Ethiopia. Meanwhile, the weak wetting trend may marginally affect crop growth in East Africa. The negative impacts of climate change can be mitigated at least partially by an accelerating rate of adoption of agricultural technology (use of fertilizers, better seeds, etc.) and probably by horizontal expansion of croplands where precipitation is projected to increase. Our results suggest that East Africa will need to take proactive adaptation measures to mitigate the projected food production challenges.

1 Introduction

East Africa is home to 370 million people, of which approximately 40 percent faces significant food security challenges due to poor access to food (Baquedano et al. 2020). The ongoing challenges in this region are likely to worsen due to rapid and sustained population growth (Bremner 2012; UN 2019). In addition, anthropogenic climate change is generally expected to reduce agricultural productivity and local food production, increasing the number of food-insecure individuals in the near future, although with some regional differences (Thornton et al. 2011; Blanc 2012; Adhikari et al. 2015; Zhao et al. 2017; Rosenzweig et al. 2014; Gardi et al. 2022). Therefore, projecting the impacts of near-term climate change at a high spatial resolution is of crucial importance for planning sound adaptation strategies to address food insecurity in this region.

Sudan and Ethiopia (hereafter referred to as East Africa), whose agricultural intensities are high (Fig. 1b) and economies rely heavily on rainfed agriculture, are some of the most vulnerable countries to climate variability and change (Thornton et al. 2011; Degefu et al. 2018; Siddig et al. 2020). A large fraction of the croplands in the two countries lies between the southern edge of the Sahara Desert and the northern fringe of wooded savanna (Fig. 1b), with sharp precipitation gradients (Fig. 1c). Farming in this transition zone is dominated by smallholder farmers reliant on rainfall as a vital water resource, especially for agriculture. We hypothesize that rainfed agriculture in the region could be significantly affected by the impacts of climate change as a projected warming will influence growth of crops, and small shifts in the position of wet regions could dramatically change water availability.

Until recently, future projections of agricultural productivity yielded inconsistent results across East Africa (Lobell et al. 2008; Muluneh et al. 2015; Abera et al. 2018). Several previous studies, based on global climate model (GCM) projections, reported that global warming would likely decrease length of growing season and reduce

✉ Yeon-Woo Choi
choiyw@mit.edu

¹ Ralph M. Parsons Laboratory, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

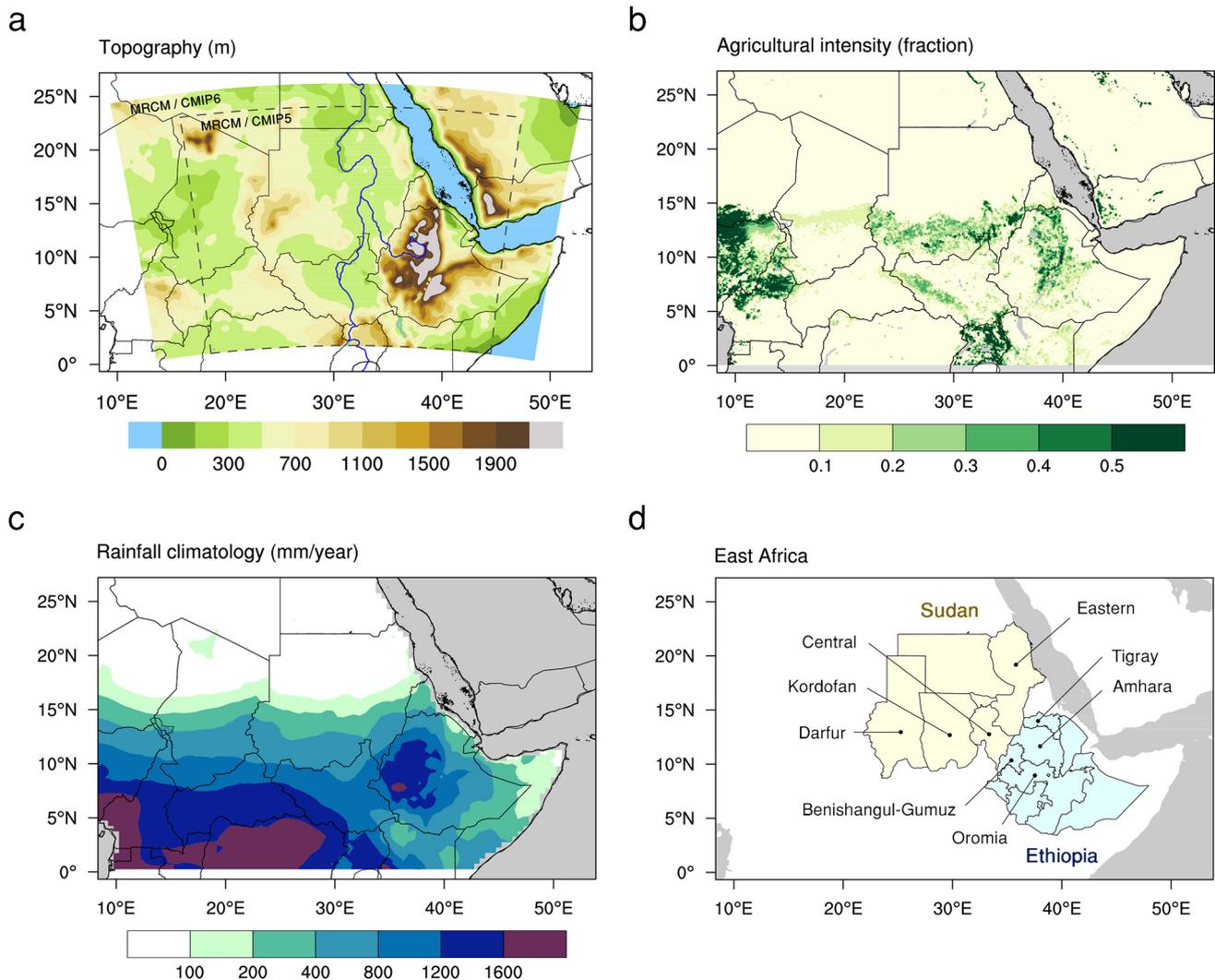


Fig. 1 MRCM simulation domain with **a** topography (unit: m), **b** agricultural intensity with approximately 10-km spatial resolution at the equator (unit: fraction; Ramankutty et al. 2008), **c** long-term

(1990–2019) mean annual total rainfall (unit: mm/year) derived from CRU, and **d** the locations of eight sub-regions in East Africa. The blue line in **a** indicates the Nile River

crop yields in sub-Saharan Africa towards the end of the century (Thornton et al. 2011; Blanc 2012; Adhikari et al. 2015; Dale et al. 2017). Additionally, Schlenker and Lobell (2010) showed that, by mid-century, East Africa is likely to experience significant yield losses of maize, sorghum, and millet due to climate change. However, according to Lobell et al. (2008), responses of crop yields to future climate change are not likely to be spatially uniform and would vary widely across regions. For example, the Sahel region will likely experience decreased yields of sorghum, maize, and wheat. By contrast, East Africa may experience noticeable increases in barley, wheat, and sorghum yields. The heterogeneous impacts of climate change are more obvious on a smaller spatial scale (Muluneh et al. 2015; Abera et al. 2018; Yang et al. 2020; Ginbo 2022). That is, the yield of maize is projected to rise in the highland areas in Ethiopia as

temperature increases. Meanwhile, crop productivity in the lower elevation regions is projected to decrease (Thornton et al. 2009). Therefore, high-resolution regional climate projections should be considered in agricultural impact studies to identify local changes in crop yields.

Most previous studies in this field have focused on the country scale using GCMs (Schlenker and Lobell 2010; Thornton et al. 2011; Blanc 2012; Adhikari et al. 2015). However, GCMs are in general not suitable for agricultural impact studies due to their coarse resolution and inadequate representation of physical processes (Seneviratne et al. 2012; Flato et al. 2013; Im et al. 2017a). In particular, reproducing the historical climate over East Africa with its complex topography and various agro-climatic zones is one of the great challenges for GCM-based studies (Flato et al. 2013). In contrast, regional climate models (RCMs) with a finer

resolution can facilitate an in-depth analysis for regions with complex topography (Choi et al. 2022).

To date, few studies addressed near-term climate change impacts on the food security at the local scale in Sudan and Ethiopia. Here, we study how near-term climate change affects the agricultural sector in the two countries at national and sub-national levels, using high-resolution climate change information. The following section describes the data used in this study. We specifically investigate (1) the sensitivity of crop yield to climate variability using an empirical approach in Section 3.1, (2) examine how precipitation and temperature will change in the near-term future using high-resolution (20 km) regional climate model simulations in Section 3.2, and (3) project how these changes would impact crop yields at the local scale in Section 3.3. Section 4 presents a discussion. The summary and conclusion are presented in Section 5.

2 Data and method

2.1 Agricultural production in the study area

This study focused on two countries, Sudan and Ethiopia, which are geographically located in the climatic transition zone between the subtropical Sahara Desert to the north and the humid tropical climate to the south (Fig. 1a, c, d). These countries are major producers of food crops like sorghum, millet, sesame, wheat, maize, teff, and barley (Fig. S1; CSA 2016) which are the main sources of human calories (Fig. S2). Most of the crop consumption in the region is met by domestic production, except for wheat in Sudan (Fig. S3). A large fraction of the croplands (i.e., cultivation area) in East Africa is located in semi-arid regions of Sudan with annual total precipitation of 400 to 800 mm and in the highlands of Ethiopia with annual total precipitation of 800 to 1600 mm alongside altitudes greater than 1500 m above sea level (Fig. 1a, b and Fig. S4). In Sudan, the main crops are mostly cultivated in Darfur, Kordofan, central, and eastern regions (Fig. 2a, b, c, d). Of these, the largest producer of millet is Darfur. Sorghum and sesame are primarily cultivated in the central region which includes Gezira and Gedaref areas. Wheat is mainly produced in the northern and central regions, but the northern region with irrigated areas is excluded from further analysis. In Ethiopia, maize, teff, sorghum, wheat, and barley are intensively cultivated in Tigray, Amhara, Oromia, and Benishangul-Gumuz (Fig. 2e, f, g, h, i). In particular, the alpine regions of Amhara and Oromia are major agricultural producers in Ethiopia. In this study, we focused on eight major crop-producing regions in East Africa, four in Sudan (Darfur, Kordofan, central, eastern), and four in Ethiopia (Tigray, Amhara, Benishangul-Gumuz,

and Oromia), where their agricultural systems are highly dependent on precipitation as the main source of water.

2.2 Observation data

Data on crop yields and production were collected from several sources, such as FAOSTAT (FAO 2018; available at <http://www.fao.org/faostat/en/>), annual agricultural sample survey from Central Statistical Agency (CSA; for Ethiopia; available at <https://www.statsethiopia.gov.et/our-survey-reports/>), and Food and Agriculture Organization/World Food Program (FAO/WFP) crop and food supply assessment mission (for Sudan; available at <http://www.fao.org/giews/reports/special-reports/en/>). More specifically, national-level crop data for 32 African countries (listed in Table S1) were available from the FAOSTAT, while sub-national-level crop data were only available for Sudan and Ethiopia. The crop data (production and yield) used in this study are summarized in Table S1.

Daily calorie consumption was from the FAOSTAT. The compositions of domestic crop production, imports, and exports for Sudan and Ethiopia were derived from the FAOSTAT. Nitrogen fertilizer data was provided by the FAOSTAT. Growing seasons for the crops and the countries were compiled from several sources, such as the Global Information and Early Warning Systems (GIEWS) country briefs (available at <http://www.fao.org/giews/countrybrief/index.jsp>) and the FAO crop calendar database (available at <https://cropcalendar.apps.fao.org/#/home>). Crop production areas for sorghum, millet, maize, barley, and wheat were acquired from the global agro-ecological zones (GAEZ+ 2015) data (Frolking et al. 2020; available at https://dataverse.harvard.edu/dataverse/GAEZ_plus_2015;jsessionid=8e89bcad5b094e99ede8ba1ff760). Population density data was derived from the gridded population of the world (GPW) v4 data set (CIESIN 2018).

Monthly temperature and precipitation observations were taken from the climate research unit product (CRU; Harris et al. 2020) with a horizontal resolution of $0.5^\circ \times 0.5^\circ$ for the period 1961–2019. Our earlier study verified that the CRU has the appropriate quality standards for climate analysis in East Africa (Choi et al. 2022).

2.3 Empirical crop model

A non-parametric empirical crop model was constructed. The aim of the model was to investigate if projected temperature and precipitation are likely to approach or move away from optimal growth conditions for the selected crops and sub-regions, assuming optimal thresholds do not change with time. For example, crop yield generally increases as temperature or precipitation approaches certain thresholds, while crop yield decreases as climate

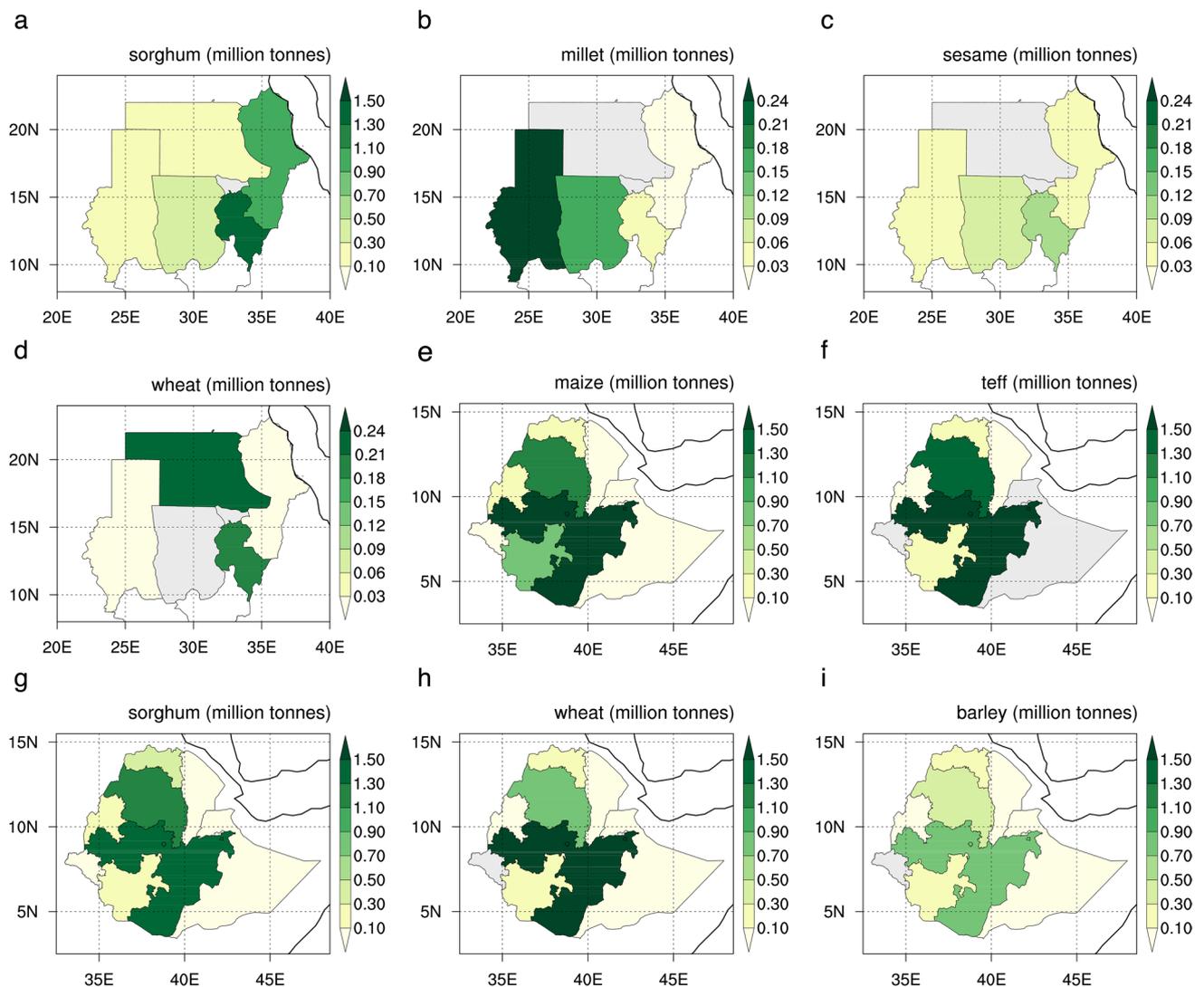


Fig. 2 Spatial distribution of crop production (million tons) in **a–d** Sudan (1993–2006 average) and **e–i** Ethiopia (1995–2019 average). Note that the color scale is different for each panel

conditions are away from these thresholds. For crop modeling, we first estimated the optimal-growing temperature and precipitation for each crop using the long-term historical data from 32 African countries (listed in Table S1). We then used a high-resolution regional climate model to project changes in temperature and precipitation for the near-term future (2026–2050) under RCP8.5 and SSP5-8.5 scenarios, against the reference period (1976–2000) (see Section 2.4 for more details). To assess the climate change impacts on crop yields, the high-resolution climate change information was used as input for the empirical crop model. The advantages and limitations of using multiple African countries to train the crop model will be addressed in the discussion section. To increase the reliability of crop yield projections, sub-national level observation data were used,

especially for Sudan and Ethiopia. Since the availability of observed sub-national level crop data is limited, we applied linear regression to extend them back to 1961 using national-level FAOSTAT statistics spanning the period 1961–2019. That is, we fitted a simple regression of sub-national-level crop yield against the national-level crop yield during its overlapping period (Table S1).

To better assess the dependence of crop productivity on weather factors, we considered the climatic conditions, to which each crop is exposed during the growing season. That is, we calculated agricultural-weighted (based on crop cultivation area) average temperature and precipitation for each month within each administrative unit. Since the cultivation areas of sesame and teff are not provided by the GAEZ + _2015, we assumed that they are grown in the regions with the same climate as the other major crops.

2.4 Regional climate model and experimental setup

Massachusetts Institute of Technology Regional Climate Model (MRCM; Im et al. 2017b), a state-of-the-art regional climate model, was used to project future climate change and its impacts in East Africa. The dynamical core of the MRCM is rooted in the International Center for Theoretical Physics (ICTP) Regional Climate Model version 3 (RegCM3; Pal et al. 2007), but with notable improvements: (a) coupling with the Integrated BIOSphere Simulator land surface scheme (IBIS; Winter et al. 2009), (b) new surface albedo assignment (Marcella 2012; Marcella and Eltahir 2012), (c) an irrigation scheme (Marcella 2012; Marcella and Eltahir 2014), (d) new convective cloud and precipitation autoconversion schemes (Gianotti 2012; Gianotti and Eltahir 2014a, b), and (e) modified boundary layer height and boundary layer cloud schemes (Gianotti 2012). Previous studies rigorously verified that the MRCM is capable of reproducing the region-specific climate information over various domains (Winter et al. 2009; Im et al. 2014, 2017b; Pal and Eltahir 2016; Choi et al. 2021, 2022; Choi and Eltahir 2022a, b).

The simulation domain of the current research covers East Africa, including Ethiopia and Sudan with a 20-km grid spacing on a Lambert conformal projection (Fig. 1a). To specify the boundary conditions for MRCM, we followed the recommendation from our earlier study (Choi et al. 2022) to select six GCMs (GFDL-CM3 (Donner et al. 2011), HadGEM2-ES (Jones et al. 2011), and NorESM1-M (Bentsen et al. 2013) from the CMIP5 archive; CMCC-ESM2 (Cherchi et al. 2019), HadGEM3-GC31-MM (Williams et al. 2018), and NorESM2-MM (Bentsen et al. 2019) from the CMIP6 archive), as the models which are most skillful in simulating the observed climate of the region. Time-slice climate simulations were performed for the historical period (1976–2005 for CMIP5 simulations; 1976–2014 for CMIP6 simulations) and future period (2006–2050 for CMIP5 simulations under the RCP8.5 scenario; 2015–2050 for CMIP6 simulations under the SSP5-8.5 scenario). High-emission scenarios (RCP8.5 and SSP5-8.5) were considered in this study, since these scenarios

would be possible, particularly for the near future, if it delays global action to cut carbon emissions (Schwalm et al. 2020). In the MRCM simulations forced by CMIP5 GCMs, time-lagged ensemble members (e.g., 1/1/1975, 1/2/1975, 1/3/1975, 1/1/2020, 1/2/2020, and 1/3/2020) were produced and used for ensemble analysis. Projected climate change impacts on food crop productivity were mainly analyzed for 2001–2025 and 2026–2050, relative to 1976–2000.

To remove the systematic bias existing in the model simulations, we applied the equidistant quantile-mapping bias correction procedure (Li et al. 2010; Choi et al. 2021, 2022). The ERA5 (Hersbach et al. 2018) and the Climate Hazards center InfraRed Precipitation with Station data (CHIRPS; Funk et al. 2015) were used to correct the bias in MRCM. To determine future atmospheric demand for evaporation, we calculated the potential evapotranspiration using the Penman–Monteith equation (Monteith 1965). A detailed description of the experimental design is shown in Table 1 and given by Choi et al. (2022).

3 Results

3.1 Relationships between climate variables and crop yields

We highlight a distinct contrast in the impact of global warming on food crops across East Africa. Figures 3 and 4 present the relationship between crop yields and climate. The sensitivity of crop yields to climate factors is highly heterogeneous spatially in these countries with a broad range of climates and altitudes. In Sudan, the yields of major crops are negatively correlated with temperature at the interannual time scale (Fig. 3a, b, c, d). In contrast, temperature and crop yields are overall positively correlated in Ethiopia (Fig. 4a, b, c, d). That is, temperature in Ethiopia appears to be a limiting factor for the growth of crops, including maize, sorghum, barley, and wheat. Based on these results, we hypothesize that rising temperature, as a result of climate change, will probably reduce crop yields in Sudan but could

Table 1 Description of MRCM experiments

Experiment	Boundary conditions	Variant label	Resolution (lon × lat)	Scenario	Time-lagged ensemble members
MRCM/CMIP5_GFDL	GFDL-CM3/CMIP5	r1i1p1	158 × 127	Historical/RCP8.5	3
MRCM/CMIP5_HAD	HadGEM2-ES/CMIP5	r1i1p1	158 × 127	Historical/RCP8.5	3
MRCM/CMIP5_NOR	NorESM1-M/CMIP5	r1i1p1	158 × 127	Historical/RCP8.5	3
MRCM/CMIP6_CMCC	CMCC-ESM2/CMIP6	r1i1p1f1	214 × 139	Historical/ssp5-8.5	1
MRCM/CMIP6_HAD	HadGEM3-GC31-MM/CMIP6	r1i1p1f3	214 × 139	Historical/ssp5-8.5	1
MRCM/CMIP6_NOR	NorESM2-MM/CMIP6	r1i1p1f1	214 × 139	Historical/ssp5-8.5	1

Fig. 3 Anomaly of annual crop yield (unit: t/ha) against anomalies of agricultural-weighted **a–d** temperature (unit: °C) and **e–h** precipitation (unit: mm/day) during the growing season for each crop (see Section 2.3 for more details about agricultural-weighted climate conditions). Anomalies are relative to the mean of 1961–2011. Four major crop-producing regions in Sudan, such as central (CE), Darfur (DA), eastern (EA), and Kordofan (KO) are considered. Values within each plot indicate the partial correlation coefficients between crop yields and climate variability, excluding the effect of nitrogen fertilizer. One and two asterisks indicate that the correlation coefficient is significant at the 95% and 99% confidence levels, respectively

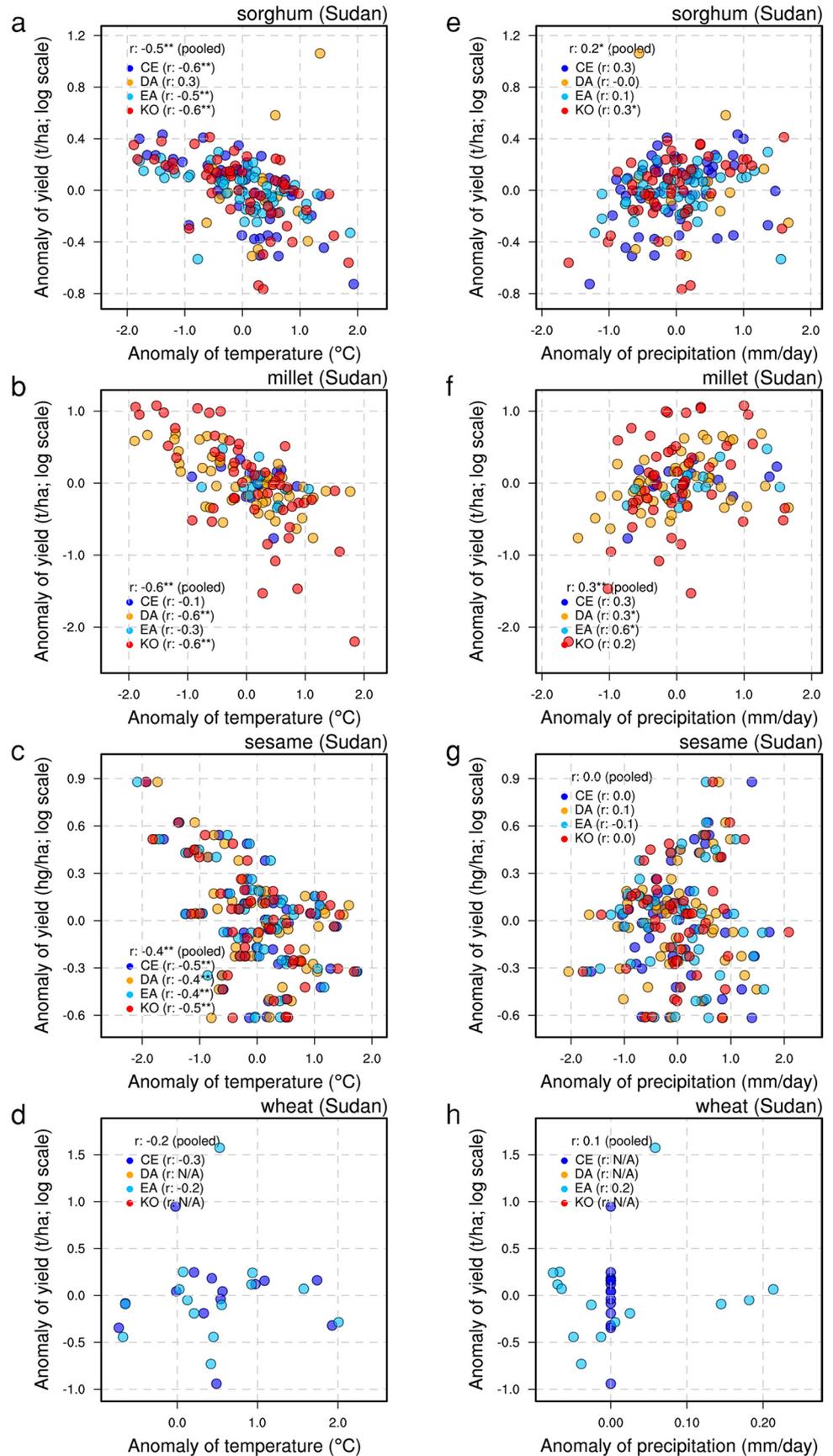
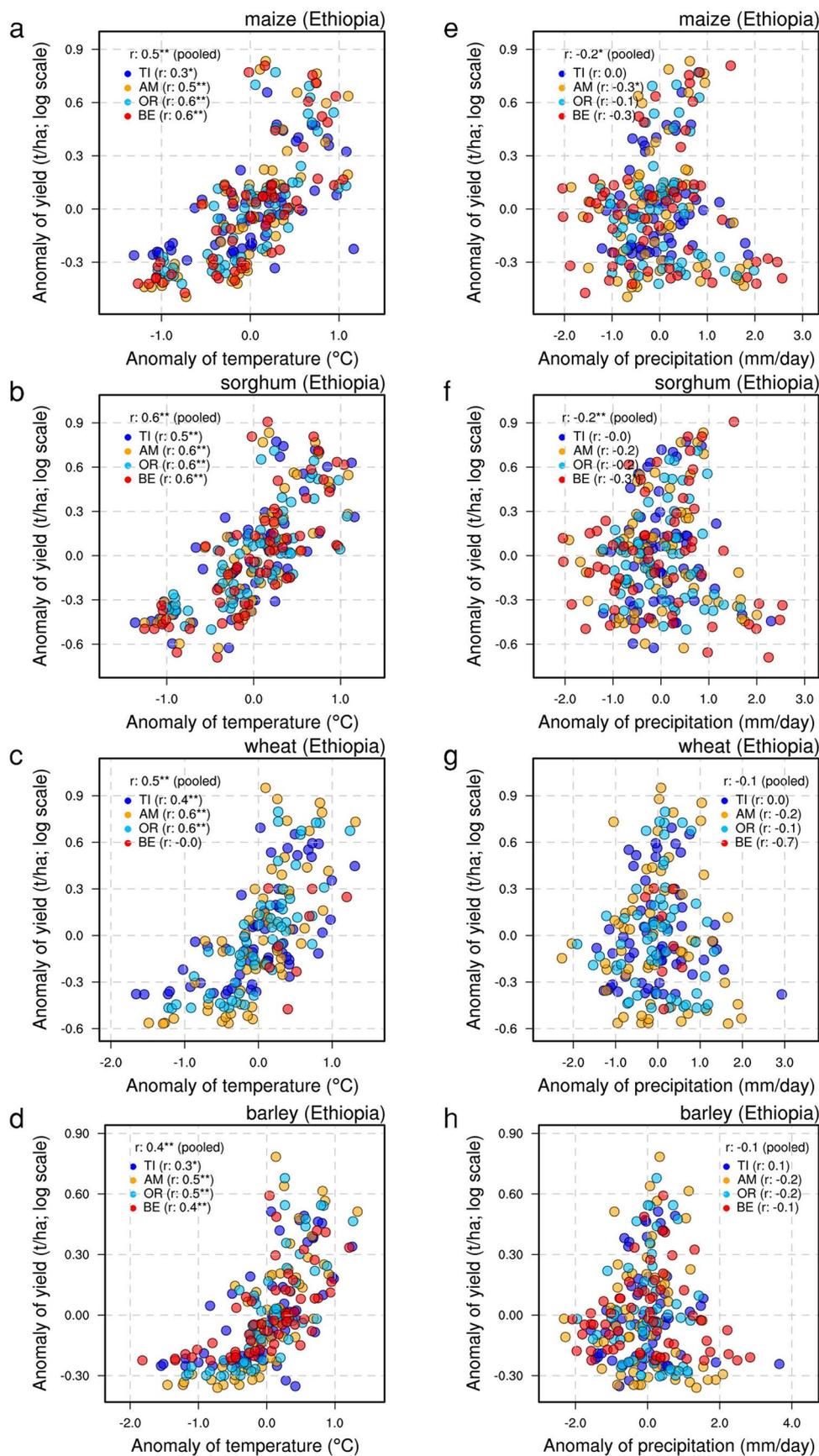


Fig. 4 Anomaly of annual crop yield (unit: t/ha) against anomalies of agricultural-weighted **a–d** temperature (unit: °C) and **e–h** precipitation (unit: mm/day) during the growing season for each crop (see Section 2.3 for more details about agricultural-weighted climate conditions). Anomalies are relative to the mean of 1961–2019. Four major crop-producing regions in Ethiopia, such as Tigray (TI), Amhara (AM), Oromia (OR), and Benishangul-Gumuz (BE), are considered. Values within each plot indicate the partial correlation coefficients between crop yields and climate variability, excluding the effect of nitrogen fertilizer. One and two asterisks indicate that the correlation coefficient is significant at the 95% and 99% confidence levels, respectively



provide some benefits for the agricultural sector in Ethiopia. This hypothesis is further supported by previous studies (Schlenker and Lobell 2010; Blanc 2012; Yang et al. 2020).

Precipitation seems to be a limiting factor for crop growth in Sudan, but not in Ethiopia (Figs. 3 and 4). In general, crop yields are positively correlated with precipitation in Sudan where relatively dry conditions prevail, while negative correlations are found in Ethiopia which receives plenty of precipitation (see Fig. 1c). Moreover, the correlation of yield with precipitation differs significantly from region to region within Ethiopia at the sub-national scale. The relationship between maize (respectively sorghum) yield and precipitation tends to be negative (p value < 0.05) in Amhara (respectively Benishangul-Gumuz), consistent with Yang et al. (2020). Meanwhile, there are negative but statistically insignificant relationships in the other sub-regions in Ethiopia. Although correlation does not imply causation, the above results may suggest that temperatures could generally have a greater impact on crop growth than precipitation, in line with the findings of Schlenker and Lobell (2010). Even ignoring the effects of fertilizers, which are known to affect agricultural productivity, the relationships between climate and crop productivity remain significant (see partial correlation coefficients shown in Figs. 3 and 4).

3.2 Near-term climate change

Based on the MRCM ensembles, we find a significant increasing trend in temperature over East Africa by 2050. Temporal and spatial changes in temperature are shown in Fig. 5 for the main growing season (July to October) when most crops grow. The temperature during the growing season is projected to increase by about 1 °C for the period 2001–2025 and by 2 °C for 2026–2050, relative to 1976–2000, consistently across MRCM/CMIP5 and MRCM/CMIP6 simulations (Figs. 5, S5, and S6). The largest increases are found in the north, strengthening the south-north temperature gradient. Similar temperature projections can be obtained when considering different growing seasons for various crops and countries (Fig. S7). A consistent pattern of the changes in temperature across all model projections is notable. We note that the increase in temperature is relatively smaller in MRCM/CMIP6 than MRCM/CMIP5 in the vicinity of the Sahara Desert border.

In accordance with the temperature rise, overall wetting trends are detected in East Africa over the next few decades (Figs. 6, S5, S6). There is a high degree of agreement across the MRCM projections (driven by different MIP generations) that the increase in precipitation is more pronounced in southeastern Sudan and the highlands of Ethiopia. In particular, growing season precipitation would increase by more than 5% in areas where agricultural intensity is relatively high (Fig. 1b), except for western Sudan

(where precipitation remains somewhat stagnant with negligible changes in CMIP6 projections). Also, precipitation in the lowlands of Ethiopia is likely to increase, albeit with the lack of inter-model consistency. These features are also found when considering different growing seasons for different crops (Fig. S8). Thus, as a result of climate change, the projected wetting is expected to reduce the water shortages to some extent and potentially affect the rainfed agricultural systems in East Africa. However, it is important to note that the projected warming in this region will enhance atmospheric evaporative demand, and thus may partially offset the advantage of the increases in precipitation, especially in terms of water availability.

Despite a projected increase in evapotranspiration due to the rising temperature, the amount of available water is still expected to increase (please see Fig. S9 showing the regional increase of the difference between precipitation and evaporation). Figure 7 presents projected changes in relative humidity and potential evapotranspiration over East Africa in a warmer climate. According to MRCM/CMIP6, the projected warming, along with small changes in relative humidity, leads to widespread increases in potential evapotranspiration with a strong agreement across models. Relative to the reference period (1976–2000), the increase in potential evapotranspiration is likely to be about 5% by 2050 in MRCM/CMIP6. Exceptionally, in the southwestern part of Ethiopia, the model projections show a small reduction in potential evapotranspiration—but there is an inconsistency between models in depicting this decrease. This insignificant change in potential evapotranspiration might be associated with the local increase in relative humidity. MRCM/CMIP5 exhibits a similar trend to that revealed by MRCM/CMIP6. Altogether, the increase in evapotranspiration is smaller than the increase in precipitation, particularly in the Upper Blue Nile catchments. The increased water availability may eventually reduce the water stress to some extent (Figs. 6 and S9) and could provide some benefits for agricultural production in the Nile basin countries (Larsson 1996), especially where precipitation is insufficient to sustain crops and irrigation is needed.

3.3 Projected impacts of climate change on agriculture

The precipitation trends could indirectly affect crop production in East Africa by altering the extent of cropland areas. The future projections, based on the MRCM/CMIP6 ensemble, highlight horizontal expansion of croplands in eastern Sudan and the lowlands of Ethiopia. Figure 8 shows projected changes in climatic zones with annual total precipitation of 0–200 mm, 400–800 mm, 800–1600 mm, and 1600–2500 mm over four sub-regions in East Africa, including western Sudan, eastern Sudan,

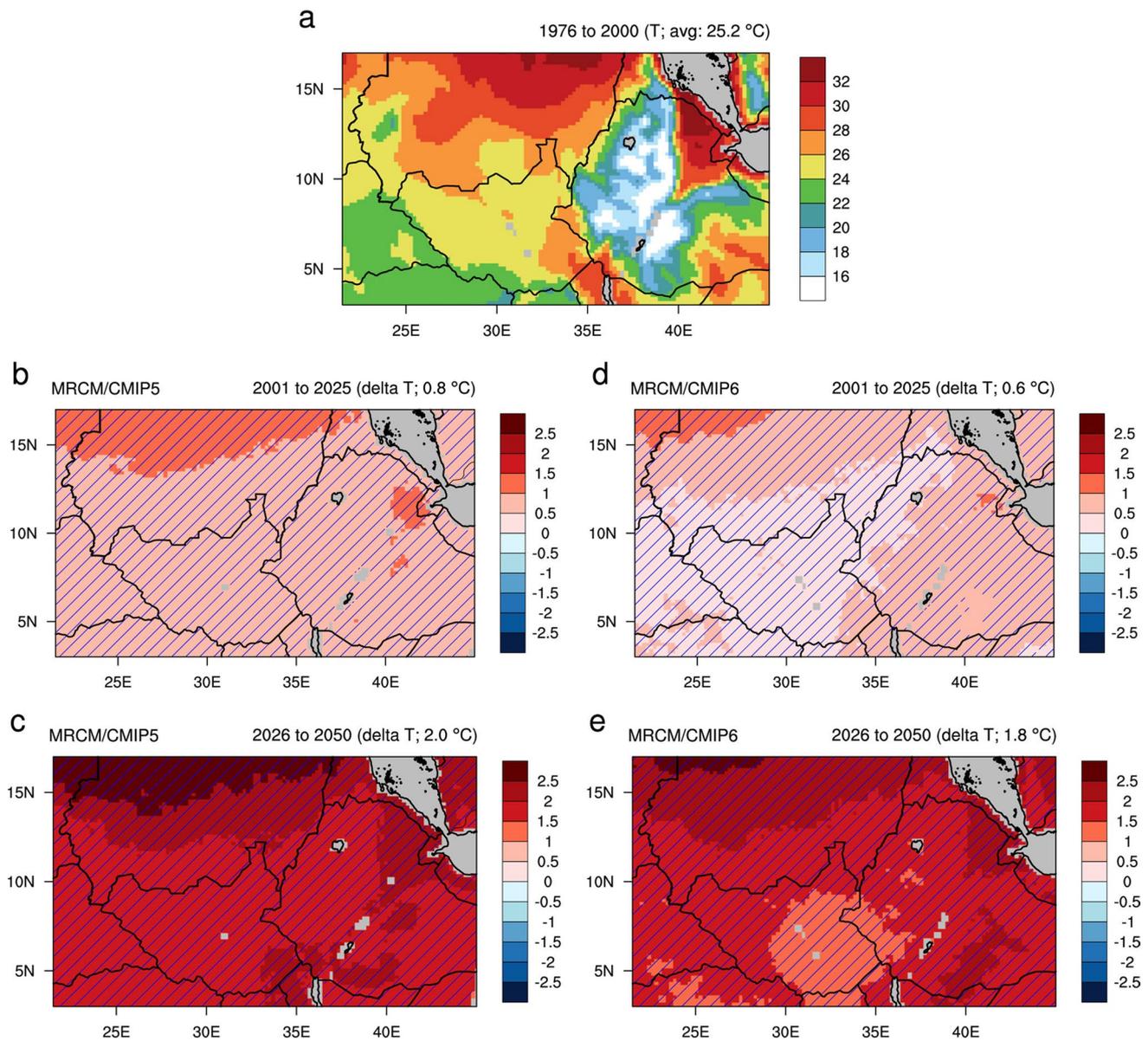


Fig. 5 **a** July to October (JASO) temperature (T) for 1976–2000 from the ensemble mean of bias-corrected MRCM/CMIP6 simulations. Projected change in JASO temperature for **b** 2001–2025 and **c** 2026–2050, relative to 1976–2000 from the ensemble mean of bias-corrected MRCM/CMIP5 simulations. **d–e** Same as **b–c**, but for the

ensemble mean of bias-corrected MRCM/CMIP6 simulations. Area-averaged values over land are given on the top right corner of each plot. Hatching indicates agreement by three MRCM simulations on the sign of the change

and the highlands and lowlands of Ethiopia. It is assumed that most crops are grown in the regions of Sudan with annual total precipitation ranging from 400 to 800 mm, while regions in Ethiopia with annual total precipitation of 800 to 1600 mm are suitable for crop cultivation (Fig. S4). Based on the climate projections, the overall increase in precipitation is expected to reduce desert areas (areas with less than 200 mm of annual total precipitation) mostly in Sudan (Fig. 8a, d). In the MRCM/CMIP6 projections, future changes in cropland (areas with annual

total precipitation of 400–800 mm) in western Sudan are found to be small and insignificant, while small but significant increases (0.5% increase; p value < 0.05) are projected in eastern Sudan. Also, there will be an expansion of cropland in the lowlands of Ethiopia. For the highlands of Ethiopia, where most crops are grown, the shift of precipitation distribution towards higher values would expand the area with annual total precipitation of 800–1600 mm, while the area with annual total precipitation ranging from 400 to 800 mm could be reduced to large degree.

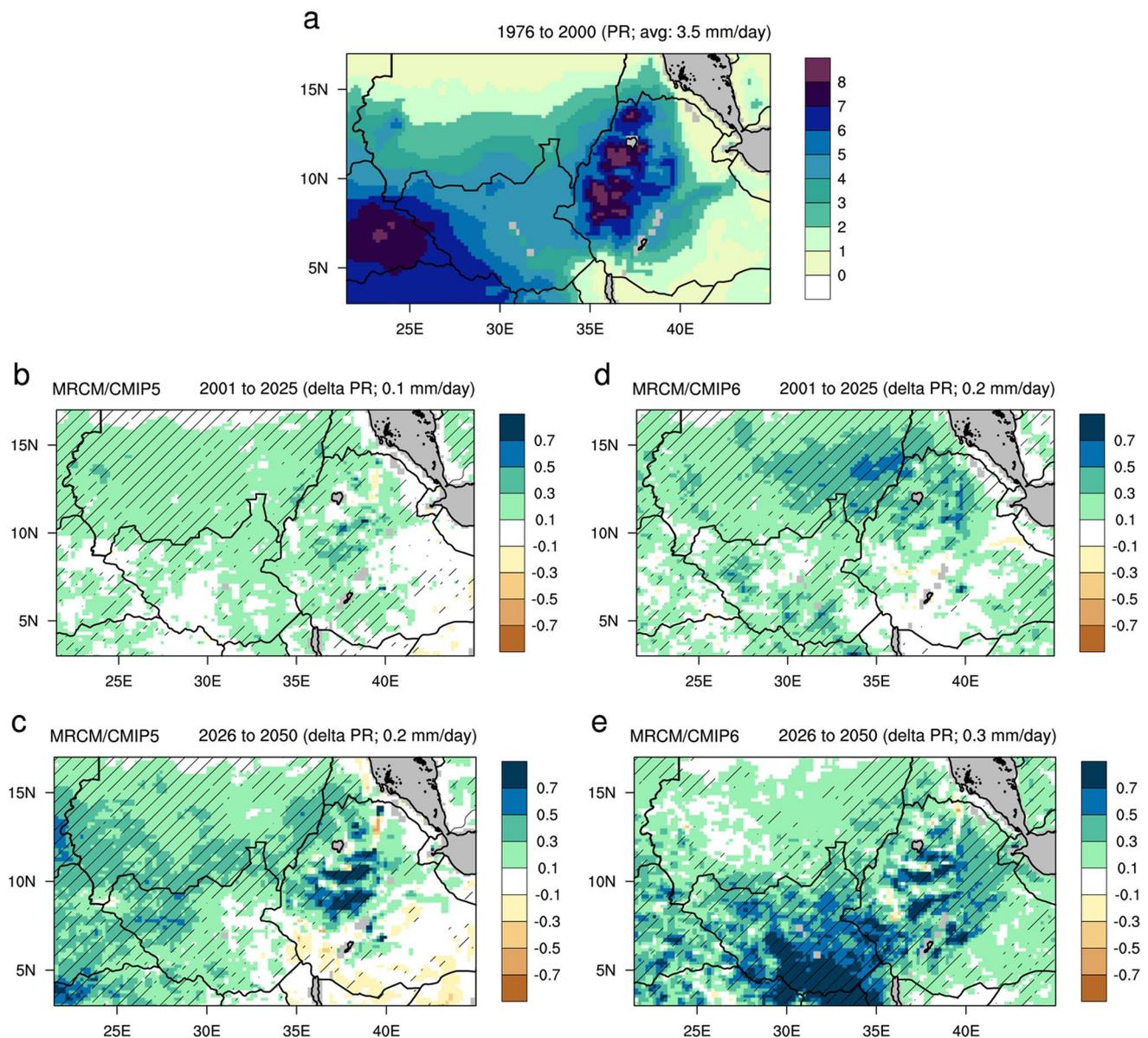


Fig. 6 a July to October (JASO) precipitation (PR) for 1976–2000 from the ensemble mean of bias-corrected MRCM/CMIP6 simulations. Projected change in JASO PR for **b** 2001–2025 and **c** 2026–2050, relative to 1976–2000 from the ensemble mean of bias-corrected MRCM/CMIP5 simulations. **d–e** Same as **b–c**, but for the

ensemble mean of bias-corrected MRCM/CMIP6 simulations. Area-averaged values over land are given on the top right corner of each plot. Hatching indicates agreement by three MRCM simulations on the sign of the change

Based on the empirical crop model (see Section 2.3 for more details), rising anthropogenic greenhouse gas concentrations will likely cause overall negative impacts on agriculture in Sudan and mixed impacts on agriculture in Ethiopia for the near-term future under the high-emission scenario (SSP5-8.5) (Figs. 9 and 10). The crop model indicates that sorghum, millet, wheat, sesame, maize, teff, and barley have an optimal-growing temperature of 25–26 °C, 25–26 °C, 17–18 °C, 24–25 °C, 24–26 °C, 20–21 °C, and 14–17 °C based on observations, respectively (Fig. 9). The ranges of

the optimal temperatures estimated are similar to those presented in previous studies (Table 2). It implies that the rising temperature will likely cause overall negative impacts on agriculture in Sudan (Figs. 9 and 10). For instance, the central region, which is the largest crop-producing region (Fig. 2a, b, c, d), will experience yield losses of sorghum, millet, wheat, sesame, and maize, albeit with some benefits from precipitation increase (Figs. 8 and 9). In Ethiopia, the impacts are spatially heterogeneous, depending on the crops and regions. That is, agricultural productivity for wheat and

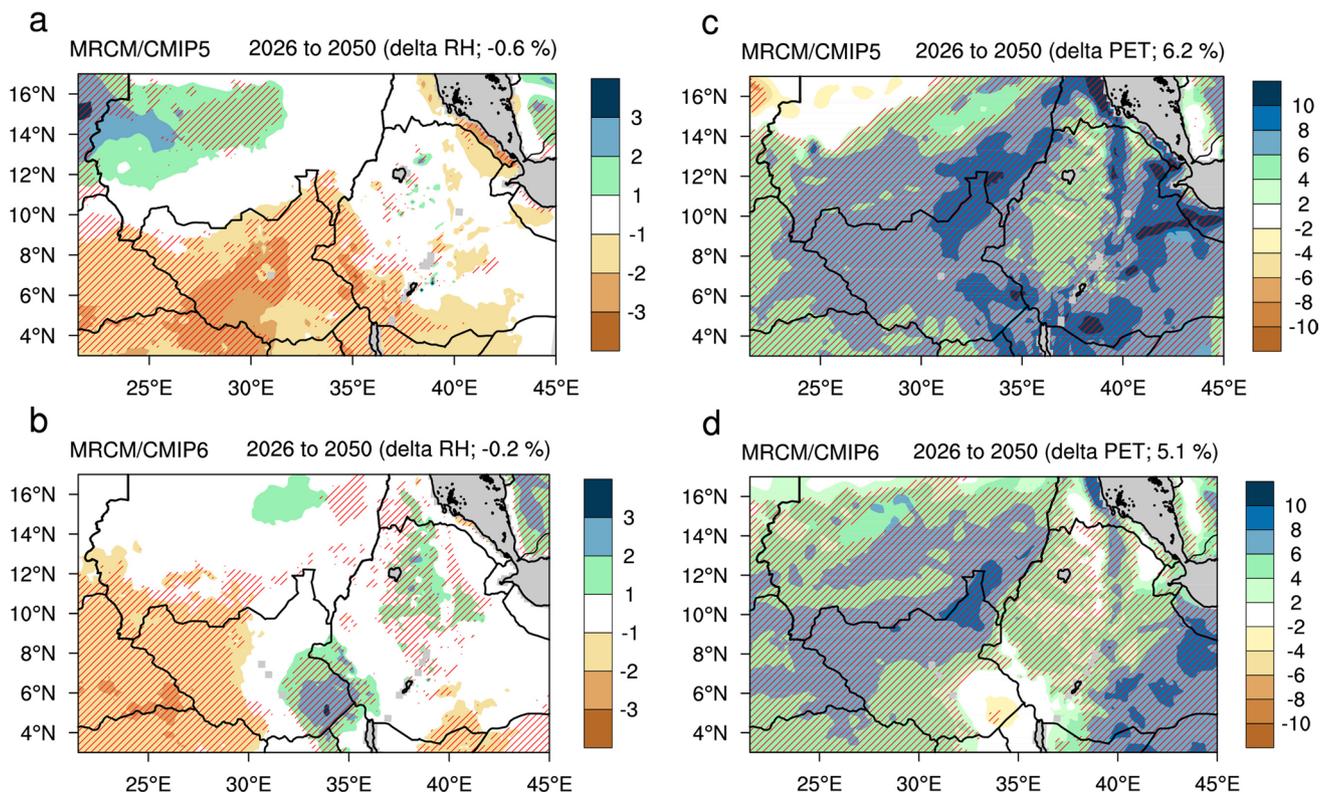


Fig. 7 Projected change in July–October (JASO) relative humidity (RH; absolute change; %) for 2026–2050, relative to 1976–2000, derived from ensemble means of **a** MRCM/CMIP5 simulations and **b** MRCM/CMIP6 simulations. **c, d** Same as **a, b**, but for potential evap-

otranspiration (PET; percent change; %). Area-averaged values over land are given on the top right corner of each plot. Hatching indicates agreement by three MRCM simulations on the sign of the change

barley will likely decrease in Ethiopia. On the other hand, increases in sorghum, maize, and teff yields are expected in Oromia (the largest crop-producing region in Ethiopia; Fig. 2e, f, g, h, i), because the projected near-term temperature over this region is likely to approach the optimal-growing temperatures in the near-term future (Fig. 9). Despite the marginal precipitation–yield relationship (Figs. 3e, f, g, h and 4e, f, g, h), optimal-growing precipitation for sorghum (5–6 mm/day), millet (5–6 mm/day), sesame (5–6 mm/day), maize (4–5 mm/day), teff (5–6 mm/day), and barley (5–6 mm/day) can be found (Fig. 9). However, the small increases in precipitation could weakly affect food crop yields in the near-term future.

4 Discussion

Our results broadly support previous findings that global climate change will likely increase temperature and precipitation during the long rainy season in Sudan and Ethiopia for the near-term future under high-emission scenarios (Muluneh et al. 2015; Déqué et al. 2017; Osima et al. 2018). Osima et al. (2018), based on an ensemble of

CORDEX-Africa regional climate simulations, projected overall warming and wetting trends over East Africa for the extended summer season (June to September). In a similar way, Déqué et al. (2017) expected an increase in precipitation in late summer as a consequence of 2 °C global warming. However, the relatively coarse-resolution models (at 50 km grid spacing) used in these previous studies could not provide some details of temperature and precipitation which are important for agricultural impact studies. Here, we used a 20-km high-resolution regional climate model and thus can provide a more in-depth assessment of climate change impacts on agricultural productivity in East Africa.

RCM simulations inevitably contain high uncertainty transferred from global climate models (Giorgi et al. 2009; Giorgi and Gutowski 2015), which to some extent could limit the ability of policymakers to design appropriate mitigation measures at the local scale (Conway and Schipper 2011). In this context, we found no perfect agreement between the six MRCM simulations on the sign of the precipitation changes, especially in western Sudan (Figs. 6 and 8). Despite the lack of consensus, most regional climate simulations, except for that driven by CMCC-ESM2, indicate wetting trends in

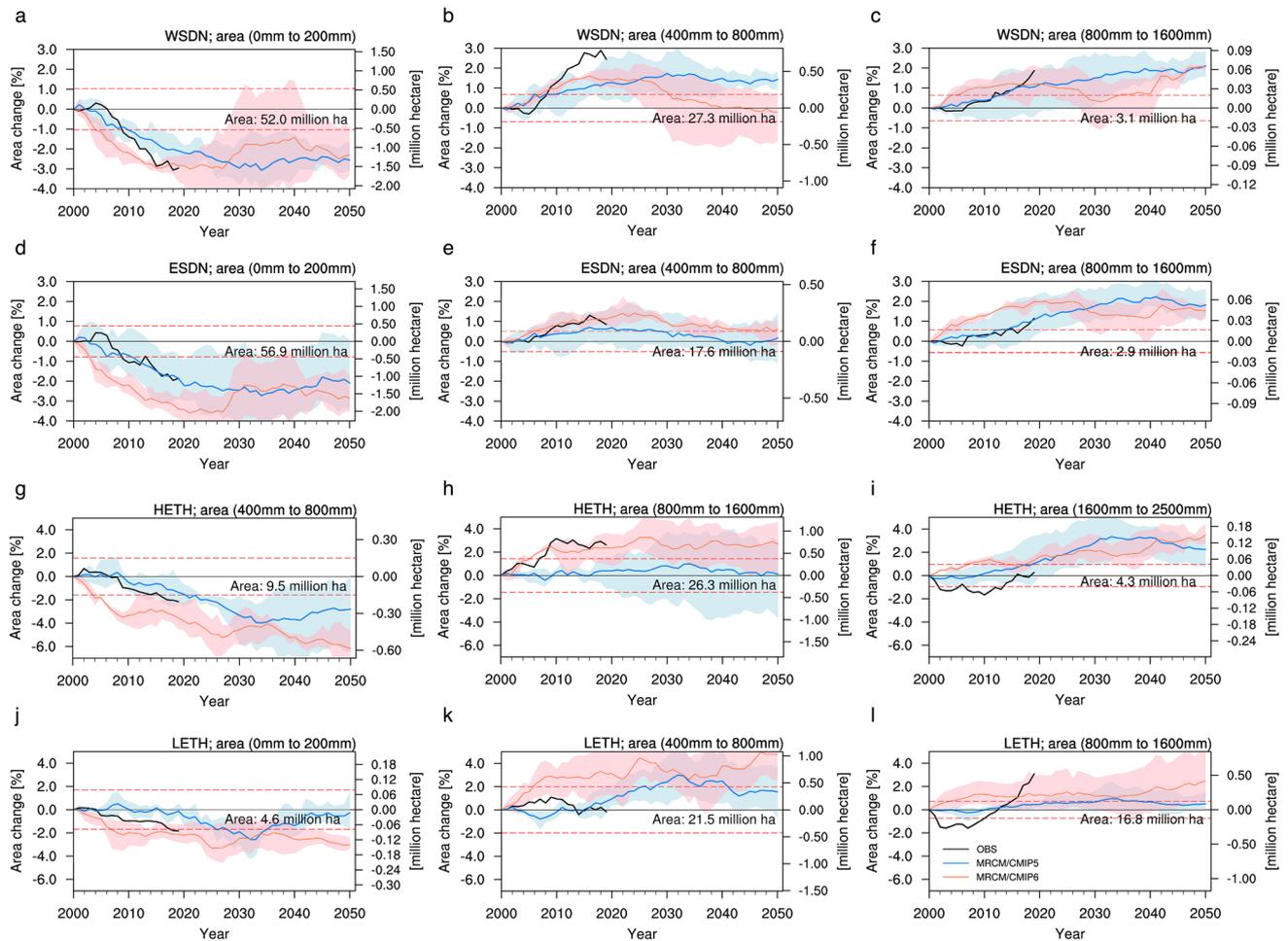


Fig. 8 Projected change in climatic zones (area) with annual total rainfall of (a, d, and j) 0–200 mm, (b, e, g, and k) 400–800 mm, (c, f, h, and l) 800–1600 mm, and (i) 1600–2500 mm over four sub-regions in East Africa, such as western Sudan (WSDN), eastern Sudan (ESDN), the highlands of Ethiopia (HETH; above 1500 m), and the lowlands of Ethiopia (LETH; below 1500 m), derived from the CRU

and bias-corrected MRCM simulations. Anomalies are relative to the mean of 1976–2000. The solid line and shading indicate a 25-year moving average and inter-model spread, respectively. The dashed line denotes the 95% confidence level. Initial area averaged over the period 1976–2000 is given on each plot

the region towards the mid-century. Also, parameterized convection schemes used for regional climate modeling can be a potential source of uncertainty in precipitation projections (Finney et al. 2020; Wainwright et al. 2021). Although we did not consider a convection-permitting model in this study, this convection-permitting model with high spatial resolution (< 4 km) could partly alleviate this concern (Wainwright et al. 2021).

We found that most crops are grown in the regions with annual total precipitation ranging from 400 to 800 mm in Sudan and from 800 to 1600 mm in Ethiopia (Fig. 1b, c and Fig. S4). This finding is further supported by evidence that estimated croplands using these criteria are comparable to the observed ones (Fig. S4). We then expected that the suitable lands for agricultural production is likely to expand in eastern Sudan and the lowlands of Ethiopia in

the near-term future. However, caution should be exercised in interpreting this result, because it does not take into account the varying soil conditions, land use, and flood/drought risks by region.

The crop projections that we provided for Sudan are generally consistent with previous studies reporting decreases in crop yields for sorghum (Schlenker and Lobell 2010; Ahmed 2022), millet (Schlenker and Lobell 2010), maize (Schlenker and Lobell 2010; Knox et al. 2012), and wheat (Iizumi et al. 2021; Tesfaye 2021). In addition, several existing studies for Ethiopia, which cohere with our findings, presented a mixture of opposing agricultural trends: increases in crop yields for sorghum (Ahmed 2022; Ginbo 2022), teff (Ginbo 2022), and Maize (Muluneh et al. 2015; Dale et al. 2017) and decreases in crop yields for barley (Gardi et al. 2022; Ginbo 2022), and wheat (Adhikari et al.

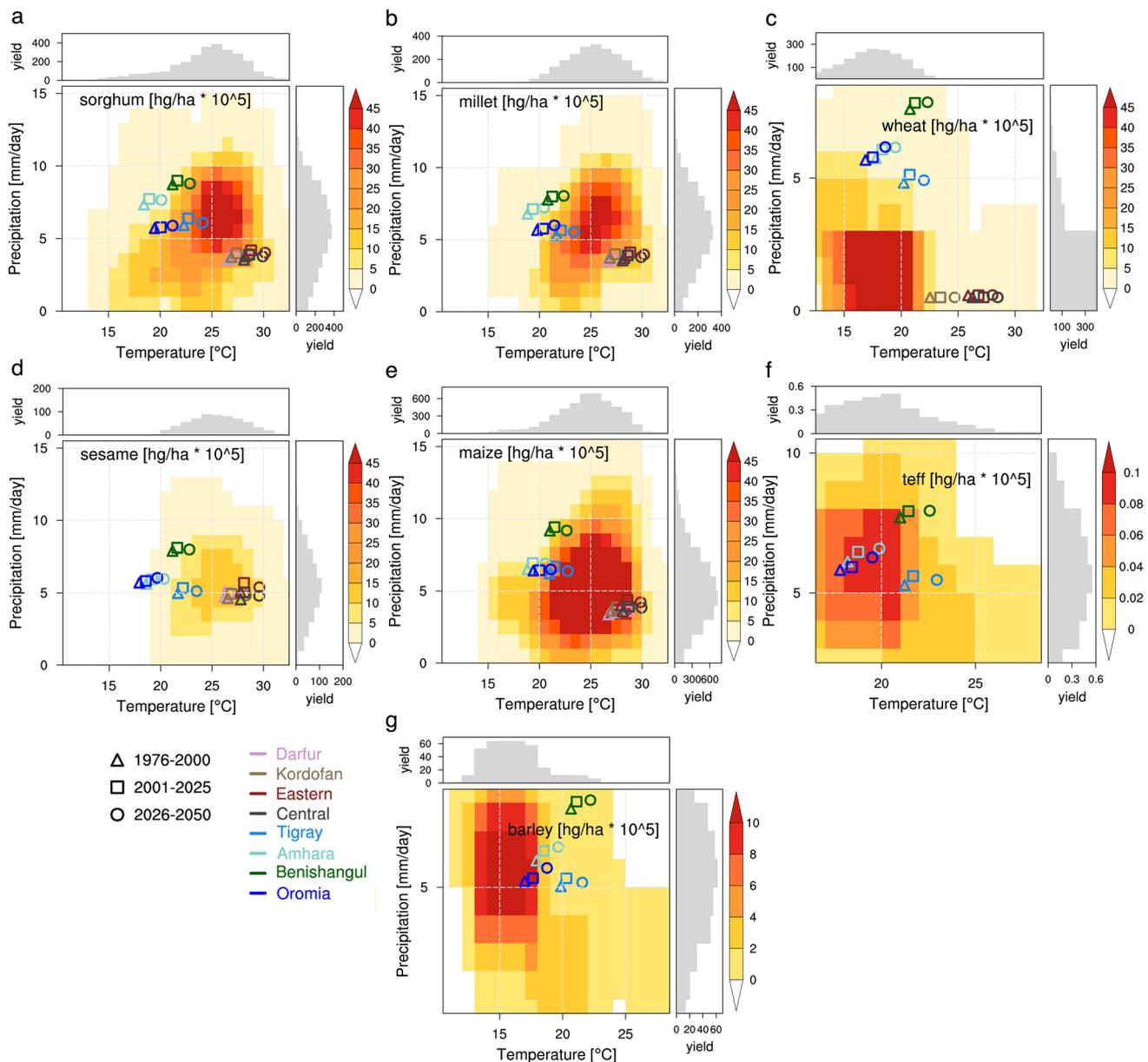


Fig. 9 Accumulated crop yields as a function of growing season mean temperature and precipitation in croplands in 32 African countries (see Table S1), based on observations for 1961–2019. Data are plotted using a nearest 25-point smoothing function. Eight major crop-producing regions (four in Sudan (Darfur, Kordofan, central,

eastern) and four in Ethiopia (Tigray, Amhara, Benishangul-Gumuz, and Oromia)) in East Africa are considered. Markers denote the climate conditions over the eight sub-regions in East Africa derived from ensemble mean of MRCM/CMIP6

2015; Ginbo 2022). However, few studies showed decreases in sorghum (Adhikari et al. 2015; Schlenker and Lobell 2010; Mohammed and Misganaw 2022) and maize yields (Schlenker and Lobell 2010; Adhikari et al. 2015; Ginbo 2022), which differs from our results. The large degree of uncertainty in crop yield projections is likely due to the following factors: (1) different climate models simulating different future climate conditions, (2) different crop modeling methodologies, and (3) lack of reliable crop data. To

minimize the uncertainty in crop yield projections, we here trained the crop model using observed long-term data with high quality and then tested the hypothesis that the rainfed agricultural systems in Sudan and Ethiopia are prone to the impacts of climate change.

We also found some evidence to suggest that rainfall and crop yield are generally negatively correlated in Ethiopia (Fig. 4), possibly implying that more precipitation may decrease crop yields (but not always). This finding is further

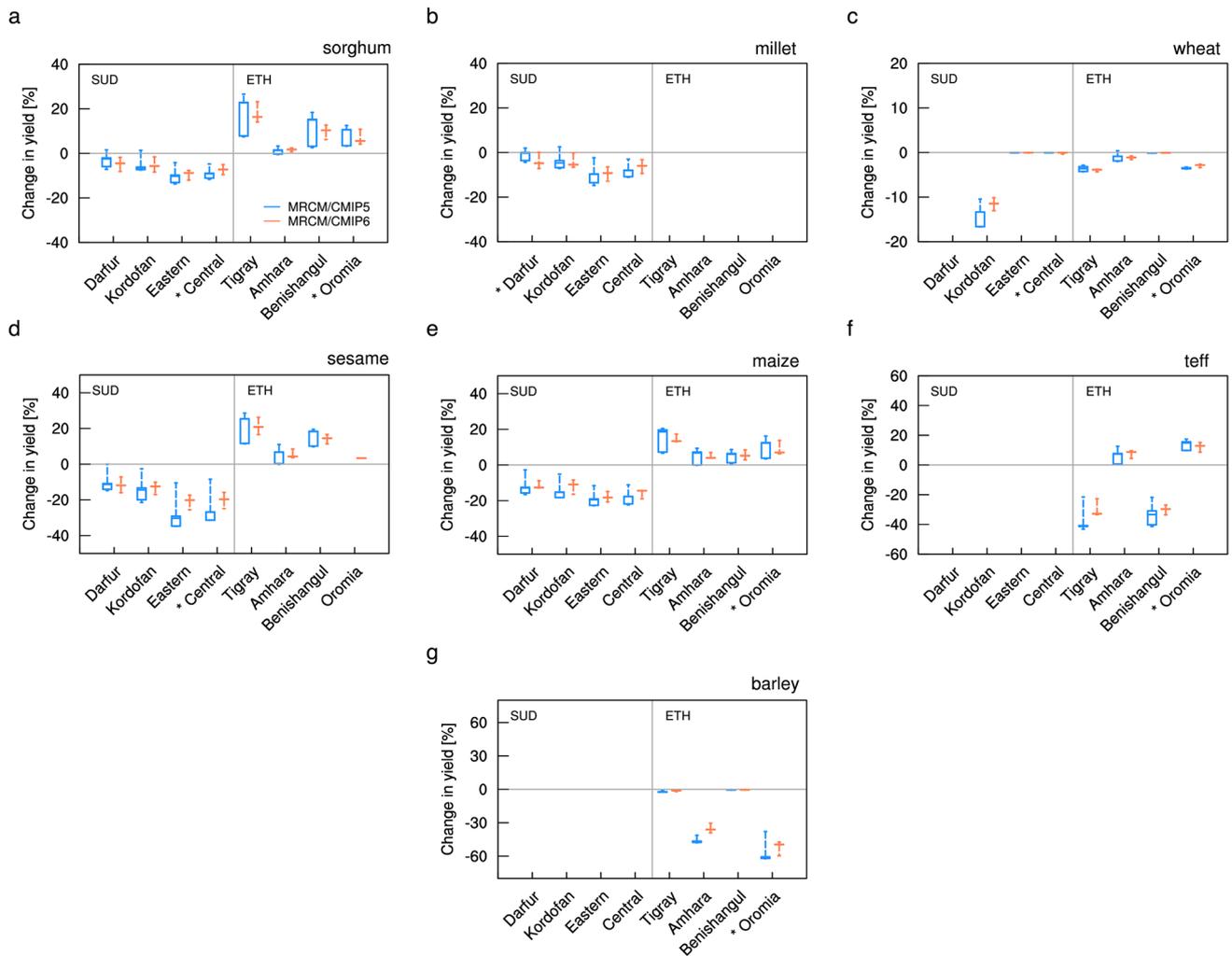


Fig. 10 Projected change in crop yields (%) for 2026–2050, relative to 1976–2000, over eight sub-regions in East Africa derived from non-parametric empirical crop model using, as input, ensemble

means of MRCM/CMIP5 simulations (blue) and MRCM/CMIP6 simulations (red). Asterisk indicates the largest crop-producing area within a country

supported by the well-calibrated process-based crop model for Ethiopia (Yang et al. 2020). However, we should acknowledge that the greatest damage to crops could mostly result from flooding/erosion or disease pressure rather than the small increase in precipitation.

Statistical and process-based crop models are widely used to assess the impact of climate change on crop yields (Schlenker and Lobell 2010; Lobell et al. 2008, 2011; Lobell and Burke 2010; Blanc 2012; Dale et al. 2017). A process-based model is a useful tool for translating

Table 2 Optimal temperature for various crops

Crops	Optimal temperature defined by previous studies	Optimal temperature derived from the empirical approach developed in this study
Sorghum	27.5 °C (Liu et al. 2008)	25–26 °C
Millet	30 °C (Liu et al. 2008)	25–26 °C
Wheat	15–20 °C (Liu et al. 2008)	17–18 °C
Sesame	25–27 °C (Oplinger et al. 1990)	24–25 °C
Maize	25 °C (Liu et al. 2008)	24–26 °C
Teff	10–27 °C (Stallknecht 1997)	20–21 °C
Barley	12–25 °C (GRDC, 2018)	14–17 °C

climate information into agricultural responses (e.g., Araya et al. 2015; Yang et al. 2020). However, to calibrate the model parameters, it requires various input data, including soil properties, cultivar parameters, and crop management practices, which are not available in many regions (Lobell and Burke 2010; Lobell et al. 2011). Accordingly, significant challenges are faced in calibrating a process-based crop model in East Africa due to the lack of available field data (Yang et al. 2020). Instead, statistical models with climatic and agricultural data as inputs can be an alternative to process-based models (Lobell and Burke 2010; Lobell et al. 2011). This statistical approach is simple and efficient because no parameters need to be defined while estimating the linear or non-linear relationship between crop productivity and climate variables. In this study, observations from 32 African countries were used to train the crop model, since crop models based on multiple sites are known to be less sensitive to length of training period (Lobell and Burke 2010). However, caution is warranted as our empirical approach does not consider different crop varieties, farm management practices, soil quality, water quality, sunlight availability, altitude, and pests/diseases across the countries. Also, we acknowledge that the result from statistical crop models could be sensitive to data sampled (i.e., sampling issue).

This study focused on changes in temperature and precipitation during growing season, which are known to have the most direct impact on the agricultural sector due to climate change (Kahsay and Hansen 2016). However, in making future projections, we do not consider other possible effects from changes in CO₂ (Long et al. 2006; Hatfield et al. 2011; Yang et al. 2020), solar radiation (Yang et al. 2020), maximum/minimum temperature (Yang et al. 2020), climate extremes (Coffel et al. 2019), fertilizer use (e.g., Sánchez 2010), and possible adaptation measures (e.g., the expansion of irrigation; Allam and Eltahir 2019; Ayyad and Khalifa 2021; Yang et al. 2021). For instance, yields of C3 crops, like barley and wheat, would increase to some extent in accordance with rising CO₂ concentrations (Long et al. 2006; Hatfield et al. 2011; Yang et al. 2020).

It is important to note that food insecurity might be further deteriorated by multiple stresses occurring at various levels, such as fragile state of national economy, the large variability of precipitation in space and time, explosively growing population, slow rate of adoption of agricultural technology, and complex conflicts between neighboring countries over resource sharing (Bremner 2012; Siam and Eltahir 2017; Allam and Eltahir 2019; UN 2019; Eltahir et al. 2019; Ayyad and Khalifa 2021). For these reasons, the current region's crop production level is insufficient to satisfy local food demand (Baquedano et al. 2020). We

projected that this food insecurity is expected to continue or worsen in the near future, especially in Sudan, in line with previous studies (Thornton et al. 2011; Blanc 2012; Adhikari et al. 2015).

5 Summary and conclusion

In this study, we aimed to examine how near-term climate change affects the agricultural sector in East Africa, especially Sudan and Ethiopia, at a sub-national level using a combination of the non-parametric empirical approach and the ensemble of high-resolution MRCM simulations.

Toward the middle of the twenty-first century, the MRCM ensemble projects overall warming and wetting trends during the main crop growing season under the high-emission scenarios (RCP8.5 and SSP5-8.5). Based on the empirical crop model, these climate trends are expected to generate spatially heterogeneous impacts on the agricultural sector in East Africa over the next few decades. Although various limiting factors in crop growth can complicate the climate change impacts, much of this heterogeneity can be explained by the temperature effects. For example, agricultural productivities for sorghum, millet, wheat, sesame, and maize in Sudan are expected to generally decrease due to the overall warming trend. By contrast, Oromia, the largest crop-producing region in Ethiopia, is projected to experience an increase in sorghum, maize, and teff yields, mainly due to the projected increase in temperature. On the other hand, the enhanced precipitation in the near-term future would provide some minor compensations for the yield losses in Sudan. The overall negative impacts of climate change can be mitigated at least partially by horizontal expansion of agriculture in relatively low regions. That is, the shift of the distribution of precipitation towards higher values could result in the expansion of the areas suitable for agriculture, especially in eastern Sudan and the lowlands of Ethiopia. The presence of inter-model consistency in the direction of these trends ensures to some extent the reliability of future projections.

Although some crops, such as sorghum, sesame, maize, and teff, in the highlands of Ethiopia may benefit from the increase in temperature, East Africa, already exposed to food insecurity, will likely face more severe food challenges due to increasing population and anthropogenic greenhouse gas concentrations. Our work suggests that East Africa needs to consider various forms of proactive adaptation measures, including irrigation, fertilization, efficient land/water management, a transition to heat-tolerant and drought-resistant crops, development of high-yield varieties, and a shift in planting dates, to help mitigate the projected food production challenges.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s00704-023-04408-1>.

Acknowledgements We are grateful for all providers of open-source datasets used in this study. We also thank Dr. Deborah J. Campbell and Dr. Muhammad Khalifa for their constructive comments on the manuscript.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Y.-W. Choi. The first draft of the manuscript was written by Y.-W. Choi and E. A. B. Eltahir. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding This material is based upon work supported by the Abdul Latif Jameel Water and Food Systems Lab (J-WAFS) at MIT and Community Jameel for Jameel Observatory CREWSnet.

Data availability Population density data were taken from <https://sedac.ciesin.columbia.edu/data/collection/gpw-v4>. Agricultural intensity data were obtained from <https://sedac.ciesin.columbia.edu/data/collection/aglands>. Data on crop yield and production were collected from several sources, such as FAOSTAT (available at <http://www.fao.org/faostat/en/>), annual agricultural sample survey data from Central Statistical Agency (available at <https://www.statethiopia.gov.et/our-survey-reports/>), and a series of special reports of Food and Agriculture Organization/World Food Program crop and food supply assessment mission (available at <http://www.fao.org/giews/reports/special-reports/en/>). A growing season for each crop in a given country was obtained and compiled from several sources, such as the Global Information and Early Warning Systems (GIEWS) country briefs (available at <http://www.fao.org/giews/countrybrief/index.jsp>) and the FAO crop calendar database (available at <https://cropcalendar.apps.fao.org/#/home>). The nitrogen fertilizer data were provided by FAOSTAT (<http://www.fao.org/faostat/en/>). Daily calorie consumption was from the FAOSTAT (<http://www.fao.org/faostat/en/>). The compositions of domestic crop production, imports, and exports for Sudan and Ethiopia were derived from the FAOSTAT (<http://www.fao.org/faostat/en/>). Crop production areas for sorghum, millet, maize, barley, and wheat were acquired from the global agro-ecological zones (GAEZ+₂₀₁₅) data (available at https://dataverse.harvard.edu/dataverse/GAEZ_plus_2015?sessionid=8e89bcad5b094e99ede8ba1ff760) (Frolking et al. 2020). Monthly mean temperature and precipitation were taken from the Climate Research Unit product (<https://catalogue.ceda.ac.uk/uuid/c26a65020a5e4b80b20018f148556681>). The regional climate simulation data generated during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Abera K, Crespo O, Seid J, Mequanent F (2018) Simulating the impact of climate change on maize production in Ethiopia. *East Africa Environ Syst Res* 7:4. <https://doi.org/10.1186/s40068-018-0107-z>
- Adhikari U, Nejadhashemi AP, Woznicki SA (2015) Climate change and eastern Africa: a review of impact on major crops. *Food Energy Secur* 4:110–132. <https://doi.org/10.1002/fes3.61>
- Ahmed SM (2022) Modeling crop yields amidst climate change in the Nile basin (2040–2079). *Modeling Earth Systems and Environment* 8(2):1977–1990
- Allam MM, Eltahir EAB (2019) Water-energy-food nexus sustainability in the Upper Blue Nile (UBN) Basin. *Front Environ Sci* 7:5. <https://doi.org/10.3389/fenvs.2019.00005>
- Araya A, Hoogenboom G, Luedeling E, Hadgu KM, Kisekka I, Martorano LG (2015) Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. *Agric for Meteorol* 214–215:252–265. <https://doi.org/10.1016/j.agrformet.2015.08.259>
- Ayyad S, Khalifa M (2021) Will the Eastern Nile countries be able to sustain their crop production by 2050? An outlook from water and land perspectives. *Sci. Total Environ* 775:145769. <https://doi.org/10.1016/j.scitotenv.2021.145769>
- Baquedano F, Cheryl C, Ajewole K, Beckman J (2020) International food security assessment, 2020–30. *Electronic Outlook Report from Economic Research Service/2020 (GFA-31):v + 74 pp 4 ref*
- Bentsen M, Bethke I, Debernard JB et al (2013) The Norwegian earth system model, NorESM1-M – Part 1: description and basic evaluation of the physical climate. *Geosci Model Dev* 6:687–720. <https://doi.org/10.5194/gmd-6-687-2013>
- Bentsen M, Olivie DJL, Seland Ø, et al (2019) NCC NorESM2-MM model output prepared for CMIP6 CMIP. <https://doi.org/10.22033/ESGF/CMIP6.506>.
- Blanc E (2012) The impact of climate change on crop yields in sub-Saharan Africa. *Am J Clim Change* 01:1–13. <https://doi.org/10.4236/ajcc.2012.11001>
- Bremner J (2012) Population and food security: Africa's challenge. *Population Reference Bureau Policy Brief*
- Cherchi A, Fogli PG, Lovato T et al (2019) Global mean climate and main patterns of variability in the CMCC-CM2 coupled model. *J Adv Model Earth Syst* 11:185–209. <https://doi.org/10.1029/2018MS001369>
- Choi YW, Campbell DJ, Aldridge JC, Eltahir EAB (2021) Near-term regional climate change over Bangladesh. *Clim Dyn* 57:3055–3073. <https://doi.org/10.1007/s00382-021-05856-z>
- Choi YW, Eltahir EAB (2022a) Heat stress during Arba'een foot-pilgrimage (world's largest gathering) projected to reach "dangerous" levels due to climate change. *Geophysical Research Letters* e2022aGL099755.
- Choi YW, Eltahir EAB (2022b) Uncertainty in future projections of precipitation decline over Mesopotamia. *Journal of Climate* 36:1213–1228.
- Choi YW, Campbell DJ, Eltahir EAB (2022) Near-term regional climate change in East Africa. *Clim Dyn* (in press)
- CIESIN (2018) Gridded population of the world, version 4 (gpwv4): population density, revision 11. NASA Socioeconomic Data and Applications Center. Accessed 30 August 2022. <https://doi.org/10.7927/H45Q4T5F>
- Coffel ED, Keith B, Lesk C et al (2019) Future hot and dry years worsen Nile basin water scarcity despite projected precipitation increases. *Earth's Future* 7:967–977. <https://doi.org/10.1029/2019EF001247>
- Conway D, Schipper ELF (2011) Adaptation to climate change in Africa: challenges and opportunities identified from Ethiopia. *Glob Environ Chang* 21:227–237. <https://doi.org/10.1016/j.gloenvcha.2010.07.013>

- CSA (2016) Agricultural Sample Survey. *Stat Bull* 1:1–111
- Dale A, Fant C, Strzepek K et al (2017) Climate model uncertainty in impact assessments for agriculture: a multi-ensemble case study on maize in sub-Saharan Africa. *Earth's Future* 5:337–353. <https://doi.org/10.1002/2017EF000539>
- Degefu MA, Assen M, McGahey D (2018) Climate variability and impact in ASSAR's east African region.
- Déqué M, Calmanti S, Christensen OB et al (2017) A multi-model climate response over tropical Africa at +2° C. *Climate Services* 7:87–95
- Donner LJ, Wyman BL, Hemler RS et al (2011) The dynamical core, physical parameterizations, and basic simulation characteristics of the atmospheric component AM3 of the GFDL global coupled model CM3. *J Clim* 24:3484–3519. <https://doi.org/10.1175/2011JCLI3955.1>
- Eltahir EAB, Adams T, Nikiel C, Siam MS, Tuel A (2019) A path forward for sharing the Nile water: sustainable, smart, equitable, incremental. Published by the Author. ISBN: 9781734069624. Available from Amazon. <https://www.amazon.com/Path-Forward-Sharing-Nile-Water/dp/1734069619>.
- FAO (2018) Food and agriculture data. Accessed 30 August 2022, <http://www.fao.org/faostat/en/#home>.
- Finney DL, Marsham JH, Rowell DP et al (2020) Effects of explicit convection on future projections of mesoscale circulations, rainfall, and rainfall extremes over Eastern Africa. *J Clim* 33(7):2701–2718
- Flato G, Marotzke J, Abiodun B et al (2013) Evaluation of climate models. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge and New York, pp741–866.
- Frolking S, Wisser D, Grogan D, et al (2020) GAEZ+ 2015 crop yield. <https://doi.org/10.7910/DVN/XGGJAV>
- Funk C, Peterson P, Landsfeld M et al (2015) The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Sci Data* 2:150066. <https://doi.org/10.1038/sdata.2015.66>
- Gardi MW, Memic E, Zewdu E, Graeff-Hönninger S (2022) Simulating the effect of climate change on barley yield in Ethiopia with the DSSAT-CERES-Barley model. *Agron J* 114(2):1128–1145
- Gianotti RL, Eltahir EAB (2014a) Regional climate modeling over the maritime continent. Part I: New Parameterization for Convective Cloud Fraction. *J Clim* 27:1488–1503. <https://doi.org/10.1175/JCLI-D-13-00127.1>
- Gianotti RL, Eltahir EAB (2014b) Regional climate modeling over the maritime continent. Part II: New Parameterization for Autoconversion of Convective Rainfall. *J Clim* 27:1504–1523. <https://doi.org/10.1175/JCLI-D-13-00171.1>
- Gianotti R (2012) Regional climate modeling over the maritime continent: convective cloud and rainfall processes. PhD Thesis, Ph.D. dissertation, Massachusetts Institute of Technology
- Ginbo T (2022) Heterogeneous impacts of climate change on crop yields across altitudes in Ethiopia. *Clim Change* 170(1):1–21
- Giorgi F, Jones C, Asrar GR (2009) Addressing climate information needs at the regional level: the CORDEX framework. *World Meteorological Organization (WMO) Bulletin* 58:175
- Giorgi F, Gutowski WJ (2015) Regional dynamical downscaling and the CORDEX initiative. *Annu Rev Environ Resour* 40:467–490. <https://doi.org/10.1146/annurev-environ-102014-021217>
- GRDC Grownotes (2018) Barley Section 4 Plant Growth and Physiology. <https://grdc.com.au/resources-and-publications/grownotes/crop-agronomy/barley-southern-region/GrowNote-Barley-South-4-Plant-Growth.pdf>. Accessed 02 December 2022.
- Harris I, Osborn TJ, Jones P, Lister D (2020) Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Sci Data* 7:109. <https://doi.org/10.1038/s41597-020-0453-3>
- Hatfield JL, Boote KJ, Kimball BA et al (2011) Climate impacts on agriculture: implications for crop production. *Agron J* 103:351–370. <https://doi.org/10.2134/agronj2010.0303>
- Hersbach H, de Rosnay P, Bell B, Schepers D, Simmons A, Soci C, Abdalla S, Alonso Balmaseda M, Balsamo G, Bechtold P, Berrisford P, Bidlot J, de Boissésou E, Bonavita M, Browne P, Buizza R, Dahlgren P, Dee D, Dragani R, Diamantakis M, Flemming J, Forbes R, Geer A, Haiden T, Hólm E, Haimberger L, Hogan R, Horányi A, Janisková M, Laloyaux P, Lopez P, Muñoz-Sabater J, Peubey C, Radu R, Richardson D, Thépaut JN, Vitart F, Yang X, Zsótér E, Zuo H (2018) Operational global reanalysis: progress, future directions and synergies with NWP, ECMWF ERA Report Series 27. <https://doi.org/10.21957/tkic6g3wm>
- Iizumi T, Ali-Babiker IEA, Tsubo M et al (2021) Rising temperatures and increasing demand challenge wheat supply in Sudan. *Nature Food* 2(1):19–27
- Im E-S, Gianotti RL, Eltahir EAB (2014) Improving the simulation of the West African Monsoon using the MIT regional climate model. *J Clim* 27:2209–2229. <https://doi.org/10.1175/JCLI-D-13-00188.1>
- Im E-S, Choi Y-W, Ahn J-B (2017a) Worsening of heat stress due to global warming in south korea based on multi-RCM ensemble projections: worsening of heat stress in South Korea. *J Geophys Res Atmos* 122:11,444–11,461. <https://doi.org/10.1002/2017JD026731>
- Im E-S, Pal JS, Eltahir EAB (2017b) Deadly heat waves projected in the densely populated agricultural regions of South Asia. *Sci Adv* 3:e1603322. <https://doi.org/10.1126/sciadv.1603322>
- Jones CD, Hughes JK, Bellouin N et al (2011) The HadGEM2-ES implementation of CMIP5 centennial simulations. *Geosci Model Dev* 4:543–570. <https://doi.org/10.5194/gmd-4-543-2011>
- Kahsay GA, Hansen LG (2016) The effect of climate change and adaptation policy on agricultural production in Eastern Africa. *Ecol Econ* 121:54–64. <https://doi.org/10.1016/j.ecolecon.2015.11.016>
- Knox J, Hess T, Daccache A, Wheeler T (2012) Climate change impacts on crop productivity in Africa and South Asia. *Environ Res Lett* 7(3):034032
- Larsson H (1996) Relationships between rainfall and sorghum, millet and sesame in the Kassala Province, Eastern Sudan. *J Arid Environ* 32:211–223. <https://doi.org/10.1006/jare.1996.0018>
- Li H, Sheffield J, Wood EF (2010) Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. *J Geophys Res* 115:D10101. <https://doi.org/10.1029/2009JD012882>
- Liu J, Fritz S, Van Wesenbeeck CFA et al (2008) A spatially explicit assessment of current and future hotspots of hunger in sub-Saharan Africa in the context of global change. *Global Planet Change* 64(3–4):222–235
- Lobell DB, Burke MB (2010) On the use of statistical models to predict crop yield responses to climate change. *Agric for Meteorol* 150:1443–1452. <https://doi.org/10.1016/j.agrformet.2010.07.008>
- Lobell DB, Burke MB, Tebaldi C et al (2008) Prioritizing climate change adaptation needs for food security in 2030. *Science* 319:607–610. <https://doi.org/10.1126/science.1152339>
- Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. *Science* 333:616–620. <https://doi.org/10.1126/science.1204531>
- Long SP, Ainsworth EA, Leakey ADB et al (2006) Food for thought: lower-than-expected crop yield stimulation with rising CO₂ concentrations. *Science* 312:1918–1921. <https://doi.org/10.1126/science.1114722>
- Marcella MP, Eltahir EAB (2012) Modeling the summertime climate of Southwest Asia: the role of land surface processes in shaping the climate of semiarid regions. *J Clim* 25:704–719. <https://doi.org/10.1175/2011JCLI4080.1>

- Marcella MP, Eltahir EAB (2014) Introducing an irrigation scheme to a regional climate model: a case study over West Africa. *J Clim* 27:5708–5723. <https://doi.org/10.1175/JCLI-D-13-00116.1>
- Marcella MP (2012) Biosphere-atmosphere interactions over semi-arid regions: modeling the role of mineral aerosols and irrigation in the regional climate systems. PhD Thesis, Ph.D. dissertation, Massachusetts Institute of Technology
- Mohammed A, Misganaw A (2022) Modeling future climate change impacts on sorghum (*Sorghum bicolor*) production with best management options in Amhara Region. *Ethiopia CABI Agriculture and Bioscience* 3(1):1–17
- Monteith JL (1965) Evaporation and environment. In: *Symposia of the society for experimental biology*. Cambridge University Press (CUP) Cambridge, pp 205–234
- Muluneh A, Biazin B, Stroosnijder L et al (2015) Impact of predicted changes in rainfall and atmospheric carbon dioxide on maize and wheat yields in the Central Rift Valley of Ethiopia. *Reg Environ Change* 15:1105–1119
- Oplinger ES, Putnam DH, Kaminski AR, Hanson CV, Oelke EA, Schulte EE, Doll JD (1990) Sesame, alternative field crops manual. University of Wisconsin Extension, Madison, WI, USA, University of Minnesota Extension, St. Paul, USA
- Osima S, Indasi VS, Zaroug M et al (2018) Projected climate over the Greater Horn of Africa under 1.5 C and 2 C global warming. *Environ Res Lett* 13(6):065004
- Pal JS, Eltahir EAB (2016) Future temperature in southwest Asia projected to exceed a threshold for human adaptability. *Nature Clim Change* 6:197–200. <https://doi.org/10.1038/nclimate2833>
- Pal JS, Giorgi F, Bi X et al (2007) Regional climate modeling for the developing world: the ICTP RegCM3 and RegCNET. *Bull Am Meteor Soc* 88:1395–1410
- Ramankutty N, Evan AT, Monfreda C, Foley JA (2008) Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Glob Biogeochem Cycles* 22(1):GB1003
- Rosenzweig C, Elliott J, Deryng D et al (2014) Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proc Natl Acad Sci* 111:3268–3273
- Sánchez PA (2010) Tripling crop yields in tropical Africa. *Nat Geosci* 3:299–300
- Schlenker W, Lobell DB (2010) Robust negative impacts of climate change on African agriculture. *Environ Res Lett* 5:014010
- Schwalm CR, Glendon S, Duffy PB (2020) RCP8. 5 tracks cumulative CO₂ emissions. *Proceed National Acad Sci* 117(33):19656–19657
- Seneviratne SI, Nicholls N, Easterling D et al (2012) Changes in climate extremes and their impacts on the natural physical environment. In: Field CB, Barros V, Stocker TF, Dahe Q (eds) *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, 1st edn. Cambridge University Press, pp 109–230
- Siam MS, Eltahir EAB (2017) Climate change enhances interannual variability of the Nile river flow. *Nat Clim Chang* 7:350–354
- Siddig K, Stepanyan D, Wiebelt M et al (2020) Climate change and agriculture in the Sudan: impact pathways beyond changes in mean rainfall and temperature. *Ecol Econ* 169:106566
- Stallknecht GF (1997) Teff, new crop factsheet. Purdue University Center for New Crops and Plant Products.
- Tesfaye K (2021) Climate change in the hottest wheat regions. *Nature Food* 2(1):8–9
- Thornton PK, Jones PG, Alagarwamy G, Andresen J (2009) Spatial variation of crop yield response to climate change in East Africa. *Glob Environ Chang* 19:54–65
- Thornton PK, Jones PG, Ericksen PJ, Challinor AJ (2011) Agriculture and food systems in sub-Saharan Africa in a 4 C+ world. *Philosophical Trans Royal Soc a: Mathematical, Phys Eng Sci* 369:117–136
- United Nations (2019) World population prospects: the 2019 revision. UN Department of Economic and Social Affairs. Accessed 30 August 2022. <https://population.un.org/wpp/>.
- Wainwright CM, Marsham JH, Rowell DP, Finney DL, Black E (2021) Future changes in seasonality in East Africa from regional simulations with explicit and parameterized convection. *J Clim* 34(4):1367–1385
- Williams KD, Copsey D, Blockley EW et al (2018) The met office global coupled model 3.0 and 3.1 (GC3.0 and GC3.1) configurations. *J Adv Model Earth Syst* 10:357–380. <https://doi.org/10.1002/2017MS001115>
- Winter JM, Pal JS, Eltahir EAB (2009) Coupling of integrated biosphere simulator to regional climate model version 3. *J Clim* 22:2743–2757. <https://doi.org/10.1175/2008JCLI2541.1>
- Yang M, Wang G, Ahmed KF et al (2020) The role of climate in the trend and variability of Ethiopia's cereal crop yields. *Sci Total Environ* 723:137893
- Yang M, Wang G, Lazin R et al (2021) Impact of planting time soil moisture on cereal crop yield in the Upper Blue Nile Basin: A novel insight towards agricultural water management. *Agric Water Manag* 243:106430
- Zhao C, Liu B, Piao S et al (2017) Temperature increase reduces global yields of major crops in four independent estimates. *Proc Natl Acad Sci USA* 114:9326–9331. <https://doi.org/10.1073/pnas.1701762114>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.