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Less negative impacts of climate change on crop yields in West Africa in the new CMIP6 climate simulations ensemble

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Abstract

Food insecurity is among one of the greatest risks posed by climate change in Africa, where 90 to 95% of African food production is rainfed and a large proportion of the population already faces chronic hunger and malnutrition. Although, several studies have found robust evidence of future crop yield losses under climate change scenarios, there is wide variation among crops and regions as well as large modeling uncertainties. A large part of this uncertainty stems from climate projections, as climate models may differ in simulating future changes in precipitation and temperature, which could lead to different future crop production scenarios. This work examines the impacts of climate change on crop yields of maize, millet and sorghum in West Africa using climate change projections from the Coupled Model Intercomparison Project 5th Phase (CMIP5) and from the new generation of climate models from the Coupled Model Intercomparison Project 6th Phase (CMIP6). We use the SIMPLACE crop modeling framework to simulate historical and future crop yields, and bootstrap techniques to evaluate projected changes in crop productivity between the CMIP5 and CMIP6 ensembles. Using the new generation of climate models CMIP6, we find that the negative crop yield projections shown by CMIP5 simulations are largely reduced, with even large increases in crop yields when the effect of atmospheric CO_2 concentration is considered in the crop model. These differences in crop yield impacts between the CMIP5 and CMIP6 simulations are mainly due to different climate projections of temperature and precipitation in West Africa; CMIP6 projections being significantly wetter and cooler by mid-century and to a lesser extent by the end of the century. Such results highlight the large uncertainties that remain in assessing the impacts of climate change in the region and the consequent difficulty for end-users to anticipate adaptation strategies.

1 Introduction

The Intergovernmental Panel on Climate Change's Sixth Assessment Report (AR6) warned that although Africa's contribution to historical greenhouse gas emissions is among the lowest

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of historical greenhouse gas emissions, the continent is particularly vulnerable to human-induced climate change [1]. Food insecurity is among one of the major risks posed by climate change in Africa, as 90 to 95% of African food production is rainfed [2], and a large proportion of the population already faces chronic hunger and malnutrition [3]. Several studies have found robust evidence that climate change is already negatively affecting crop production in Africa [4–7]. The last IPCC report conducted a meta-analysis of crop yields projections under climate change across 35 studies and 1040 locations and cases, showing average crop yield losses with increasing global warming for staple crops in Africa [1]. Other meta-analyses of the literature [8–10] have shown that projected impacts on yield in several African countries are mainly negative (−10% to −6%), but there is wide variation among crops and regions, as well as large modeling uncertainties, making it difficult to provide a robust assessment of future yield changes at the regional scale. These uncertainties in estimating future yield changes are driven by adaptation responses such as changes in planting dates, varieties, irrigation, and other management practices. For example, Carr et al. [8] showed that adaptation strategies could increase crop yields under climate change from −4% to +19% depending on the adaptation option, relative to a no-adaptation scenario. In addition, uncertainty in future crop yield projections also comes from crop responses to increasing atmospheric CO_2 concentrations, which could mitigate climate-induced losses but with considerable variations across crop models [1,11]. A large part of this uncertainty also comes from climate projections where climate models might differ in simulating future rainfall in regions such as West Africa [12] or East Africa [13], with large differences between Global Climate Models (GCMs) and high-resolution regional climate models projections [13] and large biases of climate models for current conditions when compared to observations [14]. Furthermore, even if a robust warming is still simulated throughout the twenty-first century, the release of the Coupled Model Intercomparison Project 6th Phase (CMIP6; [15]) has shown important changes in future climate projections when compared to the previous one from the Coupled Model Intercomparison Project 5th Phase (CMIP5; [16]). For some regions such as the western Sahel, mean summer precipitation is projected to decrease drastically in CMIP5 projections while CMIP6 shows an increase over nearly 40% of the land area [13]. Changes in temperature projections have also been shown between CMIP5 and CMIP6 climate models [17]. It is likely that such changes in terms of climate change projections will drive changes in future crop yield projections, as precipitation and temperature are among the key drivers of crop simulations. Indeed, a recent study compared future global changes in crop production of major crops (i.e. maize, rice, soybean and wheat) from nine crop models forced by 45 CMIP5 and 34 CMIP6 climate projections. The authors found substantial differences in the total variance of projected changes in crop productivity between the CMIP5 and CMIP6 ensembles [18]. Global crop yield projections changes in CMIP5 and CMIP6 were also investigated in the study by Jägermeyr et al. [19] which showed greater yield losses for maize, soybean and rice and more crop yield gains for wheat using CMIP6 simulations and the more recent ensemble of crop models from the Agricultural Model Intercomparison and Improvement Project's Global Gridded Crop Model Intercomparison [19]. However, to the best of our knowledge, there are currently no studies evaluating changes in projected yields of major staple food crops such as millet and sorghum in Africa from CMIP5 to CMIP6.

This work examines the impacts of climate change on crop yields of maize, millet and sorghum in West Africa using the CMIP5 climate models and the new generation of CMIP6 climate models. We use the SIMPLACE crop modeling framework to simulate historical and future crop yields and bootstrap techniques to evaluate projected changes in crop productivity between the CMIP5 and CMIP6 ensembles.

2 Material and methods

2. 1 Climate simulations

We used daily outputs of global climate models from Coupled Model Intercomparison Project 5th Phase (CMIP5; [16]) and the Coupled Model Intercomparison Project 6th Phase (CMIP6; [15]). The climate data required for crop modeling included the daily near-surface minimum and maximum air temperature, precipitation, global radiation, and wind speed. These data were extracted in *netcdf* format in the CICLAD platform (https://mesocentre.ipsl.fr/), and we selected only climate models with complete daily fields available at the time we performed the crop simulations (S1 Table). The CMIP5 models cover the period 1950–2099, including 29 GCMs for the historical period 1950–2005 and for 2006–2099 period, 29 models for the RCP8.5 projections, 27 GCMs for the RCP4.5 projections and 20 GCMs for the RCP2.6 projections. Similarly, CMIP6 models cover the historical period 1979–2014 and the future scenarios (SSP126, SSP245 and SSP585) for 2015–2100, including 18 GCMs for maximum temperature, 16 GCMs for minimum temperature and 19 GCMs for precipitation. At the time of the crop simulations, only five CMIP6 models were available with the daily fields of global radiation and wind speed required for crop modeling.

The data were first rescaled at 0.5˚ spatial horizontal resolution and then bias corrected using the CDF-t method, following the protocol described by Famien et al. [14], using the EWEMBI forcing data as the reference dataset. This bias-correction method is widely used in Africa and globally both as a statistical downscaling model and as a bias-correction method [20–22]. We considered three different time periods: the reference period (1975–2004 for CMIP5 and CMIP6) and future horizons in the short term (2035–2064) and long term (2065–2094) future horizons.

2.2 Climate indices

In order to investigate the key drivers of yield changes in the future, we computed a set of annual climate indices that are known to have an impact of crop yields in West Africa. These indices are average minimum and maximum temperatures during crop growth and accumulated rainfall from planting to maturity. Planting and maturity dates are provided by the SIMPLACE crop model. We also used a more sophisticated index, the annual growing degree days (GDD), as defined by Lobell et al. [23]. The growing degree days (GDD) are used to estimate the growth and development of various crops during the growing season. The concept is that development occurs only when the temperature exceeds the base temperature (T_{base}). It was estimated using daily minimum and maximum temperature data at each site:

$$GDD_{base,opt} = \sum_{t=1}^{N} DD_t$$

$$DD = \begin{cases} 0 & if\ T_t < T_{base} \\ T - T_{base} & if\ T_{base} \leq T_t \leq T_{opt} \\ T_{opt} - T_{base} & if\ T_t > T_{opt} \end{cases}$$

where t is an individual time step (hour) within the growing season, T_t is the average temperature during that time step (determined by interpolating between minimum and maximum temperature with a sin curve), and N is the number of hours between planting and maturity [23]. Here, the GDD was calculated using T_{base} = 8˚C and T_{opt} = 30˚C as defined by Lobell et al. [23] for maize in Africa. Similar values of T_{base} and T_{opt} were used for millet and sorghum. Indeed, Kiniry and Bonhomme [24] indicated that a T_{base} ranging from 7˚C to 9˚C could be used for several crops such as maize, sorghum, pearl millet, rice, soybean, and sunflower. The T_{opt} is more variable from one crop to another, ranging from 26˚ to 32˚C depending on the crop but it can also vary across different genotypes of the same crop. We thus chose to have the same T_{opt} of 30˚C for the three crops since it has been widely used for maize [23] but also used for modeling crop phenology of sorghum (see for instance [25]).

2.3 The SIMPLACE crop modeling framework

The SIMPLACE crop modeling framework (www.simplace.net) was used in this study. It combines the LINTUL5 crop growth model [26], a biophysical model that simulates plant growth, biomass, and yield as a function of climate, soil properties, and crop management using experimentally derived algorithms. LINTUL5 simulates plant growth under potential, water and nitrogen (N), phosphorus (P) and potassium (K) limitation. Plant growth is simulated in LINTUL5 as a function of intercepted radiation and radiation use efficiency. Plant development times are simulated using daily temperature sums (thermal time) and crop thermal time requirements from emergence to anthesis and from anthesis to maturity, respectively. LINTUL5 has been widely used in various studies at field, national and continental scales.

A modified version of the soil water balance *Slimwater* [27,28] model simulates the soil water balance and crop water uptake using the FAO Penman-Monteith equation with the reference crop and dual crop coefficient method [29]. The change in soil water content is simulated on a daily time scale using the *SlimwaterModified* in several variable soil layers estimated from the volumes of soil evaporation, crop water uptake, surface runoff and seepage below the root zone.

The daily demand and uptake of N, P and K demand, nitrogen stress and movement in the soil profile together with leaching of soil mineral nitrogen (Nitrate-N and Ammonium-N) are simulated by the *NPKDemandSlimNitrogen* model.

The *SlimwaterModified* module simulates the turnover and leaching of nitrate and ammonium related to soil water dynamics with input data related to soil water content and soil water fluxes on the daily time scale. The *SoilCN* model provides the daily total mineral N.

The dead roots are transferred to the "root litter pool" in the *SoilCN* model, which also simulates soil organic carbon and soil nitrogen dynamics using multiple litter pools and soil layers as well as three soil organic matter pools (see [30]).

Simulated hourly canopy temperature [31] is used as an input to the heat stress model [32] when the hourly temperature is above a critical threshold temperature around the flowering period. Daily air temperature is used to drive all other processes.

Stress indices are calculated daily for the water and nutrient limitation and range from 0.0 to 1.0.

2.4 Soil data

Soil data were obtained from the Harmonized World Soil Database (HWSD; https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). The original data had a resolution of 30 arcseconds by 30 arcseconds. Physical and chemical characteristics of topsoil (0–30 cm) and subsoil (30–100 cm) were selected for clay, silt, sand, bulk density, organic carbon, and available water capacity. Data were aggregated to the 0.5˚ horizontal resolution grid of the climate data by selecting the soil class with the largest area in each grid cell. The parameters such as soil water at field capacity, wilting point and saturation were calculated using the Pedotransfer functions (https://cran.r-project.org/web/packages/medfate/index.html), and the Van Genuchten parameters were determined from texture class.

2.5 Simulation setup

The SIMPLACE model has previously been used to assess climate change impacts in the Sudan savanna of West Africa [33,34]. Simulations were performed using CMIP5 and CMIP6 climate inputs at a spatial horizontal resolution of 0.5˚ for maize, pearl millet and sorghum. For each crop, short (90 days) and long (120 days) varieties were considered. In addition, a photoperiod-sensitive variety of pearl millet and sorghum was also simulated using a photoperiod-sensitive phase that depends on both temperature and astronomical day length [35]. This allows us to sample the diversity of crop responses to climate change, which may vary widely from one crop to another. Indeed, Sultan et al. [36] showed that short (90 days) millet and sorghum cultivars are more affected by climate change than longer duration and photoperiod-sensitive cultivars. Defrance et al. [37] compared simulations of climate change impacts on crop yields of millet, sorghum and maize in West Africa and found that maize is much more sensitive to water stress variations than millet and sorghum.

A total of eight different varieties (Mais90, Mais120, Mil90, Mil120, MilPP, Sor90, Sor120, SorPP) were simulated under current fertilizer use (N limitation) and intensified fertilizer (no NPK limitation). Crop growth parameters were derived from [33], who used experimental datasets of local varieties in Africa for calibration. Since these crops are typically grown without irrigation, simulations were conducted under rainfed conditions.

Simulations were run for each year from 1975 to 2094, and each emission scenario and simulated crop yields were then averaged over the three time horizons: the baseline (1975–2004) and the two future periods 2035–2064 and 2065–2094. We did not consider any varietal adaptation between baseline or climate change scenarios.

Rising atmospheric [CO_2] has the potential to increase crop water productivity (ratio of crop yield to total crop water use) by enhancing photosynthesis and reducing leaf-level transpiration, but the amplitude of this effect is still uncertain in crop models [11]. Therefore, we replicated the simulations under ambient historical [CO_2] (no change in CO_2 concentration) and elevated [CO_2]. There was no effect of elevated [CO_2] on radiation use efficiency (RUE) for all crops since maize, pearl millet and sorghum are C_4 crops. The CO_2 concentration for each period and each scenario is shown in S2 Table.

To evaluate the performance of the crop model in simulating historical yield anomalies, we conducted an additional simulation using the reanalyzed EWEMBI datasets as climate inputs over the 1979–2013 period. The simulated historical yields were compared with observed yield data from the FAO dataset. The FAO dataset is provided at the country level for each crop without variety differentiation. Then, simulated yields were aggregated across varieties at the country level for comparison to the FAO dataset following the method of Porwollik et al. [38]. The correlation between observed and predicted crop yield time series was obtained after removing a linear trend in both time series. Indeed, FAO yield time series over the 1979–2013 period show increasing yields over time (Burkina-Faso, Senegal), while others show yield losses (Chad, Niger). Although climate variability may influence these trends, non-climatic factors such as land degradation, management and economic crises are likely to be the main drivers. Since these non-climatic factors are not included in the crop model, it is necessary to remove trends in crop yields. Thus, we removed a linear trend in both observed and simulated yields, as suggested by Sultan et al. [36].

In this study, a set of crop-specific masks were used for yield analysis. This type of mask is often used to identify pixels where specific land crops are present. The resulting land use datasets represent the harvested area of several different crops in the world around the year 2000 [39]. Three different crops in West Africa (maize, millet, and sorghum) were selected for use in this study. In order to avoid extreme values, we have set a threshold for the harvested area and we took when the average number of hectares harvested per land area of a grid was above 100 per hectare. We then interpolated the crop mask dataset, originally reported at a spatial resolution of 5 minutes by 5 minutes in latitude by longitude (approximately 10 km by 10 km), to a horizontal spatial resolution of 0.5˚ to have the same spatial resolution as the crop yield simulations.

2.6 Statistical tests of significance of differences

First, we test the statistical significance of future changes in the multi-model ensemble for each grid point and model output, using the CMIP5 and CMIP6 simulations independently. Three time periods were defined: the reference period (1975–2004) and future horizons in the short-term (2035–2064) and long-term (2065–2094) future horizons. The difference between the multi-model mean CMIP5 (resp. CMIP6) of the reference period and the future period is considered statistically significant if the 95% confidence interval of the difference does not contain 0. The absolute difference is computed for model outputs such as temperatures, GDD and the number of crop failure. The relative difference is used for precipitation and crop yield. As the number of GCMs are different in CMIP5 and CMIP6 ensembles, we resample the simulations of CMIP5 to have the same number as in CMIP6 ensemble using the bootstrap technique. To do so, we randomly select 5 models with replacement in CMIP5 in order to have the same number of GCMs as in the CMIP6 ensemble. We then calculate the significance of the multi-model mean changes in CMIP5 between the reference and the future period and we repeat this procedure 1000 times.

Second, we test the statistical significance between future changes in CMIP5 (as described in previous paragraph) and future changes in CMIP6 (as described in previous paragraph). The change between the two is considered statistically significant if multi-model mean change in CMIP6 is not within the 95% confidence interval of multi-model mean changes of CMIP5. As explained in the previous paragraph, the multi-model mean changes of CMIP5 come from a bootstrap resampling in order to have the same number as in CMIP6 ensemble.

3 Results

3.1 Evaluation of the crop model

The comparison between simulated crop yields and FAO time series data for maize, millet and sorghum on average over West Africa shows that the performance of the SIMPLACE model varies from crop to crop (Fig 1). As suggested by Sultan et al. [6], we removed the data in Nigeria when calculating average yield anomalies over West Africa, as FAO data in this country appear to be problematic. Simulations of maize yields show the best correlation with observed yields (R = 0.47), but the mean yield is overestimated (2.1 t/ha in SIMPLACE simulations versus 1.2 t/ha in the FAO dataset). The variability of maize yield is also largely underestimated in the simulations with a coefficient of variation of 0.09 in SIMPLACE versus 0.23 in the observations. Mean yield of millet and sorghum are better estimated by the crop model although still overestimated and the coefficient of variation is quite close between FAO data and SIMPLACE simulations for these two crops. However, the correlation coefficient for sorghum is a somewhat weaker than that obtained for the other two crops (R = 0.43 for sorghum versus R = 0.47 for maize and millet).

The country-level comparison (Fig 2) shows significant correlations between observed and simulated yields in many countries such as Senegal, Gambia, Niger, and Côte d'Ivoire, but the

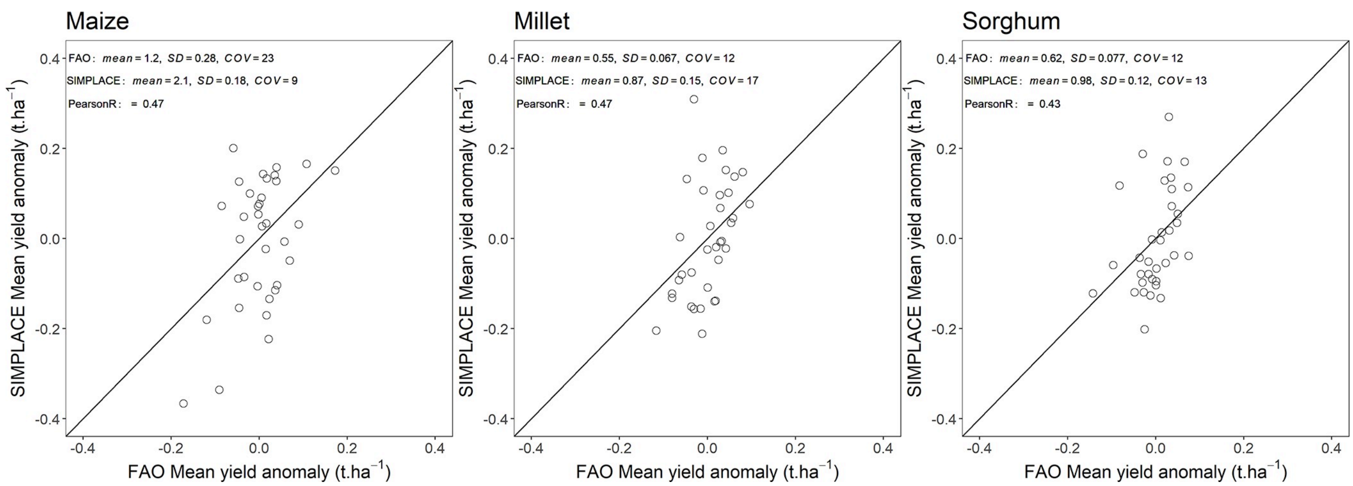

Fig 1. Comparison between simulated crop yield and FAO time series data at the country level for Maize, Millet and Sorghum 5-Year Moving Average. The yields at pixel level were aggregated over West Africa for the estimated period 1979–2013 with MIRCA2000 landuse data using EWEMBI climate dataset. Pearson correlation coefficient (R) was calculated between FAO and Simplace yields.

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correlation coefficient values remain do not exceed R = 0.62 (maize in Gambia). Slightly similar performances and similar deficits have been found in other published studies using different crop models in the region [6].

3.2 Future yield simulations

The following section examines crop yield projections under climate change scenarios using CMIP5 and CMIP6 models by comparing yield changes of maize, millet, and sorghum between the historical baseline and different future horizons using CMIP5 and CMIP6 and by comparing yield projections based on CMIP5 and CMIP6 climate models.

3.2.1. Mean crop yield evolution. Important and significant changes in mean yields are simulated in West Africa for the next decades (2035–2065) under the intermediate emissions pathway RCP4.5 / SSP245 (Fig 3). Without considering the fertilization effect of CO_2 concentration and using CMIP5 models, the SIMPLACE model simulates large mean yield losses in most cropping areas except for maize and millet in northern Nigeria. Yield losses ranged from 10% to 20% and are highest in Senegal, where they exceed 20% for the three crops, and in the northern Sahel for sorghum. Maize yield losses are generally lower than those simulated for millet and sorghum. Although such yield losses are still simulated with CMIP6 models under a similar configuration (no CO_2 concentration fertilization effect and SSP245 emissions scenario), the amplitude and the spatial extent of the yield losses are largely reduced for each crop with far less pixels with significant differences between the 2035–2065 period and the baseline and yield anomalies reduced by a factor 2 in some locations (Fig 3).

When the CO_2 fertilization effect is taken into account, the CMIP5 models still predict yield losses for the three crops, but the amplitude is slightly reduced. However, significant yield losses are still simulated in Senegal, Mali and Nigeria for millet and sorghum (Fig 3). Using CMIP6 models under a similar configuration (CO_2 concentration fertilization effect and SSP245 emission scenario), future changes in crop yields are mainly positive with an increase in mean yield of about 30% to 50% in Burkina Faso, Niger, Côte d'Ivoire and Nigeria while there are still some pixels with yield losses in Senegal, Mali, Nigeria Côte d'Ivoire and Benin.

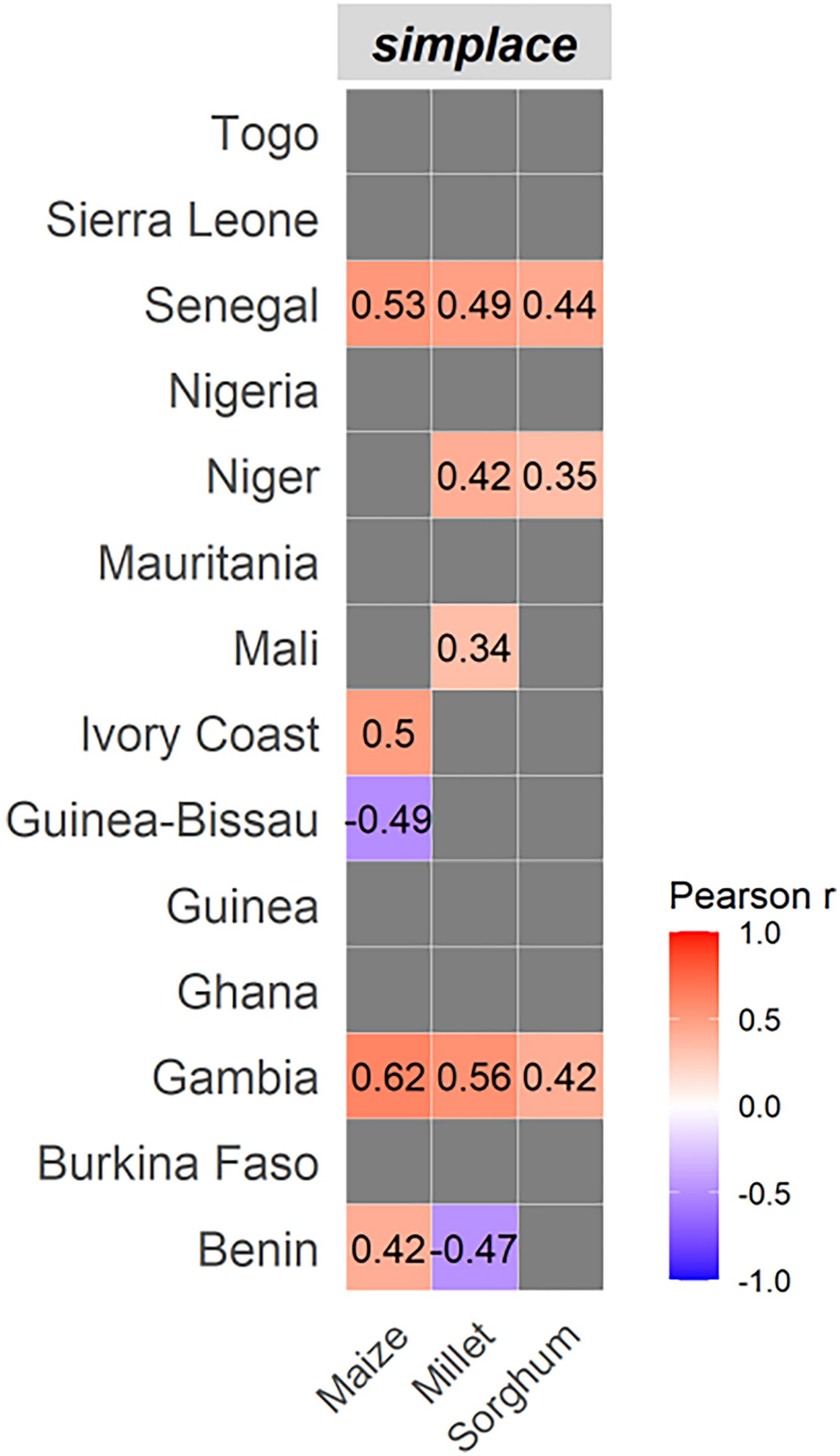

Fig 2. Heatmap of the Pearson correlation coefficient (R) between the simulated and observed FAO country level mean yields for maize, pearl millet and sorghum 5-Year Moving Average. Yields at pixel level were aggregated over countries with MIRCA2000 land use data and Pearson correlation coefficient R calculated over the period 1979–2013. Grey boxes indicate that correlations are not statistically significant (p-value > 0.05).

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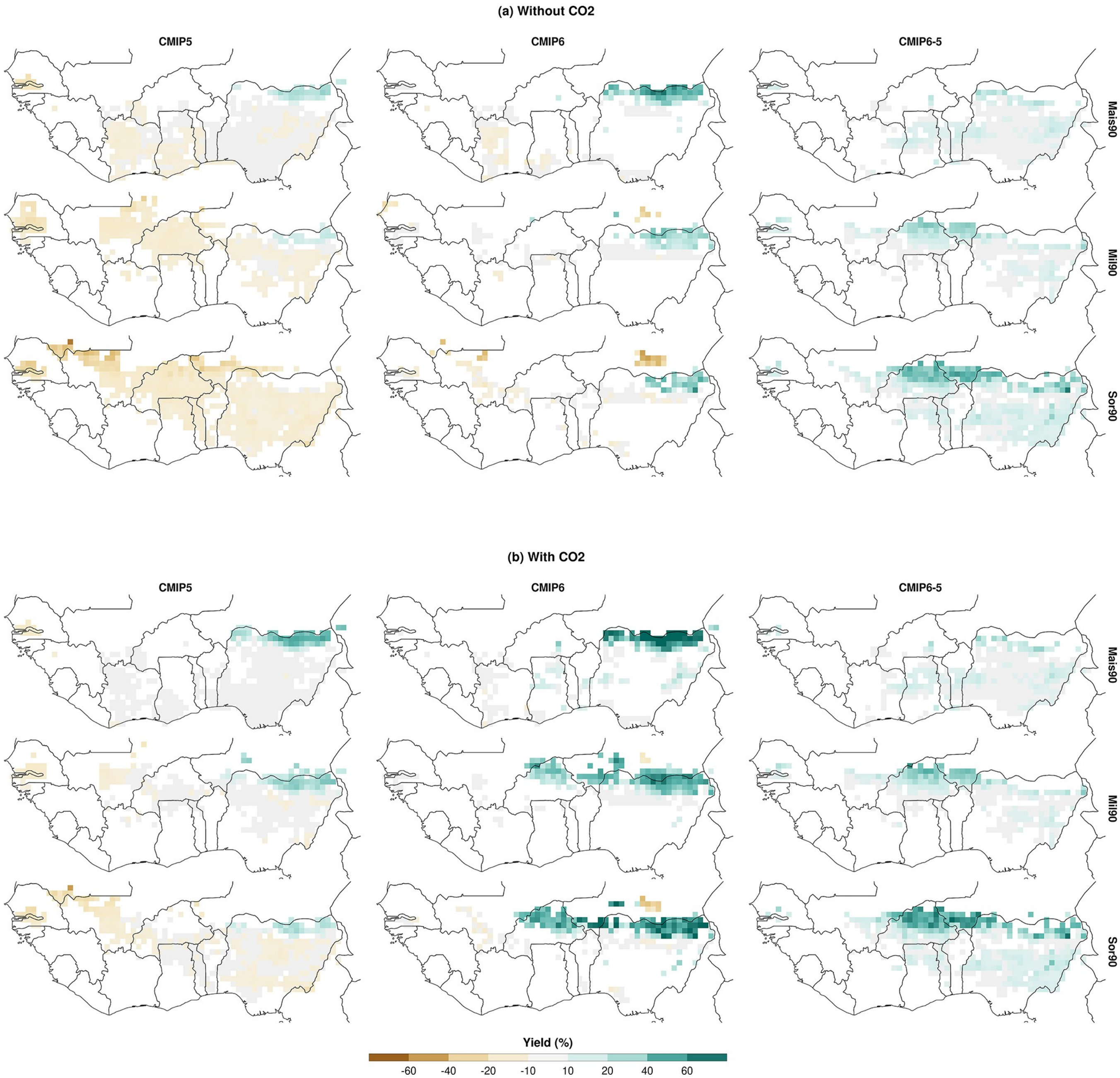

Fig 3. Relative change in mean yields for the varieties of 90 days with and without [CO_2] in West Africa under RCP45/SSP2-4.5 scenario for a near term (2035–2064) as compared with the reference period (1975–2004) in CMIP5, CMIP6 and the difference between CMIP6 and CMIP5 models. Areas with significant changes with 95% confidence level are represented (bootstrap method).

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Similar results were found under the scenarios RCP2.6 and RCP8.5 for CMIP5 and SSP2.6 and SSP8.5 for CMIP6 and for the other varieties (longer varieties of 120 days, photoperiod sensitive varieties) with a reduction of negative impacts of climate change using CMIP6 climate models instead of CMIP5 climate models, although the amplitude and the location of anomalies vary (S1–S5 Figs). In particular, the differences are limited to the Sahel using RCP8.5 for CMIP5 and SSP8.5 for CMIP6 (S2 and S5 Figs).

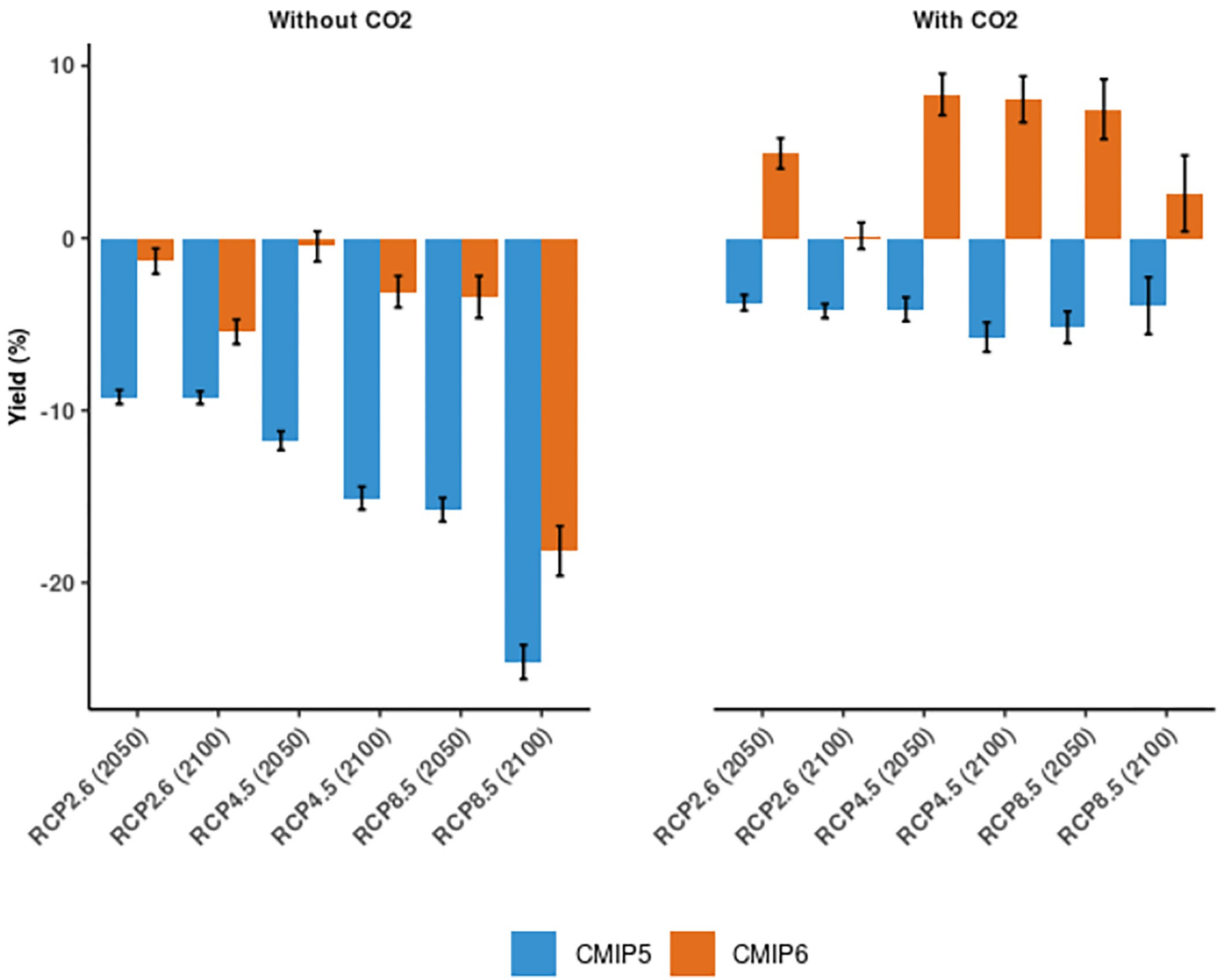

Fig 4. Projected changes in average yields for the varieties of 90 days (a) with and (b)without [CO_2] fertilization effect in the SIMPLACE crop model (b) in West Africa under three scenarios (RCP26/SSP1-2.6, RCP45/SSP2-4.5, RCP85/SSP5-8.5) for the two time periods (2035–2064 and 2065–2094) as compared with the reference period (1975–2004). The different crops were weighted according to their respective areas. The error bars represent the 95% confidence interval. Blue and orange bars represent the change of multi-model mean yields in CMIP5 and CMIP6 models.

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In addition, the mean yield changes vary by scenario, time horizon, climate model, and with and without taking into account the [CO_2] effect in the crop model. When averaging future yield changes across all West Africa (Fig 4), we found that the yield impacts under lower (RCP2.6/SSP126) and higher (RCP8.5/SSP585) emissions scenarios are always significantly larger by the end of the century than the impacts simulated at mid-century. However, the yield impacts differ significantly between the crop simulations using CMIP5 and CMIP6 models. In the absence of [CO_2] (Fig 4A), CMIP5 shows significant mean yield losses that increase with the emission level and the time horizon. Yield losses are maximal at the end of the century and under the highest emissions scenario (RCP8.5) reaching -35% for sorghum. As shown in Fig 3, these yield losses are lower using CMIP6 models but interestingly the differences between CMIP5 and CMIP6 projections tend to decrease by the end of the century (Fig 4A). Without considering the direct effect of [CO_2] on the crop, similar yield losses are found under

RCP2.6/SSP126 scenarios (-12% for CMIP5 and -13% for CMIP6) and RCP8.5/SSP585 scenarios (-35% for CMIP5 and -31% for CMIP6) by the end of the century. When the effect of [CO_2] is considered in the crop model, CMIP5 simulations still show a yield decrease in West Africa, but the amplitude is lower especially for the high emissions scenario (RCP8.5) by the end of the century, where the benefits of high level of [CO_2] for the crop outweigh the negative effects of climate change (Fig 4B). On the contrary, CMIP6 simulations show large yield increases under the SSP245 scenario reaching 20% by the end of the century, and to a lesser extent under SSP126 and SSP585 for the 2035–2065 period. However, as for the configuration using CMIP5 models, the SIMPLACE model still simulates yield losses under the high emissions scenario by the end of the century using CMIP6 models, even taking into account for the positive effects of [CO_2].

3.2.2. Mean crop yield evolution. More than average yield reduction, the risk of crop failure of staple food crops such as millet, sorghum and maize is often more problematic for smallholder farmers in Africa, as it has a direct impact on food security and livelihoods. Here, we assess future changes in terms of crop failure under the different emission scenarios using both CMIP5 and CMIP6 climate models. A crop failure is defined as a year in the future when the simulated yield is less than 10% quantile of historical yields. Yield failure varies by crop and region with and without [CO_2] fertilization (Fig 5). Without [CO_2] fertilization, the frequency of crop failures increases under the RCP4.5/SSP245 for the 2035–2065 period, especially for maize in West Africa, and to a lesser extent for millet and sorghum but restricted to the Sahel region. This increase in crop failure is less pronounced when CMIP6 climate outputs are used to simulate crop yields. When the [CO_2] fertilization effect is taken into account, the number of years of crop failure is slightly reduced but the spatial patterns and the differences between CMIP5 and CMIP6 remain the same (Fig 5). Although the magnitude of the changes varies slightly, the spatial patterns of crop failure are consistent across different scenarios (RCP26/SSP1-2.6 and RCP85/SSP5-8.5) and considering 120-days cultivars (S6–S10 Figs).

3.3 Changes in yield drivers

In order to better understand what drives future yield changes in the SIMPLACE crop model, we compare future changes in key agricultural indices, namely precipitation, minimum and maximum temperature during the crop growth cycle and GDD changes in the CMIP6 and CMIP5 models with future changes of simulated yields. Minimum and maximum temperatures refer to mean daily values. This section is based on 90-day sorghum yields but similar behaviors are obtained with other simulated crops. There is a clear negative relationship between GDD, minimum and maximum temperature changes and future yield changes indicating that as temperatures increase, yields will decrease in the future (Fig 6). This is particularly true in tropical Africa (approximately south of 12˚N) where annual rainfall is high compared to Sahelian Africa (north to 12˚N). There is also a clear linear relationship between simulated yield changes and total rainfall changes. This is particularly true in Sahelian Africa where rainfall is a limiting factor. Here, any increase (decrease) of precipitation in future scenarios leads to an increase (decrease) in future crop yields.

A hierarchical regression analysis was performed to examine the effect of climate change on crop yields independently for CMIP6 (S3 Table) and CMIP5 (S4 Table). The independent variables were entered in blocks. The first block includes minimum and maximum temperatures during the growing season and the second block includes growing degree days and rainfall during the growing season.

$$\text{Block 1}: \ \mathrm{Y_i} = b_0 + b_1\mathrm{T_{max}} + b_2\mathrm{T_{min}} + \varepsilon_i$$

$$\text{Block 2}: \ \mathrm{Y_i} = b_0 + b_1\mathrm{T_{max}} + b_2\mathrm{T_{min}} + b_3\mathrm{GDD} + b_4\mathrm{PRCPTOT} + \varepsilon_\mathrm{i}$$

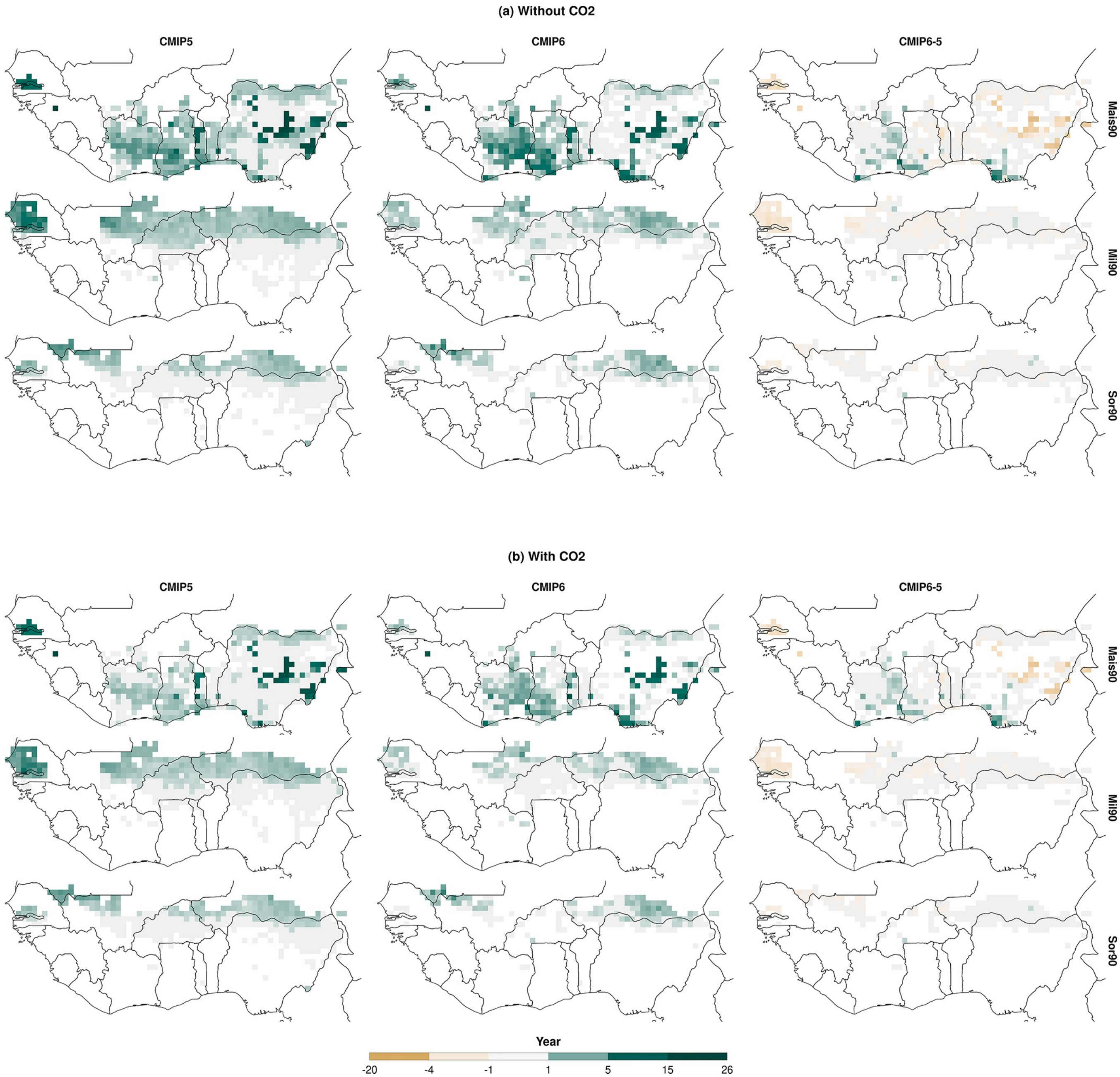

Fig 5. Relative change in the number of years of crop failure for the varieties of 90 days with and without [CO_2] in West Africa under RCP45/SSP2-4.5 scenario for a near term (2035–2064) as compared with the reference period (1975–2004) in CMIP5, CMIP6 and the difference between CMIP6 and CMIP5 models. A crop failure is defined as a year with a simulated yield below the 10% quantile of historical yields. Areas with significant changes with 95% confidence level are represented (bootstrap method).

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where Y is the relative change in average yield (sorghum 90 days) and ε is the model error. The coefficients b_1, b_2, b_3 and b_4 correspond respectively to the absolute changes in mean daily maximum (T_{max}) and minimum (T_{min}) temperatures during the growing season, the sum of growing degree days during the growing season (GDD), and PRCPTOT the relative change in rainfall during the growing season. Overall, the results using CMIP6 values (S3 Table) indicate that the first model (block 1) is significant with $F = 46.124$, $p < 0.01$, $R^2 = 0.460$. Minimum

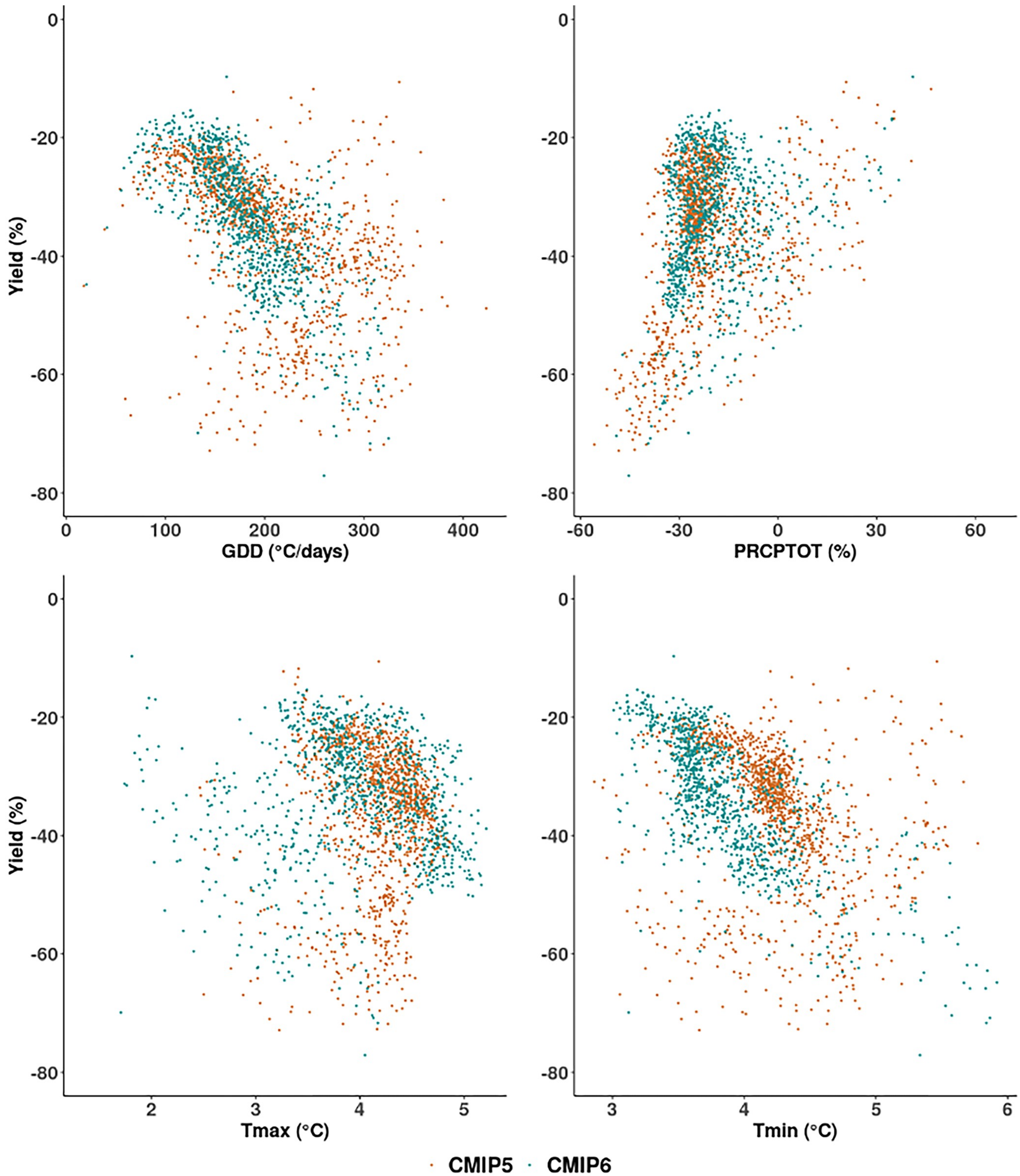

Fig 6. Relationship between climate changes (growing degree days, rainfall, maximum and minimum temperature) and relative change in mean yield of sorghum 90-day in CMIP5 and CMIP6 models. Changes are computed under RCP85/SSP5-8.5 scenario for a long term period (2065–2094) as compared with the reference period (1975–2004). Absolute changes are shown for growing degree days and minimum and maximum temperature, while relative changes were computed for rainfall and crop yields. The orange circles represent future changes projected in CMIP5 and CMIP6 is presented in cyan. This figure has a restricted y axis to zero in relative change in mean yield to enhance the clarity of the results and exclude the most extreme pixels (five pixels over 2250 pixels were excluded).

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temperature was significantly associated with changes in average sorghum yield at 90 days (b_2 = -16.438, $p < 0.01$).

The second block ($F = 363.483$, $p < 0.01$, $R^2 = 0.590$) which includes growing degree day and total precipitation (b_3 = -0.078, $p < 0.01$ and b_4 = 0.428, $p < 0.01$), shows a significant improvement over the first model (block 1) with $\Delta R^2 = 0.13$. The second block explained significantly more variance than the first block, contributing 59% to the variability of the change in average yield. Thus, minimum and maximum temperature, growing degree days, and total precipitation explain more variability when considered simultaneously. Similar results were obtained with CMIP5, indicating that the model is better explained when all factors are considered simultaneously (S4 Table).

Future changes in maximum temperature, growing degree days and precipitation show different patterns between CMIP5 and CMIP6 (Fig 7), which may explain the differences in future yield changes. Indeed, while both CMIP5 and CMIP6 models simulate a significant warming over West Africa with higher GDD and maximum temperature exceeding +2.5˚C in tropical Africa by the end of the century, compared to the historical baseline, the warming is significantly reduced in CMIP6 models especially in the Sahel compared to CMIP5 (Fig 7). This difference is more pronounced for maximum temperature than for GDDs and by mid-century and is even more pronounced for the RCP8.5/SSP585 scenarios (S11 Fig).

As with GDD and maximum temperature, there is a significant difference between CMIP6 and CMIP5 projections in precipitation under RCP4.5 (SSP245) scenario. By mid-century, CMIP6 models simulate slightly but significantly wetter conditions compared to CMIP5 models. By the end of the century, both CMIP5 and CMIP6 models simulate an increase of rainfall in northeastern Sahel (Niger, northern Nigeria) and a decrease of precipitation elsewhere but the decrease is less pronounced in CMIP6, while the increase in precipitation in the northeastern Sahel is enhanced.

Under the RCP2.6/SSP126 and RCP8.5/SSP585 scenarios, the spatial patterns of changes are similar to those under the RCP4.5/SSP245 scenario, but climate changes are much more pronounced under RCP8.5/SSP585 (S11 Fig) while changes are reduced under the RCP2.6/SSP126 scenario (S12 Fig). Similar patterns of differences between CMIP6 and CMIP5 projections were found using additional available CMIP6 models for maximum temperature and precipitation changes (S13 Fig). Using 37 CMIP6 models (18 models for maximum temperature and 19 models for precipitation) instead of five models, climate projections in the Sahel are still cooler and wetter in CMIP6 compared to CMIP5 projections. However, the warming in coastal West Africa is more pronounced in CMIP6 than in CMIP5, especially towards the end of the century (S13 Fig).

Since simulated crop yields are highly sensitive to changes in precipitation and temperature (Fig 6), less warm and wetter (or less dry) conditions in future years simulated by CMIP6 explain the higher yields in CMIP6 compared to CMIP5 models observed in Fig 4. This can also be seen in Fig 8 which shows the relationships between CMIP5-CMIP6 differences in future yield changes and future changes in temperatures (maximum and minimum), growing degree days and precipitation. Positive values indicate higher values of future changes in CMIP6 compared to CMIP5. The results show that there is a strong and positive relationship between change in mean yield change and precipitation change on the one hand, and a negative relationship between mean yield change and temperature change and growing degree days on the other hand in the difference between CMIP5 and CMIP6 models. Cooler pixels in CMIP6 future projections (lower GDD, lower maximum and minimum temperatures) tend to lead to higher simulated yields compared to CMIP5 projections. Wetter pixels in CMIP6 future projections tend to lead to higher simulated yields compared to CMIP5 projections.

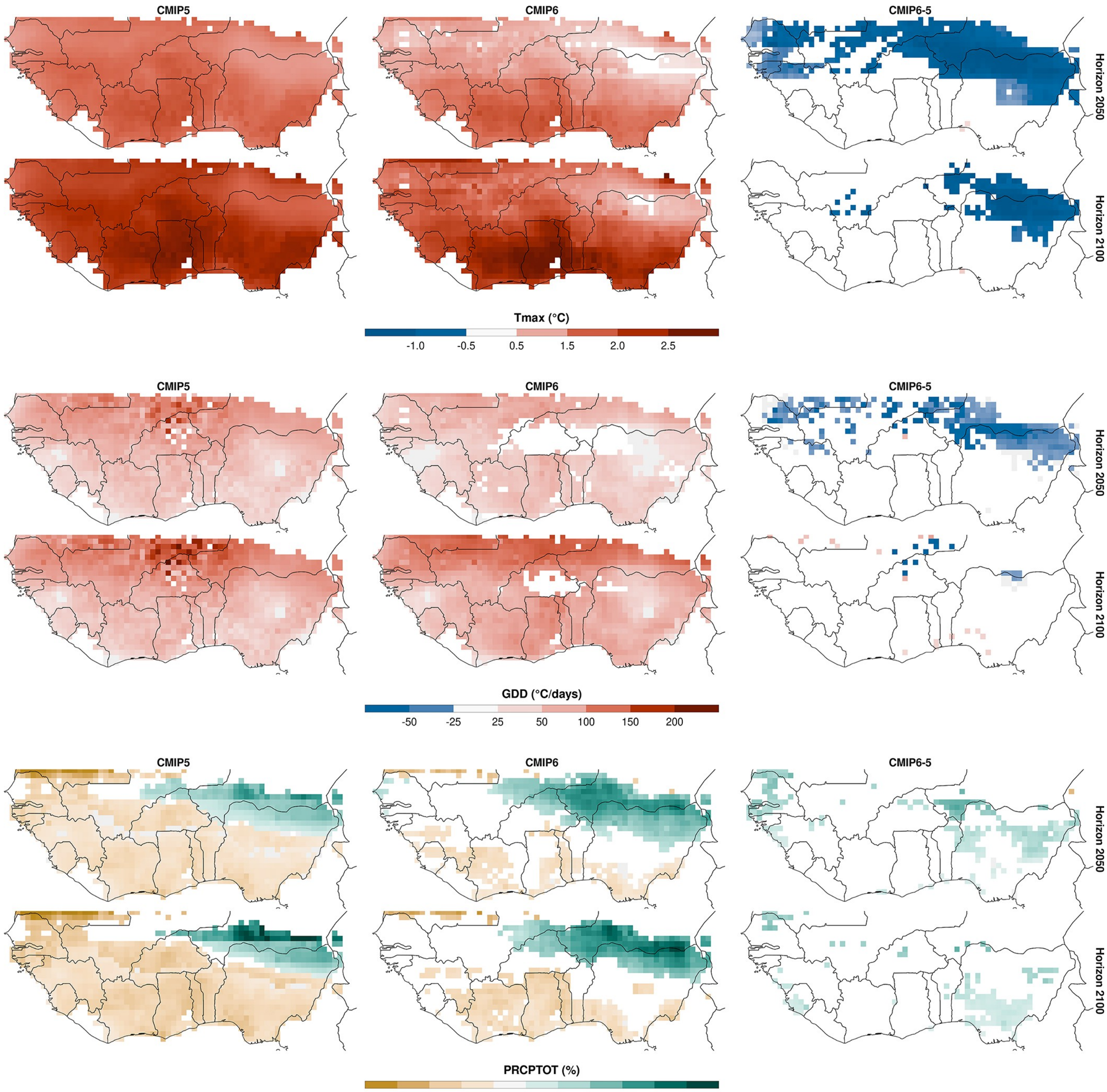

Fig 7. Future changes in maximum temperature (˚C), growing degree days (˚C/days) and precipitation (%) over West Africa under RCP45/SSP2-4.5 scenario for the two time periods (2035–2064 and 2065–2094) as compared with the reference period (1975–2004) in CMIP5, CMIP6 and the difference between CMIP6 and CMIP5 models. Areas with significant changes with 95% confidence level are represented (bootstrap method).

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4 Summary and discussions

Our study examines the impacts of climate change on crop yields of maize, millet and sorghum in West Africa using the CMIP5 climate models, the new generation of CMIP6 climate models, and the SIMPLACE crop modeling framework.

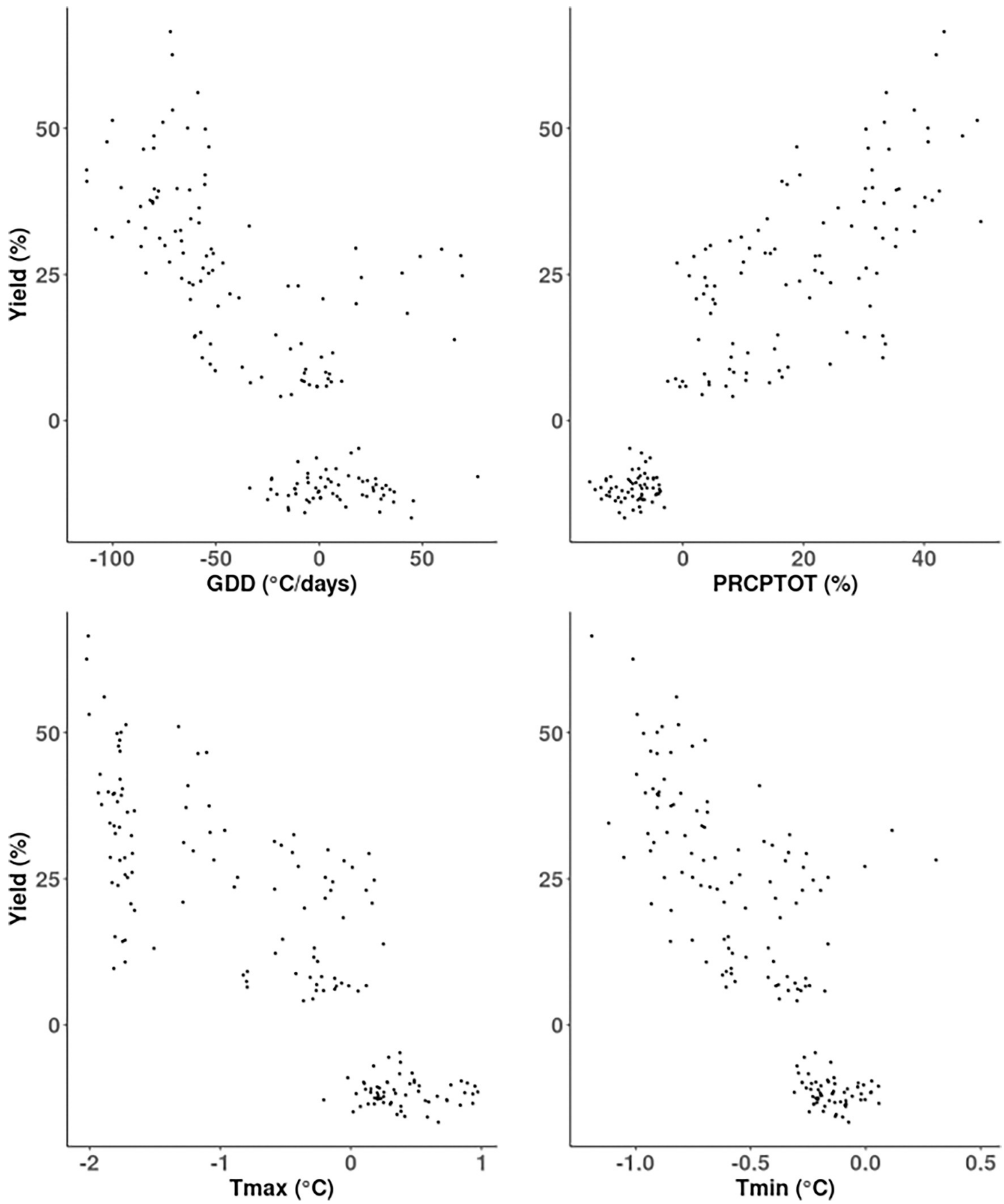

Fig 8. Relationship between climate changes (growing degree days, rainfall, maximum and minimum temperature) and yields changes of sorghum 90-days in the difference between CMIP5 and CMIP6 models. Changes are computed under RCP85/SSP5-8.5 scenario for a long term period (2065–2094) as compared with the reference period (1975–2004). Absolute changes are shown for growing degree days and minimum and maximum temperature, while relative changes were computed for rainfall and crop yields. Positive values indicate higher values of future changes in CMIP6 compared to CMIP5.

https://doi.org/10.1371/journal.pclm.0000263.g008

4.1 Evaluation of the crop model

The results suggest that the SIMPLACE crop model evaluated here, although imperfect, has a performance consistent with that of other crop models in the region. For example, Sultan et al.

[6] evaluated the performance of two crop models CYGMA and SARRA-H, against FAO yields of millet and sorghum for the period 1996–2005. Correlations were generally higher with the SARRA-H model, but simulated yields showed a similar overestimation of yields. The CYGMA model estimated mean yields and trends better, but the SIMPLACE model largely outperforms the CYGMA model in reproducing the interannual variability of millet and sorghum yields [6]. As for the SIMPLACE model, many crop models tend to overestimate mean yield and underestimate yield variability in sub-Saharan Africa [36,40–42] because they are usually calibrated against experimental data without considering for non-climatic factors such as pests, weeds, and soil-related constraints. Moreover, the comparison between observed and simulated country yields in West Africa is sometimes problematic since–although FAO yield statistics are considered as the most reliable data source–several data values are derived from data imputation or unofficial data sources and show some suspicious values for some countries (see [6]).

4.2 Crop yield projections using CMIP5 and CMIP6

The SIMPLACE crop model, without accounting for the [CO2] increase in the crop model, simulates large crop yield losses in West Africa under climate change scenarios using CMIP5 climate models. These impacts are greatest in the western part of the Sahel, particularly in Senegal, where productivity could be reduced by a factor of 2 by the end of the century and under the highest emissions scenario RCP8.5. Indeed, using CMIP5 models and RCP8.5, we found yield losses of 47% and 44%, respectively for 90 and 120-days varieties on average in Senegal by the end of the century. These yield losses are mainly driven by a significant precipitation decrease and warmer temperatures, both of which are detrimental to crop yields. Similar yields losses have been found in previous studies using different crop models without [CO_2] effect and different downscaling techniques. Using the SARRA-H model, Sultan et al. [36] showed a decrease in millet and sorghum yields of about 0–41% in the 21st century over West Africa. A decrease in future maize yields was also found by Jones and Thornton [43] and Schlenker and Lobell [44], reaching −14% for sub-Saharan Africa by 2050, according to Jones and Thornton [43], with impacts varying between −30 and +2% across sub-Saharan countries.

These yield losses can be modulated by accounting for the effect of the elevated atmospheric [CO_2], which has a beneficial effect on C4 crops such as maize, millet, and sorghum by alleviating water stress through the indirect effect of reducing transpiration [37,45]. The SIMPLACE model simulates less detrimental impacts of climate change when this effect is taken into account in the crop model, especially under high levels of [CO_2] by the end of the century and for moderate and high emissions scenarios, RCP4.5 and RCP8.5, respectively. However, the effects of climate change remain negative almost everywhere in West Africa except in northern Nigeria.

Using the new generation of climate models, CMIP6, we found that these negative crop yield projections are largely reduced, with crop yields actually mostly increasing, when the effect of [CO_2] is included in the crop model. The differences between the CMIP5 and CMIP6 projections are the largest by mid-century and using RCP4.5/SSP245 scenarios, and tend to decrease by the end of the century in RCP8.5/SSP585 where both CMIP5 and CMIP6 models lead to yield declines in the future. These differences in crop yield impacts between the CMIP5 and CMIP6 simulations are mainly due to different climate projections of temperature and precipitation in West Africa, with CMIP6 projections being significantly wetter and cooler by mid-century and to a lesser extent by the end of the century. Few papers have compared CMIP6 and CMIP5 ensemble runs over Africa, and results are not always consistent across climate model ensembles and studies, especially for seasonal mean precipitation. Dosio et al. [13]

conducted a very detailed investigation of future precipitation characteristics in Africa using CMIP5, CMIP6, but also regional simulations with CORDEX runs. For West Africa, they show that global models tend to project a wetter future compared to RCMs, with CMIP6 being slightly wetter than CMIP5 in summer. Almazroui et al. [17] analyzed both future annual temperature and precipitation in Africa using the CMIP6 and CMIP5 ensembles. They found that the median warming simulated by the CMIP6 model ensemble is higher than the CMIP5 ensemble over most of Africa which is not consistent with our results. However, their methodology is quite different from ours. Indeed, their conclusions are based on comparing annual temperatures rather than temperatures during the growing season. Furthermore, Almazroui et al. [17] directly compared future projections of CMIP6 and CMIP5, whereas we compared differences between future projections and historical projections in both CMIP5 and CMIP6. The latter approach has the advantage of isolating global warming from systematic biases in the climate simulations.

4.3 Limitations of the study

All modeling studies have limitations that must be acknowledged. First of all, only one crop model was used, whereas it is likely that estimates of crop yield changes under climate change could vary if a different crop model was used. For example, Sultan et al. [6] showed significant differences in simulated millet and sorghum yields between the CYGMA and the SARRA-H models in West Africa. However, it is likely that most crop models, given a similar configuration, would simulate higher yields under wetter and less warm climate conditions as simulated by CMIP6 models compared to CMIP5 models. Furthermore, the future yield changes in West Africa estimated by SIMPLACE using CMIP5 climate models are close to those simulated by other crop models such as SARRA-H [37], CERES [43], APSIM [46], although the different climate scenarios, time slices, crops, and methodologies make an exact comparison with the results of other studies difficult. Another important limitation is the difference in the number of available models for crop yield simulations in the CMIP5 and CMIP6 ensembles. CMIP6 crop yield simulations are based on five climate models, while the ensemble of CMIP5 models is much larger (up to 29 models; see S1 Table). To address this issue, we systematically used bootstrap techniques to test for significant changes between the CMIP5 and CMIP6 ensembles by resampling CMIP5 simulations to have the same numbers as CMIP6. In addition, since we were able to collect additional CMIP6 models for minimum and maximum temperatures and for precipitation (18 models with daily maximum temperature, 16 models with daily minimum temperature and 19 with daily precipitation), we carefully checked that the subsample of five climate models was not biased in terms of mean precipitation or temperature changes compared to a larger sample. Using the bootstrap method, we showed that our subsample of five CMIP6 models used for crop yield simulations is almost statistically identical to the larger ensemble, with very few significant differences, and with visually similar future changes in terms of rainfall and temperature changes in the five CMIP6 models and in the larger CMIP6 ensemble (S13 Fig). Indeed, similar patterns of differences between CMIP6 and CMIP5 projections in Fig 7 were found using additional available CMIP6 models for maximum temperature and precipitation changes (S13 Fig), with climate projections that are still cooler and wetter in CMIP6 compared to CMIP5 projections. It is therefore very likely that using a larger ensemble of CMIP6 models for crop yield projections would lead to similar results since yield changes are driven by changes in precipitation and temperature that are robust to changes in the number of models (S13 Fig). Similar patterns of differences between CMIP6 and CMIP5 projections in Fig 7 were also found using raw CMIP6 and CMIP5 models simulations instead of bias-corrected climate simulations (S14 Fig). This means that the bias-correction technique, required for the crop simulations, does not artificially modify the differences between the two ensembles.

5 Conclusions

Our study examines the impacts of climate change on crop yields of maize, millet and sorghum in West Africa, using CMIP5 climate models, the new generation of CMIP6 climate models, and the SIMPLACE crop modeling framework. Overall, we found less negative impacts of climate change on crop yields using the new generation of climate models compared to CMIP5 climate models under similar scenarios and configurations. This is mainly due to significantly less warm and wetter future projections in West Africa in the CMIP6 simulations. Such results highlight the large uncertainties that remain in assessing the impacts of climate change in the region and the consequent difficulty for end-users to anticipate adaptation strategies. Nevertheless, it is striking that the differences in impact projections using CMIP5 and CMIP6 models tend to diminished by the high emissions scenario RCP8.5/SSP585 by the end of the century. In this case, there is a consensus between the new and the previous generation of climate models to show a negative impact of climate change on crop yields.

Supporting information

S1 Fig. Same as Fig 3 but for RCP26 / SSP126 scenarios.
(TIF)

S2 Fig. Same as Fig 3 but for RCP85 / SSP585 scenarios.
(TIF)

S3 Fig. Same as Fig 3 but for RCP26 / SSP126 scenarios and 120-days cultivars.
(TIF)

S4 Fig. Same as Fig 3 but for RCP45 / SSP245 scenarios and 120-days cultivars.
(TIF)

S5 Fig. Same as Fig 3 but for RCP85 / SSP585 scenarios and 120-days cultivars.
(TIF)

S6 Fig. Same as Fig 5 but for RCP26 / SSP126 scenarios.
(TIF)

S7 Fig. Same as Fig 5 but for RCP85 / SSP585 scenarios.
(TIF)

S8 Fig. Same as Fig 5 but for RCP26 / SSP126 scenarios and 120-days cultivars.
(TIF)

S9 Fig. Same as Fig 5 but for RCP45 / SSP245 scenarios and 120-days cultivars.
(TIF)

S10 Fig. Same as Fig 5 but for RCP85 / SSP585 scenarios and 120-days cultivars.
(TIF)

S11 Fig. Same as Fig 7 but for RCP85 / SSP585 scenarios.
(TIF)

S12 Fig. Same as Fig 7 but for RCP2.6/SSP126 scenarios.
(TIF)

S13 Fig. Same as Fig 7 but using 37 CMIP6 models (18 models for maximum temperature and 19 models for rainfall) instead of 5 CMIP6 models in Fig 7.
(TIF)

S14 Fig. Same as Fig 7 but using raw CMIP5 and CMIP6 models simulations instead of bias-corrected CMIP5 and CMIP6 models simulations.
(TIF)

S1 Table. Number of GCMs available for each scenario RCP2.6 in CMIP5 corresponds to SSP126 in CMIP6, RCP4.5 in CMIP5 corresponds to SSP245 in CMIP6 and RCP8.5 in CMIP5 corresponds to SSP585 in CMIP6.
(XLSX)

S2 Table. Simulated CO2 concentration for each period and scenarios.
(XLSX)

S3 Table. Hierarchical regression of relative variation in mean sorghum yield at 90 days with explanatory variables using CMIP6 model. Explanatory variables are daily mean maximum (T_{max}) and minimum temperature (T_{min}) during the growing season, the sum of growing degree days during the growing season (GDD) and the relative change in rainfall during the growing season (PRCPTOT).
(TIF)

S4 Table. Same as S3 Table but for CMIP5 ensemble.
(TIF)

Author Contributions

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Investigation: Benjamin Sultan, Aicha Ilmi Ahmed, Babacar Faye.

Methodology: Benjamin Sultan, Aicha Ilmi Ahmed, Babacar Faye, Yves Tramblay.

Software: Aicha Ilmi Ahmed, Babacar Faye.

Supervision: Yves Tramblay.

Validation: Yves Tramblay.

Writing – original draft: Benjamin Sultan.

References

1. Trisos CH, Adelekan IO, Totin E, Ayanlade A, Efitre J, Gemeda A et al. Africa. In: Change Climate 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Pörtner H.-O., Roberts DC, Tignor M., Poloczanska E.S., Mintenbeck K., Alegría A, Craig M., Langsdorf S., Löschke S., V., Okem A, Rama B (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 1285–1455, https://doi.org/10.1017/9781009325844.011
2. Adams L. Unlocking the potential of enhanced rainfed agriculture. SIWI, Stockholm. 2008. Available from: https://www.siwi.org/wp-content/uploads/2018/12/ Unlocking-the-potential-of-rainfed-agriculture-2018-FINAL.pdf.
3. FAO, IFAD, UNICEF, WFP and WHO. The State of Food Security and Nutrition in the World 2021. Transforming food systems for food security, improved nutrition and affordable healthy diets for all. 2021. Rome, FAO.

4. Iizumi T, Shiogama H, Imada Y, Hanasaki N, Takikawa H, and Nishimori M. Crop production losses associated with anthropogenic climate change for 1981–2010 compared with preindustrial levels. International Journal of Climatology. 2018; 38: 5405–5417.
5. Ray DK, West PC, Clark M, Gerber JS, Prishchepov AV, Chatterjee S. Climate change has likely already affected global food production. PLoS ONE 2019; 14(5): e0217148. https://doi.org/10.1371/journal.pone.0217148 PMID: 31150427
6. Sultan B, Defrance D and Iizumi T. Evidence of crop production losses in West Africa due to historical global warming in two crop models. Scientific Reports. 2019; 9(1): 12834, https://doi.org/10.1038/s41598-019-49167-0 PMID: 31492929
7. Ortiz-Bobea A, Ault TR, Carrillo CM, Chambers RG and Lobell DB. Anthropogenic climate change has slowed global agricultural productivity growth. Nature Climate Change. 2021; 11: 306–312.
8. Carr TW, Mkuhlani S, Segnon AC, Ali Z, Zougmoré R, Dangour AD et al. Climate change impacts and adaptation strategies for crops in West Africa: a systematic review. Environ. Res. Lett. 2022; 17: 053001, 14p.
9. Knox J, Hess T, Daccache A, and Wheeler T. Climate change impacts on crop productivity in Africa and South Asia. Environ. Res. Lett. 2012; 7: 034032. https://doi.org/10.1088/1748-9326/7/3/034032
10. Roudier P, Sultan B, Quirion P and Berg A. The impact of future climate change on West African crop yields: what does the recent literature say? Glob. Environ. Change. 2011; 21: 1073–1083.
11. Deryng D, Elliott J, Folberth C, Müller C, Pugh TAM, Boote KJ et al. Regional disparities in the beneficial effects of rising CO2 concentrations on crop water productivity. Nature Clim Change 2016; 6: 786–790.
12. Sultan B and Gaetani M. Agriculture in West Africa in the Twenty-First Century: Climate Change and Impacts Scenarios, and Potential for Adaptation. Frontiers in Plant Science. 2016; 7: 1262. https://doi.org/10.3389/fpls.2016.01262 PMID: 27625660
13. Dosio A, Jury MW, Almazroui M, Ashfaq M, Diallo I., Engelbrecht F. et al. Projected future daily characteristics of African precipitation based on global (CMIP5, CMIP6) and regional (CORDEX, CORDEX-CORE) climate models. Clim Dyn 2021; 57: 3135–3158.
14. Famien AM, Janicot S, Ochou AD, Vrac M, Defrance D, Sultan B et al. A bias-corrected CMIP5 dataset for Africa using the CDF-t method—A contribution to agricultural impact studies. Earth Syst. Dyn. 2018; 9: 313–338.
15. Eyring V, Bony S, Meehl GA, Senior CA, Stevens B, Stouffer RJ et al. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, Geosci. Model Dev. 2016; 9: 1937–1958.
16. Taylor KE, Stouffer RJ and Meehl GA. An overview of cmip5 and the experiment design. Bull Am Meteorol Soc. 2012; 93(4): 485–498.
17. Almazroui M, Saeed F, Saeed S, Islam MN, Ismail MF, Klutse NA et al. Projected Change in Temperature and Precipitation Over Africa from CMIP6. Earth Syst Environ. 2020; 4: 455–475.
18. Müller C, Franke J, Jägermeyr J, Ruane AC, Elliott J, Moyer E et al. Exploring uncertainties in global crop yield projections in a large ensemble of crop models and CMIP5 and CMIP6 climate scenarios. Environ. Res. Lett. 2021; 16: 3, 034040, https://doi.org/10.1088/1748-9326/abd8fc
19. Jägermeyr J, Müller C, Ruane AC, Elliott J, Balkovic J, Castillo O et al. Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nat Food 2021; 2: 873–885. https://doi.org/10.1038/s43016-021-00400-y PMID: 37117503
20. Vigaud N, Vrac M and Caballero Y. Probabilistic downscaling of GCM scenarios over southern India. International Journal of Climatology. 2013; 33: 1248–1263.
21. Vrac M and Ayar PV Influence of Bias Correcting Predictors on Statistical Downscaling Models. Journal of Applied Meteorology and Climatology. 2017; 56: 5–26.
22. Lanzante JR, Adams-Smith D, Dixon KW, Nath M, Whitlock CE. Evaluation of some distributional downscaling methods as applied to daily maximum temperature with emphasis on extremes. Int J Climatol. 2020; 40:1571–1585.
23. Lobell DB, Bänziger M, Magorokosho C and Vivek B. Nonlinear heat effects on African maize as evidenced by historical yield trials, Nat. Clim. Chang., 2011; 1: 42–45.
24. Kiniry JR and Bonhomme R. Predicting Crop Phenology (ed. Hodges T.) 1991;115–131, CRC Press.
25. Hammer GL, Carberry PS, Muchow RC Modeling genotypic and environmental control of leaf area dynamics in grain sorghum. I. Whole plant level, Field Crops Research. 1993; 33: 293–310.
26. Wolf J. User Guide for LINTUL5: Simple Generic Model for Simulation of Crop Growth Under Potential, Water Limited and Nitrogen, Phosphorus and Potassium Limited Conditions. 2012; Wageningen University (p. 63).

27. Addiscott T, Heys PJ, Whitmore A Application of simple leaching models in heterogeneous soils. Geoderma. 1986; 38: 185–194.

28. Addiscott T, Whitmore A Simulation of solute leaching in soils of differing permeabilities. Soil Use Manage. 1991; 7: 94–102.

29. Allen RG, Pereira LS, Raes D, Smith M. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements. 1998. FAO Irrigation and Drainage Paper 56 300. FAO, Rome, pp. D05109.

30. Corbeels M, McMurtrie RE, Pepper DA, O'Connell AM. A process-based model of nitrogen cycling in forest plantations. Part I. Structure, calibration and analysis of the decomposition model. Ecological Modeling, 2005; 187: 426–448.

31. Webber H, White JW, Kimball BA, Ewert F, Asseng S, Rezaei E et al. Physical robustness of canopy temperature models for crop heat stress simulation across environments and production conditions. Field Crops Res. 2018; 216: 75–88.

32. Gabaldón-Leal C, Webber H, Otegui M, Slafer G, Ordóñez R, Gaiser T et al. Modelling the impact of heat stress on maize yield formation. Field Crops Res. 2016; 198: 226–237.

33. Faye B, Webber H, Diop M, Mbaye ML, Owusu-Sekyere JD, Naab JB et al. (2018) Potential impact of climate change on peanut yield in Senegal, West Africa. Field Crops Research, 2018; 219: 148–159.

34. Falconnier G, Corbeels M, Boote KJ, Affholder F, Adam M, MacCarthy DS et al. Modeling climate change impacts on maize yields under low nitrogen input conditions in sub-Saharan Africa. Global Change Biology, 2020; 26: 5942–5964.

35. Dingkuhn M, Kouressy M, Vaksmann M, Clerget B and Chantereau J. A model of sorghum photoperiodism using the concept of threshold-lowering during prolonged appetence. European Journal of Agronomy. 2008; 28: 74–89.

36. Sultan B, Roudier P, Quirion P, Alhassane A, Muller B, Dingkuhn M et al. Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa. Environ. Res. Lett. 2013; 8: 014040. https://doi.org/10.1088/1748-9326/8/1/014040

37. Defrance D, Sultan B, Castets M, Famien AM, Baron C Impact of Climate Change in West Africa on Cereal Production Per Capita in 2050. Sustainability. 2020; 12: 7585. https://doi.org/10.3390/su12187585.

38. Porwollik V, Müller C, Elliott J, Chryssanthacopoulos J, Iizumi T, Ray DK et al. Spatial and temporal uncertainty of crop yield aggregations. European Journal of Agronomy. 2017; 88: 10–21.

39. Ramankutty N, Evan AT, Monfreda C, and Foley JA. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. Global Biogeochemical Cycles 2008; 22: GB1003. http://dx.doi.org/10.1029/2007GB002952.

40. Challinor AJ, Wheeler TR, Slingo JM, Craufurd PQ and Grimes DIF. Simulation of crop yields using ERA-40: limits to skill and nonstationarity in weather–yield relationships. J. Appl. Meteorol. 2005; 44: 516–31.

41. Challinor AJ, Slingo JM., Craufurd PQ. and Grimes DIF. Design and optimisation of a large-area process-based model for annual crops. Agric. For. Meteorol. 2004; 124: 99–120.

42. Bondeau A, Smith PC, Zaehle S, Schaphoff S, Lucht W, Crameret al. Modeling the role of agriculture for the 20th century carbon balance. Glob. Change Biol. 2007; 13: 679–706.

43. Jones P and Thornton P. The potential impacts of climate change on maize production in Africa and Latin America in 2055. Glob. Environ. Change. 2003; 13: 51–9.

44. Schlenker W and Lobell D. Robust negative impacts of climate change on African agriculture Environ. Res. Lett. 2010; 5: 014010.

45. Durand JL, Delusca K, Boote K, Lizaso J, Manderscheid R, Weigel HJ et al. How accurately do maize crop models simulate the interactions of atmospheric CO2 concentration levels with limited water supply on water use and yield? Eur. J. Agron. 2018; 100: 67–75.

46. Sultan B, Guan K, Kouressy M, Biasutti M, Piani C, Hammer GL et al. Robust features of future climate change impacts on sorghum yields in West Africa. Environmental Research Letters. 2014; 9: 10,104006.