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LETTER

Impact of climate change on crop suitability in sub-Saharan Africa in parameterized and convection-permitting regional climate models

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Abstract

Due to high present-day temperatures and reliance on rainfed agriculture, sub-Saharan Africa is highly vulnerable to climate change. We use a comprehensive set of global (CMIP5) and regional (CORDEX-Africa) climate projections and a new convection-permitting pan-Africa simulation (and its parameterized counterpart) to examine changes in rainfall and temperature and the impact on crop suitability of maize, cassava and soybean in sub-Saharan Africa by 2100 (RCP8.5). This is the first time an explicit-convection simulation has been used to examine crop suitability in Africa. Increasing temperatures and declining rainfall led to large parts of sub-Saharan Africa becoming unsuitable for multiple staple crops, which may necessitate a transition to more heat and drought resistant crops to ensure food and nutrition security. Soybean was resilient to temperature increases, however maize and cassava were not, leading to declines in crop suitability. Inclusion of sensitivity to extreme temperatures led to larger declines in maize suitability than when this was excluded. The results were explored in detail for Tanzania, Malawi, Zambia and South Africa. In each country the range of projections included wetting and drying, but the majority of models projected rainfall declines leading to declines in crop suitability, except in Tanzania. Explicit-convection was associated with more high temperature extremes, but had little systematic impact on average temperature and total rainfall, and the resulting suitability analysis. Global model uncertainty, rather than convection parameterizations, still makes up the largest part of the uncertainty in future climate. Explicit-convection may have more impact if suitability included a more comprehensive treatment of extremes. This work highlights the key uncertainty from global climate projections for crop suitability projections, and the need for improved information on sensitivities of African crops to extremes, in order to give better predictions and make better use of the new generation of explicit-convection models.

1. Introduction

Sub-Saharan Africa is one of the most food insecure regions in the world (FAO *et al* 2018). This is partly because agricultural yields, particularly maize, are low compared to other major producers such as the USA, China and Brazil (Cairns *et al* 2013). This region is also highly vulnerable to climate change due to high present-day temperatures combined with a reliance on rain-fed agriculture and low adaptive capacity (Asafu-Adjaye 2014, IPCC 2014). For example, rising temperatures will likely shorten the growing season for current crop varieties in arid and semi-arid areas (Calzadilla *et al* 2013), while extreme temperatures can damage crops, particularly if they occur at sensitive points during development, such as flowering (Teixeira *et al* 2013). Rainfall amount and variability also impacts crop yields (Lema and Majule 2009, Rowhani *et al* 2011); however uncertainty in the sign and magnitude of rainfall projections (e.g. Rowell and

Chadwick 2018, Kendon *et al* 2019) makes adapting to changing rainfall patterns challenging (Jones *et al* 2015).

Previous work on climate change impacts for sub-Saharan African agriculture found that without adaptation, yields of most crops, including wheat, maize, and rice, are expected to decline in the second-half of the century (Lobell *et al* 2008, Knox *et al* 2012, Challinor *et al* 2014, Adhikari *et al* 2015, Serdeczny *et al* 2017). However, much of this work used only a limited number of the available global climate models (GCMs), and impact assessments for sub-Saharan Africa have only recently been derived from larger GCM ensembles (Knox *et al* 2012, Zougmoré *et al* 2016, Dale *et al* 2017). Using a broad ensemble of climate models in impact assessments is necessary to avoid under-estimating the range of uncertainty in climate projections (Hawkins and Sutton 2011) and, therefore, in projected crop yields.

There has been limited work on agricultural impacts in Africa using regional climate models (RCMs); however the CORDEX (COrdinated Regional Downscaling EXperiment) project (Kerandi *et al* 2017, Lennard *et al* 2018) provides an effective source of regional climate model data for impact assessments. Using RCMs helps to further explore key sources of uncertainty because they may respond differently to climate forcings than their driving GCM, particularly for precipitation (Dosio and Panitz 2016, Giorgi 2019). This occurs because the higher resolution of RCMs can improve the representation of smaller-scale processes and extremes (Paeth and Mannig 2013, Diallo *et al* 2015, Gibba *et al* 2018). The differences can be as large as a change in the sign of projected precipitation changes (Saeed *et al* 2013), which would significantly alter crop responses.

The parameterization of deep convection in GCMs and RCMs makes up a large part of the uncertainty in climate projections for tropical regions (Prein *et al* 2015). In contrast, convection-permitting (i.e. explicit-convection) RCMs, are run at high enough horizontal resolution to allow the deep convection parameterisation to be switched off. This capability represents a step-change in model performance, potentially reducing key model uncertainties, and has recently become available for Africa (Stratton *et al* 2018). Convection-permitting models have been shown to improve the representation of precipitation and dry spells compared to parametrized convection RCMs (such as those available through CORDEX), which generally produce too widespread light rainfall and insufficient heavy rainfall (Prein *et al* 2015, Kendon *et al* 2019). Convection-permitting models can also improve representation of the West African Monsoon (Marsham *et al* 2013, Birch *et al* 2014b), the Indian monsoon (Willetts *et al* 2017), and the simulation of crop planting dates (Garcia-Carreras *et al* 2015).

The convection-permitting RCM available for Africa is known as CP4 A (4 kilometre resolution Pan-African Convection-Permitting Regional Climate Simulation with the Met Office Unified Model; Stratton *et al* 2018). CP4 A has improved the representation of regional rainfall in southern and western Africa (Hart *et al* 2018, Stratton *et al* 2018). Across Africa, CP4 A has similar biases in mean rainfall to the parameterized configuration of the same model, but demonstrates improved representation of rainfall occurrence, intensity and extremes (Stratton *et al* 2018, Finney *et al* 2019, Kendon *et al* 2019). The improved representation of rainfall characteristics holds the potential for improving our understanding of climate impacts on agriculture in Africa.

This study explores projected end-of-century (RCP8.5; Representative Concentration Pathway) changes in climate suitability for maize, soybean and cassava in sub-Saharan Africa, with a focus on Tanzania, Malawi, Zambia and South Africa. We use the CMIP5 (Coupled Model Intercomparison Project 5) GCM and CORDEX-Africa RCM ensembles to evaluate whether GCMs and RCMs give different results for crop suitability assessment. We also use one convection-permitting simulation (CP4 A), and its parameterized counterpart (P25) to highlight the differences between the results for convection permitting and parameterized climate models. This also allows us to see how the CP4 A model and its parameterized counterpart, P25, fit into the range of climate models already available. Maize and cassava were chosen for this study due to their importance as staple crops in the target countries, while soybean was chosen as it may be an important climate-resilient crop for Africa in the future (FAO 2019, Foyer *et al* 2019). All CMIP5 and CORDEX models use parametrisations for convection which introduce well established biases to rainfall characteristics (Stephens *et al* 2010). As such, although CP4 A and P25 are regional models run for only one model realisation of global change, the difference between them gives unique insight into how the biases from convection parametrisation affects crop suitability analysis.

2. Methods

2.1. Model description

This work uses a set of 28 bias-corrected CMIP5 GCM simulations (Famien *et al* 2018), the CORDEX-Africa RCMs (Jones *et al* 2011), and a pair of RCM simulations; one convection-permitting (CP4 A) and one with parametrized convection (P25) (Stratton *et al* 2018, Kendon *et al* 2019).

The CMIP5 models are described in Taylor *et al* (2012). We use the GCM simulations which were bias-corrected as part of the AMMA-2050

(African Monsoon Multidisciplinary Analysis) project (Famien *et al* 2018), excluding the ACCESS1-3 model due to issues with bias-correction (see supplementary material 2 (available online at stacks.iop.org/ERL/15/094086/mmedia)).

The CORDEX-Africa model data are given at 0.44° × 0.44° horizontal resolution and the multimodel ensemble includes 6 RCMs with 11 different GCMs providing initial and boundary driving conditions. The matrix of GCM/RCM combinations is presented in table 1.

The CP4 A and P25 configurations of the MetUM (Met Office Unified Model) are both driven by an N512 resolution (0.35° × 0.234°) protoype version of the MetUM Global Atmosphere 7.0 (Kendon *et al* 2019). CP4 A and P25 are atmosphere-only simulations and cover the pan–Africa region with a horizontal grid-spacing at the equator of 4.5 × 4.5 km and 26 km × 39 km, respectively (Stratton *et al* 2018). P25 has the same land surface as CP4 A, but there are key differences in the cloud and boundary layer schemes, while moisture conservation is applied in CP4 A but not P25 (Stratton *et al* 2018). Most importantly, in CP4 A, convective clouds are explicitly represented by model dynamics, whereas P25 uses the Edwards-Slingo convective parameterization (Stratton *et al* 2018). For large-scale clouds, CP4 A uses the Smith scheme while P25 uses the PC2 scheme. Both models use Wilson and Ballard for cloud microphysics (Stratton *et al* 2018). CP4 A uses a blended boundary layer scheme, which transitions from the one-dimensional vertical scheme of (Lock *et al* 2000), suitable for low resolutions, to a three-dimensional turbulent mixing scheme based on Smagorinsky (1963). In the historical period, both models are forced by sea surface temperatures (SSTs) from the Reynolds daily observations (Reynolds *et al* 2007, Kendon *et al* 2019). For future climate, the average SST change between 1975–2005 and 2085–2115 in the HadGEM2-ES RCP8.5 run is added to historical SSTs (Kendon *et al* 2019). This corresponds to a global mean SST increase of 4 K and a global mean 1.5 m air temperature change of 5.2 K for the period of the future simulations (Kendon *et al* 2019). Further details on CP4 A and P25 are available in Stratton *et al* (2018) and Kendon *et al* (2019).

For all models, we compare the 'historical' period and the 'business-as-usual' end-of-century RCP8.5 scenario. RCP8.5 was selected as it has a strong climate change signal compared to natural climate variability, and is the only scenario for which CP4 A and P25 simulations are available. Data for all models were regridded using area-weighting to the bias-corrected CMIP5 0.5° x 0.5° grid.

The CORDEX-Africa and CMIP5 models use a historical period of 1971–2000, whereas CP4 A and P25 models use 1997–2006. The future time period was from 2071–2100 for the CORDEX-Africa and CMIP5 models (except for the HadGEM models, which finish in 2099) and 2097–2106 for CP4 A and P25. While CP4 A and P25 cover different time periods to CORDEX and CMIP5, there is a 100-year difference between the future and historical periods for all sets of models, and so we expect the changes to be similar.

2.2. Bias correction

As part of the AMMA-2050 project (Famien *et al* 2018), 29 of the CMIP5 GCM simulations were bias corrected to the EWEMBI reference dataset using a cumulative distribution function transform (CDF-t) method (Michelangeli *et al* 2009). EWEMBI is a merged dataset which includes longwave and shortwave radiation from EartH2Observe and WFDEI, and ERA-Interim data (Lange 2018). The CMIP5 data was first interpolated to a 0.5° x 0.5° grid using bilinear interpolation. The CDF-t method was applied to daily near-surface average, maximum, minimum temperature, surface-downwelling shortwave radiation, wind speed and specific humidity (Famien *et al* 2018). A different method was applied to rainfall, which corrects both rainfall occurrence and intensity (Vrac *et al* 2016, Famien *et al* 2018). The list of bias-corrected CMIP5 models used here are the same as those listed in Famien *et al* (2018), excluding ACCESS1-3.

Prior to estimating crop suitability, it was necessary to bias-correct the daily mean temperature and rainfall diagnostics from the CORDEX, CP4 A and P25 simulations. We did not use the AMMA-2050 bias-correction method due to its complexity and the number of variables required. Temperature was bias-corrected using the linear scaling method described in Teutschbein and Seibert (2012) and the Climatic Research Unit (CRU) TS4.03 reference dataset (Harris 2019, University of East Anglia Climatic Research Unit 2019). Rainfall amounts, rainfall intensity and number of wet days were corrected using the local intensity scaling method described in Fang *et al* (2015) and the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) v2.0 reference dataset (Funk *et al* 2015). After bias-correction, the seasonal mean temperatures of CORDEX, CP4 A and P25 were within 0.1 °C of CRU and seasonal mean rainfall was within 1 mm/month of CHIRPS rainfall in most areas. See supplementary material 2 for further detail.

Despite using a different reference dataset, the historical (1971–2000) average temperatures were very similar between the AMMA-2050 dataset and a subset of the CMIP5 models tested using our bias correction method (< 0.1 °C difference). The climate change temperature signal (magnitude and sign of change) is also the same, as both methods use linear scaling. The bias-correction method also has minimal impact on the climate change signal for rainfall and rainy season duration (see supplementary

Table 1. The GCM/RCM combinations available for CORDEX Africa for historical and future (RCP8.5) scenarios.

	RCM					
GCM	SMHI-RCA4	CLMcom-CCLM4-8-17	MPI-CSC or GERICS REMO2009	KNMI-RACMO22 T	DMI-HIRHAM5	CCCma-CanRCM4
HadGEM2-ES	X	X	X	X		
EC-EARTH	X	X	X	X	X	
MPI-ESM-LR	X	X	X			
CNRM-CM5	X	X				
MIROC5	X		X			
CSIRO-Mk3-6-0	X					
IPSL-CM5 A-MR	X					
IPSL-CM5 A-LR			X			
CanESM2	X					X
NOAA-GFDL-ESM2 M	X					
NorESM1-M	X					

material 2 for further comparison of the bias correction methods). The difference in reference datasets and bias correction methods between CMIP5 and CORDEX should therefore account for only a small part of any differences in climate change impacts between these sets of models across most of the study area.

2.3. Rainy season onset

The rainy season onset, cessation and duration were estimated following the method of Dunning *et al* (2016). We compared model and rainy season characteristics from the CHIRPS reference dataset (CHIRPS compares well with other satellite observational datasets in most areas of Africa; Dunning *et al* 2016).

2.4. Crop suitability

Crop suitability was estimated based on the EcoCrop method (Ramirez-Villegas *et al* 2013) using temperature and rainfall during the growing period to determine a suitability index that varies between 0 and 1. For soybean and maize, the rainy season defines the growing period; cassava is perennial, meaning that the entire year was used as the growing period.

Total suitability was calculated by multiplying temperature and rainfall suitability (equation (1)), which are shown in equations (2) and (3).

$$TotalSuitability = T_{suit} * R_{Suit} \tag{1}$$

$$T_{suit} = \begin{cases} 0 & T_{mean} < T_{abs\_min} \\ 0 & T_{mean} > T_{abs\_max} \\ 1 & T_{opt\_min} \leq T_{mean} \leq T_{opt\_max} \\ 1 - \frac{T_{opt\_min} + T_{mean}}{T_{opt\_min} - T_{abs\_min}} & T_{abs\_min} \leq T_{mean} < T_{opt\_min} \\ 1 - \frac{T_{opt\_max} + T_{mean}}{T_{opt\_max} - T_{abs\_max}} & T_{opt\_max} < T_{mean} \leq T_{abs\_max} \end{cases} \tag{2}$$

$$R_{suit} = \begin{cases} 0 & R_{total} < R_{abs\_min} \\ 0 & R_{total} > R_{abs\_max} \\ 1 & R_{opt\_min} \leq R_{total} \leq R_{opt\_max} \\ 1 - \frac{R_{opt\_min} + R_{total}}{R_{opt\_min} - R_{abs\_min}} & R_{abs\_min} \leq R_{total} < R_{opt\_min} \\ 1 - \frac{R_{opt\_max} + R_{total}}{R_{opt\_max} - R_{abs\_max}} & R_{opt\_max} < R_{total} \leq R_{abs\_max} \end{cases} \tag{3}$$

where T_{mean} refers to mean growing season temperature and R_{total} refers to total growing season rainfall (see figure 1). T_{opt_min}, T_{opt_max}, T_{abs_min} and T_{abs_max} refer to the optimal minimum and maximum temperatures, and the absolute minimum and maximum temperatures (table 2). The optimal and absolute thresholds come from the FAO (Food and Agriculture Organization) EcoCrop database, which are based on literature and expert views on crops (Ramirez-Villegas *et al* 2013) (table 2). For cassava, we also tested the thresholds used by Rippke *et al* (2016), as the maximum temperature threshold is 10 °C higher than the FAO EcoCrop threshold (see supplementary material 1, figure S13).

For maize, we included an additional constraint: the minimum of suitability due to mean temperature *or* suitability due to extreme temperatures. Suitability due to extreme temperatures was calculated from the fraction of the growing season with daily average temperature above 30 °C (equation (2)), and motivated by the link between high temperatures and lower maize yield in Africa (Lobell *et al* 2011). We were unable to include sensitivity to extreme temperatures for cassava and soybean due to a lack of information on how they are affected by extreme temperatures.

$$TotalMaizeSuitability = MIN(T_{suit}, T_{max\_suit}) * R_{Suit} \tag{4}$$

$$T_{\max\_suit} = 100 - \%ofgrowingseasonwithdailyT_{mean} > 30^{\circ}\mathrm{C} \tag{5}$$

The optimum temperature threshold for maize was also set to 30 °C rather than 33 °C as in the EcoCrop database, for consistency with the daily temperature threshold.

See supplementary material 1 for a comparison of the suitability scores estimated from climate model data for the historical period with the MIRCA2000 (Monthly Irrigated and Rainfed Crop Areas) rainfed observational dataset (Portmann *et al* 2010).

2.5. Best and worst futures for crop suitability

To present the average crop suitability as one metric, we combined the suitability of maize (including extremes), soy and cassava. For this, a grid cell was considered suitable for a crop if the suitability was $\geq$ 0.55, following the standard of using 0.5 as 'marginal' for crop growth (Ramirez-Villegas *et al*

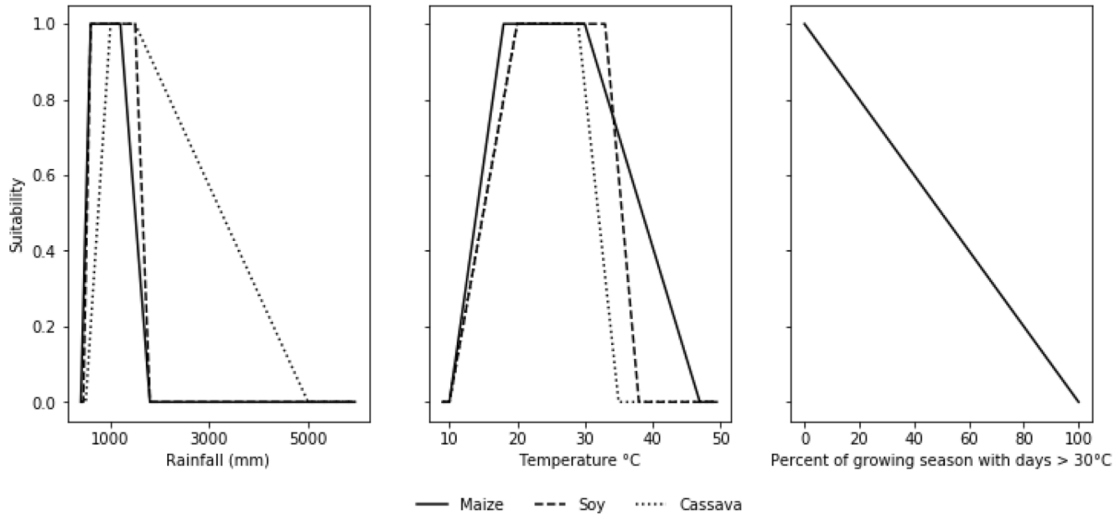

Figure 1. Suitability curves for maize, soybean and cassava. Maize and soybean use total rainfall and average temperature during rainy season, cassava uses annual data. Maize overall suitability uses the minimum of temperature suitability or percent of growing season with daily average temperature > 30 °C.

Table 2. Temperature and rainfall thresholds used in calculating crop suitability for soybean, maize and cassava. Thresholds came from the FAO EcoCrop database (2007). Second set of cassava thresholds is from Rippke (2014) and Rippke *et al* (2016). Maize optimal maximum temperature set to 30 °C rather than 33 °C for consistency with daily average temperature threshold.

	Temperature (°C)				Rainfall (mm/growing period)			
	Optimal		Absolute		Optimal		Absolute	
Crop	Min	Max	Min	Max	Min	Max	Min	Max
Soybean	20	33	10	38	600	1500	450	1800
Cassava	20	29	10	35	1000	1500	500	5000
Cassava Rippke	22	32	15	45	800	2200	300	2800
Maize	18	30	10	47	600	1200	400	1800

2013). In order to show the variation in future crop suitability across the different climate models, we also identified the models with the 'best' and 'worst' futures for crop growth, out of the full model set (CMIP5, CORDEX, CP4 A and P25). For this assessment we counted the number of grid cells where each crop had a suitability ≥ 0.55. The models with the highest and lowest suitability counts respectively were considered the 'best' and 'worst' futures.

3. Results

3.1. Rainy season

Even after bias-correction, there are still areas of mismatch between the models and CHIRPS rainy season characteristics, with all models having difficulty in capturing the observed border between the unimodal and bimodal areas. The bias-corrected ensemble mean of CMIP5 performs best, which may be partly due to the more extensive bias-correction used in the AMMA2050 project.

Figure 2 also shows that the CORDEX ensemble mean rainy season duration tends to be too short. South of the equator this is due to early cessation; north of the equator it is mainly due to late onset, i.e. the tropical rain belt stays too far south for too long. The CP4 A and P25 rainy seasons are similar to each other, showing that explicit-convection gives little to no improvement over parameterized convection for describing broad rainy season characteristics. For both CP4 A and P25, the rainy season tends to be too short, except in Tanzania. The underestimated rainy season duration in CP4 A and P25 combined with overestimated seasonal rainfall suggests that rainfall intensity during the rainy season is higher than in CHIRPS. Kendon *et al* (2019) found a similar result when examining CP4 A and P25 rainy season rainfall intensity.

3.2. Climate change impact

For end-of-century rainfall, the CMIP5 and CORDEX ensemble means show a projected increase near the equator and a decrease in more southerly areas (figure 3). This is consistent with a slower southward retreat of the tropical rain belt in northern-hemisphere autumn (Dunning *et al* 2018). The percentage change in rainfall is similar for both the CMIP5 and CORDEX ensemble means, except in the Congo; however, this is also an area of model disagreement, as shown by the stippling in figure 3. The pattern of rainfall change is also similar in CP4 A and P25 for 2097–2106, with both showing rainfall

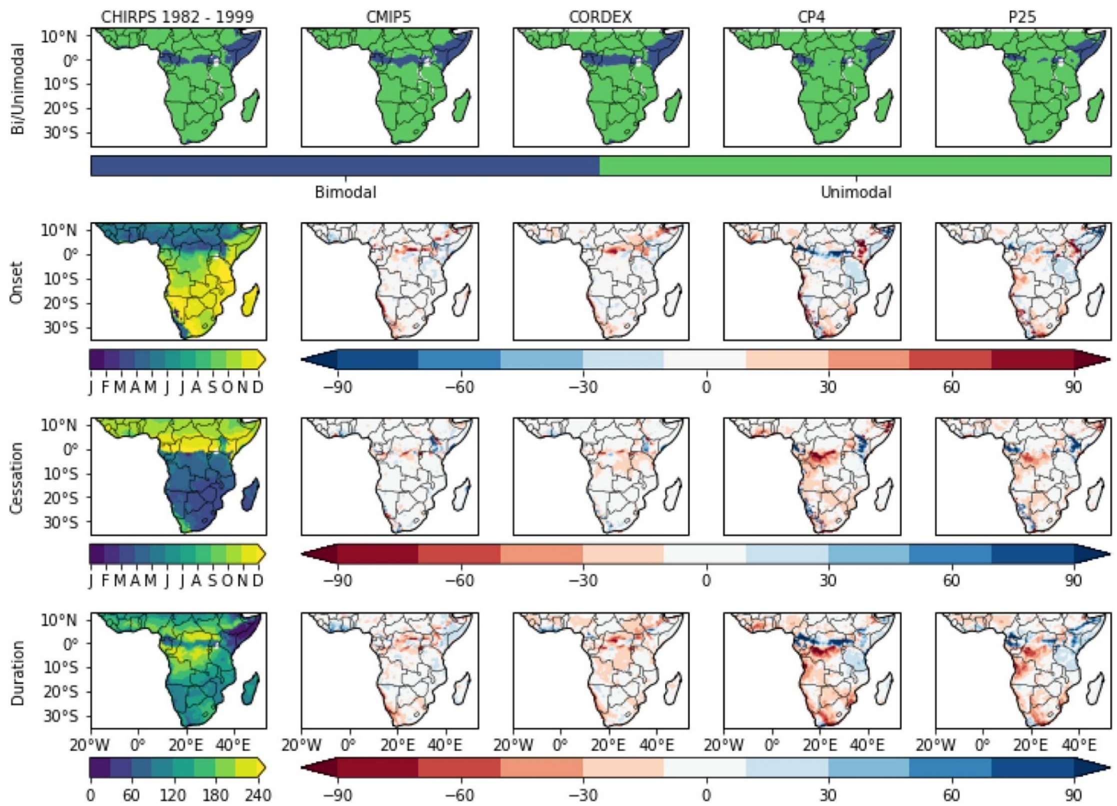

Figure 2. Bimodal/unimodal rainfall classification (first row) and difference (in days) between average onset, cessation and duration of the rainy season in CHIRPS and the bias-corrected ensemble mean of CMIP5 and CORDEX and the CP4 A and P25 models. In bimodal areas data from the short rains (October–December) are used (supplementary material 1 shows equivalent using March–May). CORDEX and CMIP5 data from 1982–1999 compared to CHIRPS data from 1982–1999. CP4 A and P25 data from 1998–2005 compared to CHIRPS data from 1998–2005. All data regridded to 0.5° x 0.5°.

increases across most of the study area during the rainy season. Bias correction had a minor impact on the results for the dry season (supplementary material 2).

The CP4 A and P25 temperature projections are broadly similar and show larger increases than the CMIP5 and CORDEX ensemble mean (figure 3). P25 and CP4 A temperature and rainfall changes are, however, within the ensemble member range for temperature and rainfall in the focus countries (figure 4).

Climate change impacts on rainy season characteristics were similar for the CORDEX and CMIP5 ensemble means, with the mean onset of the rainy season being later by up to 2 weeks across most of sub-Saharan Africa, and little change in cessation dates (< 2 weeks) (supplementary material, figure S2 and S3) leading to declines in rainy season duration. This occurred even in areas where seasonal rainfall increased, suggesting some increases in rainfall intensity and/or frequency during the rainy season—see Dunning *et al* (2018) for more details on projected changes in rainy season characteristics for the CMIP5 ensemble.

For the CMIP5 and CORDEX models, the ensemble mean projected change in rainfall is often close to zero, obscuring large differences between the individual model responses to climate change (figure 4). Relative to the spread in projections for the set of CORDEX and CMIP5 models, the future rainfall changes produced by CP4 A and P25 are fairly similar to each other. The magnitudes of the future rainfall increases in CP4 and P25 are higher than for those CORDEX RCMs driven by HadGEM2-ES. This is not unexpected since, although CP4 and P25 receive SSTs from HadGEM2-ES, their atmospheric boundary conditions are provided by a different configuration of the Met Office Unified Model, of which HadGEM is one variant.

3.3. Crop suitability

Crop suitability was calculated using the bias-corrected climate model data for both the historical and future periods. Figure 5 shows the combined suitability of all three crops. In the historical period, most areas north of 20°S, except the Horn of Africa (HOA), were suitable for all three crops (figure 5). Future declines in suitability were primarily driven by reductions in rainfall (supplementary material, figures S5–S7). Most countries across Africa are presently within the optimal temperature range for all three crops, meaning that the suitability is relatively insensitive to small changes in mean temperature. As such, projected temperature increases led to no change or increases in suitability for soybean,

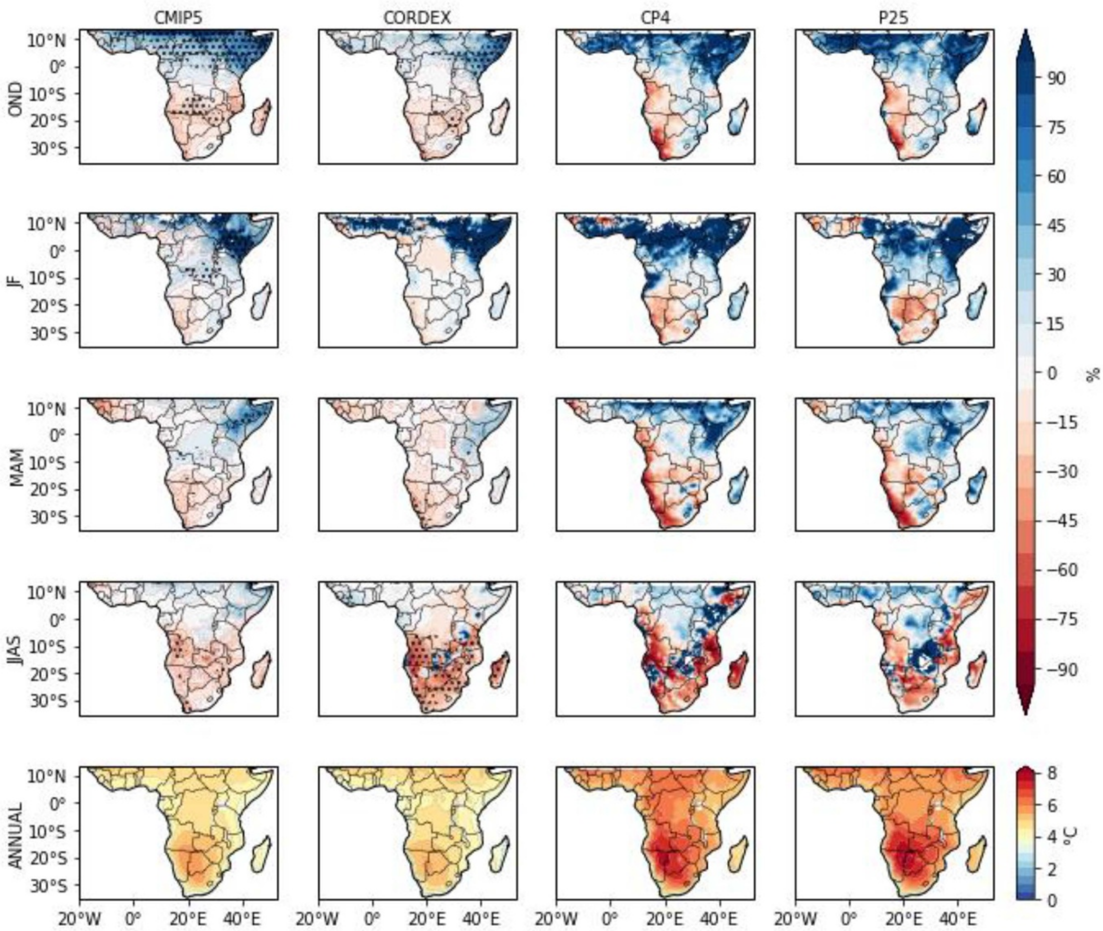

Figure 3. Percentage change in seasonal rainfall with climate change (i.e. 100% × (Future/Historical–1) for the bias-corrected CMIP5 ensemble, CORDEX ensemble CP4 A and P25 data and annual change in near-surface air temperature. Historical and future periods for CMIP5 and CORDEX data are 1971–2000 and 2071–2100 respectively, historical and future periods for CP4 A and P25 data are 1997–2006 and 2097–2106 respectively. Stippling shows areas where over two-thirds of models (> 15 for CORDEX, > 18 for CMIP5) agree on sign of change. No stippling is shown for temperature plot as all models show increasing temperatures. OND = October, November, December. JF = January, February. MAM = March, April, May. JJAS = June, July, August, September. All data regridded to 0.5° x 0.5°.

and reduced suitability for maize and cassava near the equator. Crop suitability increases occurred only in South Africa, due to present-day temperatures being too low for all three crops.

More generally, the projected changes in maize and soybean suitability are similar (when extremes are excluded) because their thresholds are similar (figure 6). Therefore, the difference in soybean and maize suitability shown by figure 5 largely reflects the inclusion of extreme temperatures for maize.

By the end of century, non-HOA bimodal areas in CORDEX models show higher suitability for cassava than soybean and maize. This is because the total rainfall in the individual rainy seasons was too low to meet cassava's requirements. However, these suitable areas are mostly in the Congo which, while climatically suitable, is predominantly rainforest.

By the end-of-century, there were reductions in the total area with high suitability (i.e. suitability $\geq$ 0.8) for maize, soybean and cassava (table 3). Maize suitability was also very sensitive to the inclusion of the number of days above 30 °C (figure 6 and table 3), showing the importance of accounting for extremes in suitability. For example, when temperature extremes were included, most countries became unsuitable for growing maize; when excluded, large parts of sub-Saharan Africa remained suitable for maize at the end of the century. Despite CP4 A having slightly higher increases in extremes than P25, reductions in maize suitability were larger in P25 due to more widespread declines in rainfall (supplementary material, figure S7).

Focussing on the four countries of interest, we find that most individual models projected declines in suitability within Zambia and Malawi for soybean and cassava (figure 7, see also supplementary material figures S8–S12 for individual model soybean results). In Tanzania, soybean suitability changes were closely related to changes in rainfall, more so for CORDEX models than CMIP5 models. CORDEX models that

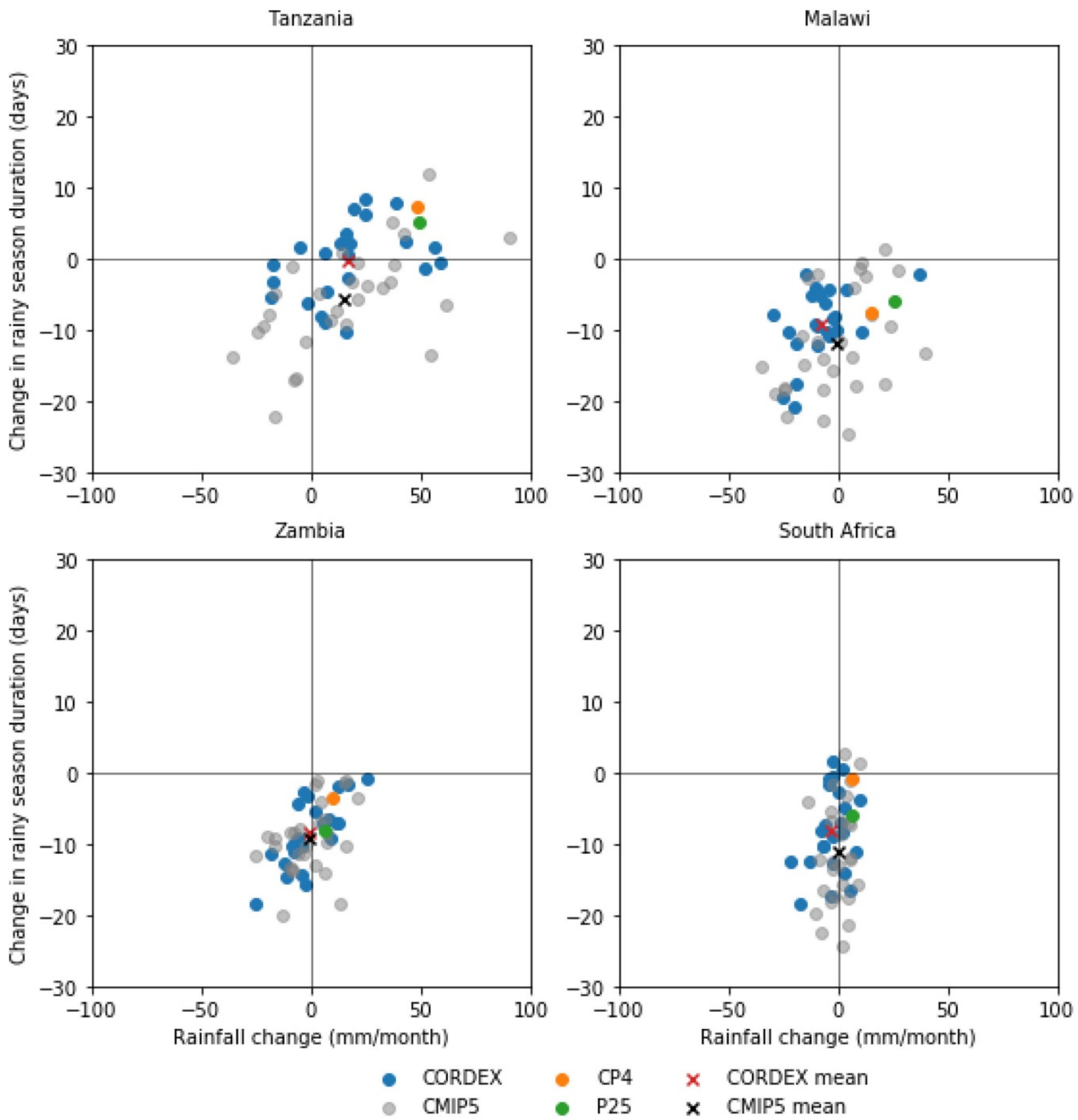

Figure 4. End-of-century climate change impact on rainy season duration and amount of rainfall for each focus country during main rainy season months (RCP8.5—historical) for bias-corrected CMIP5 models and bias-corrected CORDEX, CP4 A and P25. For Tanzania, the main rainy season months (October—November, and March—May) are combined. For all other countries the rainy season is defined as November—April. Historical and future periods for CMIP5 and CORDEX data are 1971–2000 and 2071–2100 respectively, historical and future periods for CP4 A and P25 data are 1997–2006 and 2097–2106 respectively.

Table 3. Percentage decrease in the number of grid cells classified as highly suitable (suitability ≥ 0.8) for crops with climate change (RCP8.5) for CMIP5 and CORDEX ensemble mean, CP4 A and P25. Any decline refers to any decline in suitability in highly suitable areas. Declines > 0.4 refers to highly suitable areas where suitability changed by more than 0.4.

Crop		CMIP5	CORDEX	CP4 A	P25
Cassava	Any decline	84	84	91	92
	Declines > 0.4	13	9	35	34
Soybean	Any decline	68	65	50	60
	Declines > 0.4	4	3	3	7
Maize	Any decline	94	92	98	98
	Declines > 0.4	38	33	67	71
Maize (no extremes)	Any decline	81	77	82	89
	Declines > 0.4	4	3	5	11

projected rainfall declines in Tanzania, or only small increases in rainfall, had declines in soy suitability.

Interannual climate variations contribute to overall declines in average crop suitability. The CORDEX ensemble mean of annual future climate had lower declines in average crop suitability than individual models, particularly in Malawi (figure 7 suitability contours). Individual models had larger interannual

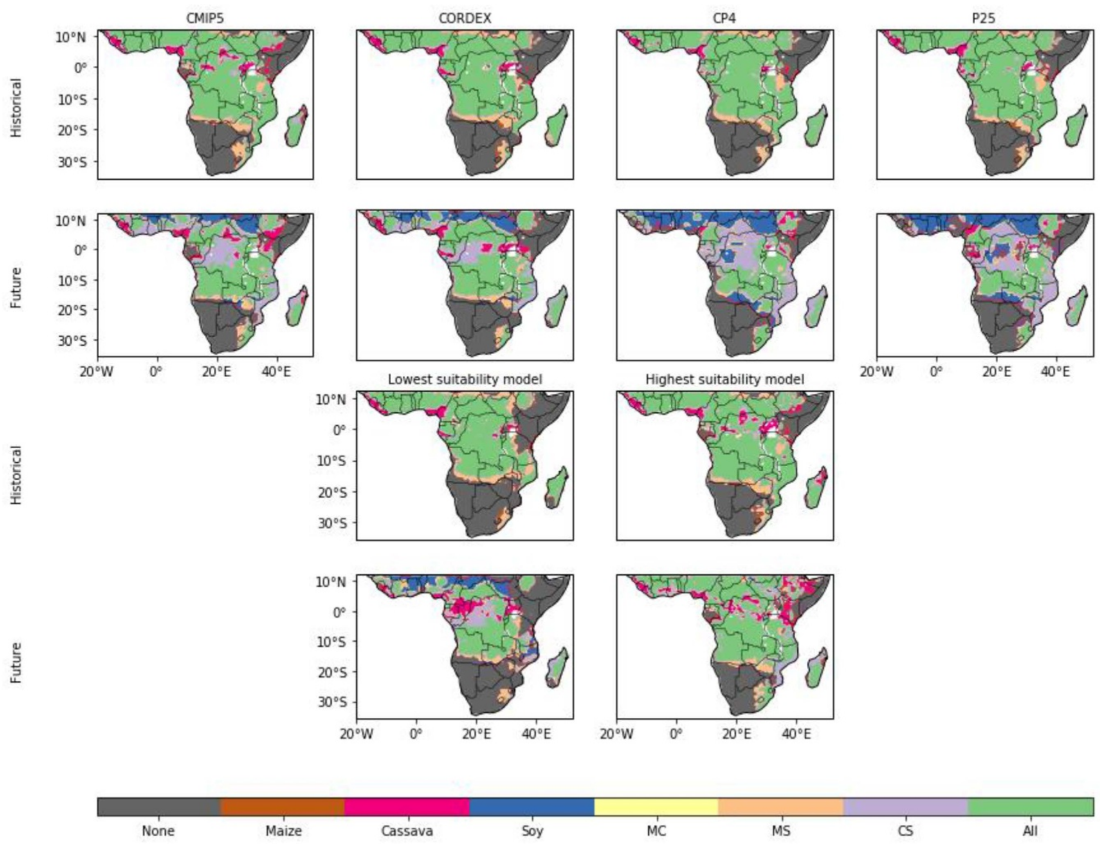

Figure 5. Combined crop suitability in historical and future periods for bias-corrected ensemble mean of CMIP5 and CORDEX models, and CP4 A and P25. Historical and future periods for CMIP5 and CORDEX data are 1971–2000 and 2071–2100 respectively, historical and future periods for CP4 A and P25 data are 1997–2006 and 2097–2106 respectively. Maize suitability includes sensitivity to extreme temperature. Crop shown as suitable if average suitability in the grid cell over the time period (historical or future) $\geq$ 0.55. Lowest and highest suitability model refer to the model out of the full set (CMIP5, CORDEX, CP4 and P25) which scored lowest and highest for future total suitability. Highest future suitability model = BNU-ESM, lowest future suitability model = HadGEM2-ES CCLM4. MC = Maize and cassava, MS = Maize and soybean, CS = Cassava and soybean. All data regridded to 0.5° x 0.5°.

rainfall and temperature variability than the ensemble mean (CORDEX ensemble mean rainfall and temperature standard deviation = 46 mm/year, 0.2 °C, standard deviation for individual models ranged from 152–238 mm/year, 0.5–0.8 °C). Of the CORDEX models, CanESM2_CanRCM4 had the highest rainfall increases for Malawi. Despite overall rainfall increases in this model, the high frequency of low rainfall years led to lower average crop suitability, particularly in southern Malawi. Soybean appears more vulnerable to this than cassava, despite having a lower absolute rainfall threshold, perhaps because soybean suitability is calculated from rainy season rainfall, whereas cassava suitability is based on total annual rainfall.

4. Discussion and conclusions

We used bias-corrected CMIP5, CORDEX, CP4 A and P25 climate model simulations to examine the impact of climate change on the crop suitability of maize, soybean and cassava in sub-Saharan Africa. For many locations the model ensemble shows both rainfall increases and decreases. Ensemble mean rainfall, however, decreased in the focus countries, leading to reduced crop suitability. In Tanzania and South Africa, models simulating decreased rainfall, or only small increases in rainfall, showed decreased crop suitability, while the models simulating large increases in rainfall showed increased suitability. In Zambia and Malawi, models with overall increasing rainfall showed reduced suitability because of annual variability in rainfall. CMIP5 and CORDEX gave similar crop suitability results, which suggest these results are robust to differences in bias-correction methods.

The reductions in crop suitability across large parts of sub-Saharan Africa found here are consistent with previous work showing projected reductions in yields of tropical during the second-half of the century (Challinor *et al* 2014, Rippke *et al* 2016, Serdeczny *et al* 2017) and that including the impact of extreme events leads to larger reductions in crop suitability with climate change (Mangani *et al* 2019). However, the results presented here are also dependent on the specific thresholds used to calculate the suitability for each crop, highlighting a key

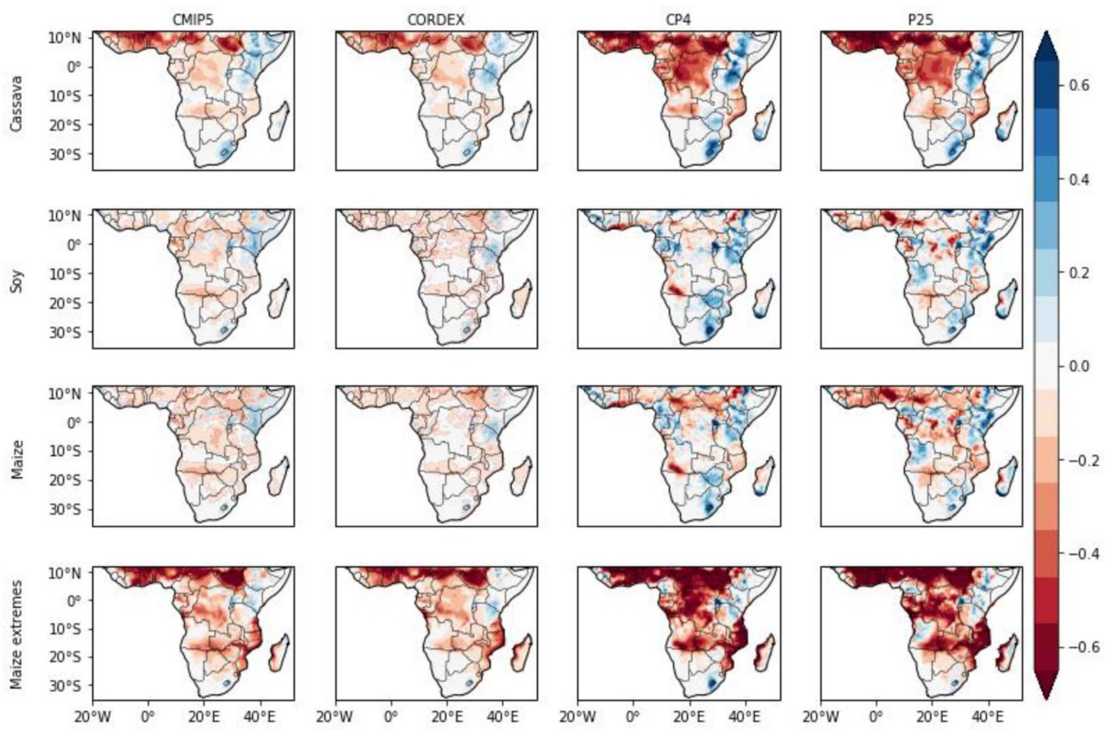

Figure 6. End-of-century change in crop suitability with RCP8.5 of soybean, cassava and maize in bias-corrected CMIP5, CORDEX, CP4 A and P25 models, relative to the historical period. Historical and future periods for CMIP5 and CORDEX data are 1971–2000 and 2071–2100 respectively, historical and future periods for CP4 A and P25 data are 1997–2006 and 2097–2106 respectively. Change in maize suitability shown with and without extreme temperature. Change in suitability in bimodal areas is the average of change in both seasons. All data regridded to 0.5° x 0.5°.

challenge in identifying robust adaptation decisions particularly at small spatial scales. For example, if cassava is only as heat tolerant as suggested by the EcoCrop database (absolute maximum temperature threshold of 35°), some cassava areas may have to transition to more heat resistant varieties by the end of the century. In contrast, if cassava's heat tolerance is as high as suggested by Rippke *et al* (2016), it may remain a viable crop in most areas of sub-Saharan Africa at the end of the century.

To our knowledge, this is the first crop suitability assessment that uses a convection-permitting climate model. CP4 A and P25 gave similar crop suitability results, and the difference between them was small compared to the spread in the CORDEX and CMIP5 ensembles. Most added-value from convection-permitting models comes from small scales and extreme values (Prein *et al* 2015), and so averaging over large areas and long time periods may eliminate some of the added value from convection-permitting models. However, previous work has found that convection-permitting models can provide a more accurate representation of regional climates and improve on biases present in the driving global model (Marsham *et al* 2013, Birch *et al* 2014a, Willetts *et al* 2017, Hart *et al* 2018, Stratton *et al* 2018). In this study, CP4 A had the potential to improve the most on representation of the rainy season, as this was calculated using daily data and not long-term averages. However, the bias-corrected CP4 A had similar rainy season characteristics and projected rainfall changes to the bias-corrected P25 parameterized-convection counterpart simulation. Therefore, while CP4 A did not improve on the representation of the rainy season over P25, it contributes to the robustness of the results provided by the global and regional models, by showing convection-permitting models give results within the range of results from those models. The differences between CP4 A and P25, may translate to the differences that could be expected between convection-permitting and parameterized versions of other regional models. These results suggest that GCM uncertainty, rather than convection parameterizations, still makes up the largest part of the uncertainty in projecting future changes to crop suitability. However, had it been possible to include extremes more comprehensively in the suitability analysis (requiring other Africa-specific crop thresholds), the results for CP4 A and P25 may have been more different, since CP4 A has both higher increases in rainfall extremes and dry spells with climate change than P25 (Kendon *et al* 2019). For this reason, future convection-permitting models may be more useful in agricultural impact assessments that incorporate the impact of extreme daily rainfall and length of dry spells on crops.

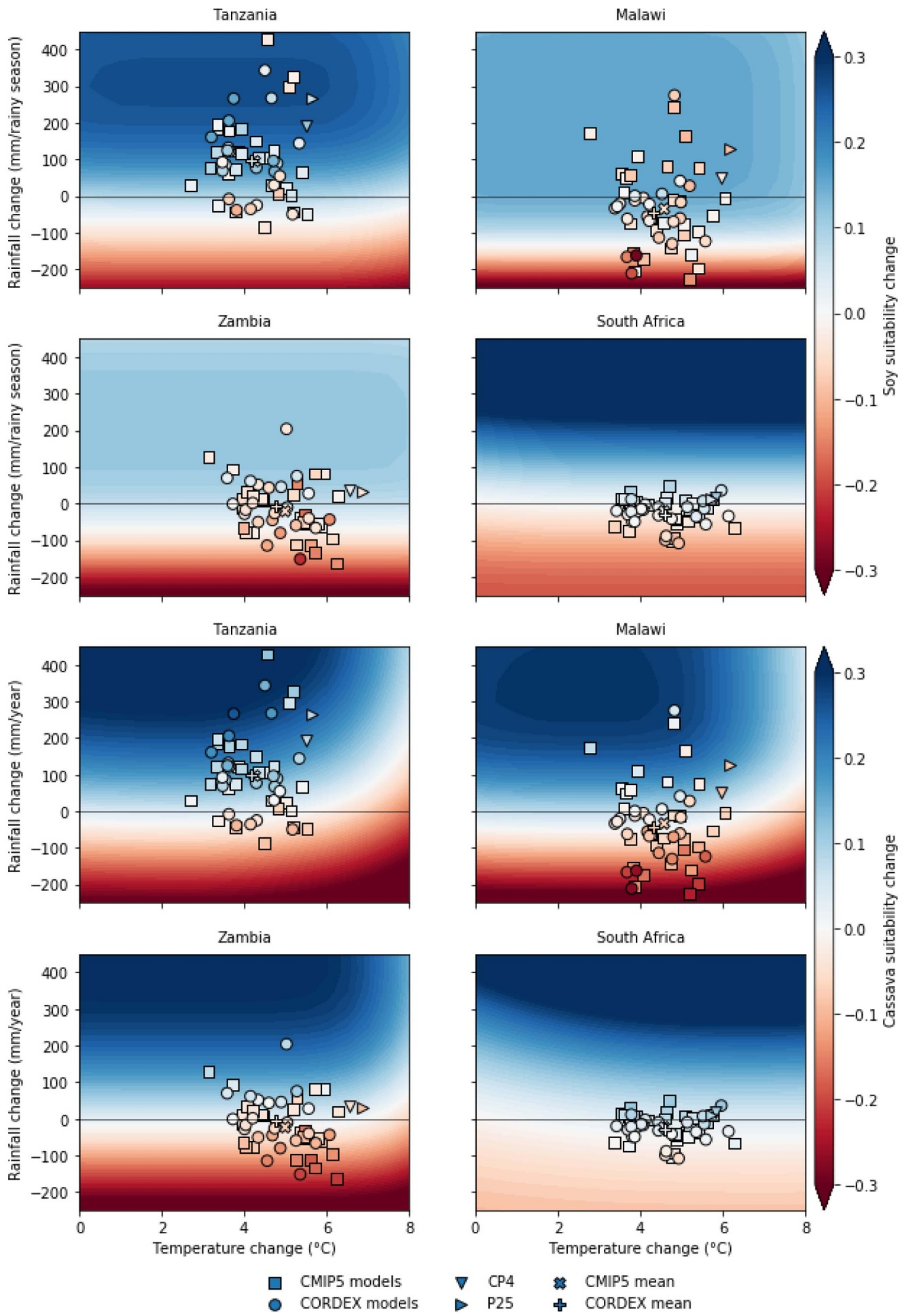

Figure 7. Future climate change impact on mean rainfall, temperature and soybean and cassava suitability (RCP8.5—present) for bias-corrected CMIP5, CORDEX, CP4 A and P25 (maize not shown as three metrics are used in the calculation), relative to the historical period. Historical and future periods for CMIP5 and CORDEX data are 1971–2000 and 2071–2100 respectively, historical and future periods for CP4 A and P25 data are 1997–2006 and 2097–2106 respectively. The contours show the change in suitability as a function of the CORDEX ensemble mean for temperature and rainfall. Colours (for markers and contours) show the change in suitability.

There are also several important caveats to consider in interpreting the results presented here. First, the EcoCrop model is a simple crop suitability model, in this case focussing only on how total rainfall and mean temperature impact crop suitability. Second, we only considered the impact of extreme temperatures for maize, due to a lack of documented Africa-specific crop thresholds. Including sensitivity to high temperatures had a large, negative impact on future maize suitability, which suggests that the future suitability for soybean and cassava could be similarly over-estimated. Third, the analysis does not account for other factors such as soil moisture and evapotranspiration or non-climatic factors such as soils, pests and diseases, which will constrain suitability more than shown here (Piikki *et al* 2015). Fourth, we did not consider the impact of climate change on cassava toxicity, which increases during droughts, particularly when combined with high temperatures (Bokanga *et al* 1994, Burns *et al* 2010, Oluwole 2015, Brown *et al* 2016). Finally, we did not explicitly consider adaptation options, such as changing varieties, irrigation or crop management which could result in yields 7%–15% higher than without adaptation according to some models (Challinor *et al* 2014). However, our analysis used rainfall and temperature during the rainy season, the timing of which varied between the present and future—this can be effectively viewed as allowing planting dates to vary with climate change.

Despite these caveats, the key benefit of using the EcoCrop model is that it is transparent and straightforward to apply, the amount of data needed is limited, and we have greater confidence in both observations and model representations of temperature and rainfall than in soil moisture or evapotranspiration (Ramirez-Villegas *et al* 2013, Myeni *et al* 2019). Despite its simplicity, the climate change impacts of EcoCrop are consistent with the results found using more complex crop models (Ramirez-Villegas *et al* 2013).

Given the crops we examined are drought and heat tolerant, we expect similar or greater reductions in suitability for other crops. However more drought and heat tolerant crops may do better. There were fewer suitable areas for crop growth in the future in the CORDEX ensemble than in the CMIP5 ensemble, mainly due to differences in rainfall. Overall, however, the ensemble mean suitability change in CORDEX and CMIP5 was similar, as was the intermodel spread. This intermodal spread was far greater than the difference between the pair of convection-permitting simulations that were driven by the same GCM, showing that the difference between GCMs is more important than the within-model setup when considering sub-Saharan African crop suitability. Reducing this model uncertainty is necessary to be able to project with confidence the impact of climate change on crop suitability. Most benefits from RCMs and convection-permitting models over GCMs are realised when considering climate extremes. To make better use of the next generation of climate models, more information on the impact of extremes on crop suitability and ways to include this are needed.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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