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Projected changes in crop yield mean and variability over West Africa in a world 1.5 K warmer than the pre-industrial

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Abstract. The ability of a country or region to feed itself in the upcoming decades is a question of importance. The population in West Africa is expected to increase significantly in the next 30 years. The responses of food crops to short term climate change is therefore critical to the population at large and the decision makers tasked with providing food for their people. An ensemble of near term climate projections are used to simulate maize, millet and sorghum in West Africa in the recent historic and near term future.

The mean yields are not expected to alter significantly, while there is an increase in inter annual variability. This increase in variability increases the likelihood of crop failures, which are defined as yield negative anomalies beyond one standard deviation during a period of 20 years. The increasing variability increases the frequency and intensity of crop failures across West Africa. The mean return frequency between mild maize crop failures from process based crop models increases from once every 6.8 years to once every 4.5 years. The mean return time frequency for severe crop failures (beyond 1.5 standard deviations) also almost doubles from once every 16.5 years to once every 8.5 years.

Two adaptation responses to climate change, the adoption of heat-resistant cultivars and the use of captured rainwater have been investigated using one crop model in an idealised sensitivity test. The generalised adoption of a cultivar resistant to high temperature stress during flowering is shown to be more beneficial than using rainwater harvesting by both increasing yields and the return frequency of crop failures.

1 Introduction

The densely populated region of West Africa has been identified as a region vulnerable to climate change impacts, from shifts in the monsoon system to desertification. The global climate is projected to pass 1.5 K above the pre-industrial control in the coming decades. The arrival and strength of the West African monsoon is a key component of the cropping system as it provides much of the water used in the growing season. The uncertainty in how the monsoon will respond to climate change is therefore of high importance, which requires the use of more than one climate model when studying impacts. Studies have shown that the monsoon may start later in the year in West Africa under climate change, this in turn exposes the crops to the summer months when temperatures are higher (Biasutti and Sobel, 2009; Sultan et al., 2014). Temperatures and rainfall are not the only drivers of crop yield that are expected to change; there are also possible changes in fertiliser deployment and thus nutrient availability as well as farmers adaptation, e.g. through irrigation of planting heat or drought resistant varieties in the case of dryer and warmer conditions. Another factor is the increase in ambient carbon dioxide concentrations and therefore the potential carbon dioxide fertilisation of yields (Berg et al., 2013). This is primarily for C3 plants, the carboxylation of C4 plants is insensitive to carbon dioxide but carbon dioxide impacts maize development through stomatal closure and soil moisture conservation.

To maintain current levels of food intake the crop yields in West Africa will need increase in step with the increasing population. However current trends in African agriculture are not sufficient to provide this yield increase and shortages are therefore to be expected even without the adverse effects of climate change (Ray et al., 2013).

There have been multiple studies investigating the future of maize, millet and sorghum yields in West Africa. In most cases the crop yields are expected to decrease with climate change and that several growing regions may no longer be viable in the upcoming decades (Jones and Thornton, 2003). A meta-analysis of 52 studies for several crops shows reductions in African yield of 5%, 10% and 15% for maize, millet and sorghum respectively (Knox et al., 2012). The reduction in yields in Africa under climate change is further supported by the meta-analysis in Roudier et al. (2011) where multiple crops were shown to experience decreases in yield. One process which increases yield is the carbon dioxide fertilisation effect, however it has also been shown the nutritional quality of the resultant crops is lower than in an atmosphere with current carbon dioxide concentrations (Roudier et al., 2011). Much of the area currently used to grow maize in West Africa is also predicted to be unsuitable in the long term, with only 59.8% of the currently cultivated area predicted to be viable in 2100. Of the lost cultivated area, 40% can be used to grow sorghum or millets which are hardier to heat and drought stresses, however the remaining 60% has no suitable alternative (Rippke et al., 2016). The millet and sorghum growing areas however are not predicted to suffer as much as maize. Many of the above mentioned studies use climate projections that find high warming levels at the end of the century.

The expected change in yield for maize was also calculated as part of a meta analysis where the response of maize to increasing temperatures with and without adaptation methods was investigated. Tropical maize was found to experience a decline in yields as temperatures increase for both studies with and without adaptation (Challinor et al., 2014). There are multiple potential adaptation methods to ameliorate the impacts of climate change, a non-exhaustive list contains, intercropping, changing the variety or species grown, use of fertilisers and crop rotation to replenish nutrients in the soil. Several adaptation methods for sorghum were investigated in Guan et al. (2017) using two crop models. The proposed adaptation methods included changing the planting date, rainwater capture and re-use and increasing resilience to high temperature stress during flowering amongst others. The results in Guan et al. (2017) show that growing varieties with high temperature stress resistance during flowering is of more benefit in the future climate than rainwater harvesting. Sorghum yields are expected to decrease with climate change and while carbon dioxide fertilisation will ameliorate some of the losses, it will not eliminate them (Sultan et al., 2014). Lastly, for millet a model analysis produced an expected reduction in yields of 6% across two scenarios from CMIP3 (Berg et al., 2013).

In this paper we use four crop models simulating three crops and driven by meteorological outputs from several regional climate models. Three crops have been selected for this analysis; maize, sorghum and millet. They are a staple foods over much of West Africa and an important source of many nutrients. The aim of this paper is to identify and quantify some of the sources of uncertainty in the West African agricultural system as the global climate passes 1.5 K above the pre-industrial control. This study makes use of newly available input data from CORDEX-Africa to differentiate from previous works. There are several possible responses to the increasing temperatures and altered precipitation regimes: these include modifying the planting window, using a new variety of a crop or changing the crop entirely. The use of two adaptation methods to mitigate the impacts of climate change has been investigated. These methods include an idealised crop which is resistant to heat stress during flowering and rainwater harvesting. A global temperature increase of 1.5 K is drawing closer, with annual average carbon dioxide levels above 400 ppm in 2016.

2 Methods

2.1 Meteorological data

The input data for the crop models in this study was provided as part of the CORDEX-Africa project (Nikulin et al., 2012). CORDEX-Africa uses a selection of CMIP5 Global Climate Models (GCMs) to drive a number of Regional Climate Models (RCMs). The simulations used in this study are based on CMIP5 simulations of a high emission, low adaptation future climate where the radiative forcing at the end of the 21^{st} century is +8.5 Wm^{-2} (Taylor et al., 2011; Meinshausen et al., 2011). The outputs from CORDEX-Africa were bias corrected as part of the HELIX project using multisegment statistical bias correction (Grillakis et al., 2013; Papadimitriou et al., 2015). The observations used to bias correct the CORDEX-Africa simulations was the WATCH-Forcing-Data-ERA-Interim: WFDEI (Weedon et al., 2014) record. The bias corrected CORDEX-Africa data was provided at a horizontal resolution of 0.44° and at a temporal resolution of one day.

An ensemble of 10 GCMs and four RCMs were used as inputs to crop models and a total of 16 GCM-RCM combinations were utilised. None of the GCMs were used to drive all of the RCMs and of the RCMs, only RCA4 was used with every GCM. A table of the GCM-RCM combinations used is shown in Table 1. The control time slice for the experiment was 1986-2005 corresponding to the final 20 years of the CMIP5 historic simulations. The future time slice was taken as the 30 year period where the global average temperature was closest to 1.5 K above the pre-industrial control of 1870-1899. The time slices used for this experiment and the mean time slices weighted by both GCMs and RCMs are shown in Table 2. The crop models that simulate carbon dioxide fertilisation also use the carbon dioxide concentrations as inputs for the future climate scenarios reached by each GCM when warming reaches 1.5 K. Thus, because of different transient climate responses of the GCMs, the crop models are exposed to a different carbon dioxide concentrations for each GCM climate forcing. Our choice of not normalizing the carbon dioxide levels for simulating crop yields is justified because we want to capture the full uncertainty of West African yield responses to both regional climate and global carbon dioxide conditions in a 1.5K warmer world.

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2.2 Crop models

Four different crop models were used in this study, the Global Large Area Model for annual crops (GLAM) (Challinor et al., 2004), ORCHIDEE-Crop (Wu et al., 2016) which is the crop specific version of the ORganizing Carbon and Hydrology in Dynamic EcosystEms (ORCHIDEE) land surface model (Krinner et al., 2005), System of Agroclimatological Regional Risk Analysis Version H (Sarra-H) (Kouressy et al., 2008) and a series of generalised linear models (Lobell and Burke, 2010). Both GLAM and ORCHIDEE-Crop were used to simulate maize, Sarra-H and the generalised linear models were used to simulate maize, sorghum and millet. Descriptions of each crop model can be found in the Supplemental material.

2.3 Agronomic data

The crop model's output were all analysed against their ability to reproduce observed crop yields and variability. The gridded input crop data for maize was taken from a dataset built from satellite observations combined with yields reported by the Food and Agriculture Organization of the United Nations (FAO) (FAOSTAT, 2014; Iizumi et al., 2014; Iizumi and Ramankutty, 2016). The millet and sorghum data were country level data from the Food and Agriculture Organization of the United Nations (FAO) (FAOSTAT, 2014). The cultivated areas for maize, millet and sorghum were defined by regridding the results from Monfreda et al. (2008) on the meteorological grid. To prevent the results being swamped by signals from grid cells with low cultivated area (Challinor et al., 2015), any grid cell with less than 1% coverage of each crop type of interest was eliminated.

3 Results

3.1 Crop model results

The four crop models were driven using the outputs of the four bias corrected CORDEX-Africa RCM simulations as listed in table 1. The CORDEX-Africa simulations were driven by ten GCMs as part of CMIP5. We present the first use of these data for a specific warming level of 1.5 K above the pre-industrial control.

The results in Figures 1, 2 show the multi-model mean maize yield and yield interannual variability (hereafter IAV) respectively. The + and · symbols show grid cells where three of the four crop models agree with the sign of the response for the multi-model GCM-RCM mean, where + shows an increase and · shows a decrease. The model agreement is high in Côte d'Ivoire and Ghana but there is a spread of positive and negative impacts across Nigeria. The potential increases in yield in Côte d'Ivoire and Nigeria are also associated with to increases in IAV as shown in Figure 2. The millet results are shown in SI Figures 1 and 2 where a dipole can be seen in the yield response, the yield increases in northern Nigeria and southern Niger, however to the West in Burkina Faso and Mali there is a decrease in yields. The dipole is not as significant in the IAV results with increases in IAV in Niger, Nigeria and Burkina Faso. The IAV is reduced in Mali along with the yield. The stippled Sorghum results (SI Figures 3 and 4) present a smaller dipole effect that has positive yield change in Niger and a negative

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yield change over much of West Africa. Where the yield increases in Niger the IAV also increases which is expected to cause problems for food security.

The multimodel ensemble mean yields for the control and future time slices are calculated for each crop model and plotted against the observations in Figure 3. Of the process based models GLAM and Sarra-H are closest to the observed yields whereas ORCHIDEE-Crop is further away. The linear models by design match the observed yields. The future climate responses for GLAM and Sarra-H are limited however ORCHIDEE-Crop shows a strong reduction in yields. Sarra-H and the linear models show an increase in yields at +1.5 K. The control simulation has temperatures that are 0.7 K above the pre-industrial control, therefore the temperature difference experienced by the crops is 0.8 K. The maize yield reductions are less than 2 kg/ha for GLAM, 84 kg/ha for ORCHIDEE, whereas Sarra-H increases by around 20 kg/ha and the linear models increase by 62 kg/ha. In percentage terms these are less than 1% for GLAM, 5.7% for ORCHIDEE and increases of 1.6% for Sarra-H and 5.3% for the linear models. The responses for most models are smaller than those found in the meta analysis by Knox et al. (2012), however this study is not projected as far into the future. The four different model results presented are within the range of results from Challinor et al. (2014).

The multimodel ensemble yield results contain two sources of uncertainty, the inter annual variability (IAV) and the variability across the meteorological input datasets. The results for the IAV are shown in Figures 4. The results in Figure 4 show that ORCHIDEE-Crop has the most skill in reproducing the observed IAV followed by the linear models. Both GLAM and Sarra-H overestimate the IAV for maize. Despite these differences, the IAV increases for all models in the future climate scenario. For the process based models the IAV is significantly larger than the variability resulting from differences in input meteorological data. Both GLAM and ORCHIDEE-Crop show little variability across the input data in the control scenario. For ORCHIDEE-Crop, GLAM and the linear models the variability increases in the future climate, this is in contrast to the results in Sarra-H.

Figures 5 and 6 show the mild and severe crop failure rate for maize in the control (20 years) and future (30 years) climate scenarios. A mild crop failure is one standard deviation below the observed yield for that grid cell, a severe crop failure is 1.5 standard deviations below the observed yield for that grid cell. GLAM slightly underestimates the mild crop failure rate, whereas ORCHIDEE-Crop and Sarra-H overestimate slightly. The differences however are minor in comparison to those found in the linear models. The severity of the change in mild crop failure rate varies across the process based models but the signal is consistent, at 1.5 K above pre-industrial there is an expectation of more crop failures. ORCHIDEE-Crop is particularly pessimistic with the return time between crop failures falling from 6.1 years to 2.5 years per grid cell. For severe crop failures the process based models are again more realistic than the linear models. The future climate results show an increase in severe crop failures, with ORCHIDEE-Crop again showing the strongest response.

The millet and sorghum results are shown in SI Figures 5 - 12. The millet and sorghum analyses for three varieties simulated by the Sarra-H model and the linear models. The linear models are more able to predict the observed yield and inter annual variability than Sarra-H for millet and sorghum (SI Figures 5, 6, 9 and 10). In the millet simulations the linear models are close to the observed yield whereas the Sarra-H varieties are spread above and below the observations. Of the Sarra-H varieties the

90 day cultivar is most capable of reproducing the observed sorghum yields, however the yields are still about 20% too low. The response of the 90 day cultivar to the future climate are consistent with the simulations in Sultan et al. (2014).

The three variants of Sarra-H like the linear models underestimate the frequency of crop failures in the control (SI Figures 7, 8, 11 and 12). Across all three crops and all models there is an increase in the crop failure rate in the future climate when compared with the historic climate.

With ensembles of input data it is possible to calculate two different uncertainty values, the IAV and the spread across the ensemble. The ratio of IAV to input data spread is shown in SI Figures 13-15 for maize, millet and sorghum. The results show that the IAV is always larger than the model spread. The ratio for the IAV in GLAM is much larger than for all other models, this is due to the simulations in for the historical period in GLAM being calibrated on a per model basis and therefore having a very low model spread.

The results in Tables 3, 4, 5 show the change in national yields for each model and the multi-model mean. Countries with fewer than 10 grid cells analysed have been omitted from the tables. The results for maize show a spread in expected yield changes by nation, with the Côte d'Ivoire experiencing an increase in yield and Ghana showing a decrease. Nigerian yields are uncertain and the average is a very small change. ORCHIDEE-Crop finds a yield reduction in all three countries, whereas GLAM, Sarra-H and the Linear models are only negative for one country. In the future climate simulations at the 1.5 K warming level Burkina Faso, Mali, and Senegal all suffer a more than 5% loss in millet yields while Niger is predicted to experience an increase of 3.2%. The sorghum results (Table 5) nearly always show a yield reduction with climate change with the exception of Niger which has a small yield increase. The sorghum results show a 10% yield reduction for Burkina Faso, Mali and Senegal.

3.2 Adaptation results

In one of the four crop models (GLAM) simulations of two idealised adaptation methods were performed. There were three experiments, crops with a resistance to high temperature stress during flowering, crops grown with rainwater harvesting and crops resistant to high temperature stress with rainwater harvesting deployed. To simulate high temperature stress resistance the GLAM is rerun with the high temperature stress routine disabled, a description of high temperature stress in flowering is found in Challinor et al. (2005). The rainwater harvesting system collects runoff from the crop and stores it with 50% efficiency, the water is deployed if the soil moisture falls below the wilting limit for the crop. The adaptation methods are simulated in both the control climate and the future climate using the approach described in Lobell (2014).

The adaptation results for GLAM (Figure 7) show that rainwater harvesting is provides a smaller increase in yields in the global 1.5 K warmer climate than in the historic climate. The results for the return time between crop failures show an improvement in the control climate that is greater than in the future climate. In contrast the high temperature stress resistant crops show a benefit in both cases and a larger benefit in future climates. The return time between crop failures also increase more in future climates. However when combined with rainwater harvesting, high temperature stress resistance has a smaller relative improvement than when it is deployed in isolation. The maize results from GLAM presented here agree show similar responses to the sorghum results in Guan et al. (2017) where high temperature stress resistance is more important than rainwater harvesting.

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The results in Figure 3, SI Figures 5 and 9, show that as the global climate warms through 1.5 K the yield response is uncertain. For maize, GLAM and ORCHIDEE-Crop simulate a reduction in yields. Across all crops and models the largest reduction is 16.5% for Sarra-H 90 day sorghum. The largest increase is found for the linear models and is 5.3% for maize. This range of results is within the range found for tropical maize in Challinor et al. (2014).

ORCHIDEE-Crop is successful at replicating the observed IAV and does not suffer from spread from the input data, however the mean yield results do show a significant bias. The ORCHIDEE-Crop results show the greatest increase in crop failure rate with crop failures occurring once every 2.5 years in the future climate scenarios. The crop failure rates for GLAM and Sarra-H are similar with future failures happening every 6 and 5 years respectively. The linear models consistently underestimate the crop failure rate and this is one of their weaknesses. The results in Figures 5 and 6 show consistency across all three process based models and therefore should be treated with confidence.

The varieties of Sarra-H are unable to replicate the observed yields for the millet and sorghum analyses and mis-estimate the yield by several hundred kg/ha (SI Figures 5 and 9). The crop failure rate is defined by the model yield and the Sarra-H simulations all underestimate the crop failure rate. They do however all find a relative increase in crop failure rate in future climates for both millet and sorghum.

The adaptation methods tested in GLAM for maize are shown in Figure 7 and show that rainwater harvesting is not an effective adaptation method. The higher rainfall in future climates reduces the likelihood of water limiting the crop growth. The high temperature stress adaptation is a more efficient adaptation and provides a benefit in the future climate. The combined HTS resistant and rainwater harvesting adapted crop is less of an adaptation than solely HTS resistant crop. Therefore in the case of limited resources it is better decision to explore HTS resistance than building systems to capture runoff, especially as the systems require substantial investment to construct and maintain.

The changes in national yields is a cause for concern as it is well documented that populations in West Africa are expected to increase quickly in the 21^{st} century. Crop yields need to double by 2050 to feed the population (Ray et al., 2013), whereas the largest increase found in this study is millet in Niger at +3.20%. The mean yield changes are not the only message, in many cases where the mean yield increase there is an accompanying increase in IAV. The increase in IAV means that yield are more uncertain and there is an increasingly likelihood of crop failures. The reductions in yields on national levels indicate a need for new breeds of crop or changing species entirely, however the rate of deployment of new breeds in Africa is slow (Challinor et al., 2016).

5 Conclusions

Four crop models of varying design and complexity have been used to project crop yields across West Africa for three crops as global temperatures reach 1.5 K above the pre-industrial levels. The crops models were driven by the outputs of four RCMs which were in turn driven by 10 GCMs. The crop models show differing levels of skill at reproducing the yield and variability found in the observed record. The process based models are able to predict the crop failure rate for maize with moderate skill.

The varieties of crop simulated by Sarra-H for millet and sorghum are less able to replicate observations than the linear models, but they are more capable for the crop failures. This study is limited by the number of crop models used, in particular only one process based model was used to millet and sorghum. The use of bias corrected RCMs to provide input data removes some of the problems associated with GCM data. The large size of the grid (50km) prevents the formation of true convective storms and therefore the intensity of the weather is likely to be underestimated (Garcia-Carreras et al., 2015).

The crop yields and percentage changes in yield were calculated for several West Africa countries. The yield changes are not consistent across national borders and some nations are expected to lose more than others. The yield gains predicted herein need to be considered as part of longer term trends that show severe yield reductions as the 21stst century progresses. As global temperatures approach 1.5 K above the pre-industrial levels, the knowledge of the most effective adaptation methods becomes critical and therefore it is of high importance to develop models capable of simulating them.

The results from this study show that for several crops the mean yield may not change much, however the increase in variability is likely to result in an increase in crop failures. The average crop yield responses are sometimes negative and none are positive enough to increase yields sufficiently to prevent food shortages.

Data availability. The input data for the crop models is part of the HELIX project and is currently under embargo. Upon the expiration of the embargo the data will be made available by the HELIX project. Contact information is at https://www.helixclimate.eu/contact/ . The yield data output for the crop models can be found at https://doi.pangaea.de/10.1594/PANGAEA.876579

Author contributions. BP acquired the data and performed the simulations in GLAM, ORCHIDEE-Crop and the Linear models. DD ran the Sarra-H simulations. XW provided technical support for ORCHIDEE-Crop. All authors contributed to the manuscript.

Competing interests. The authors declare no competing interests.

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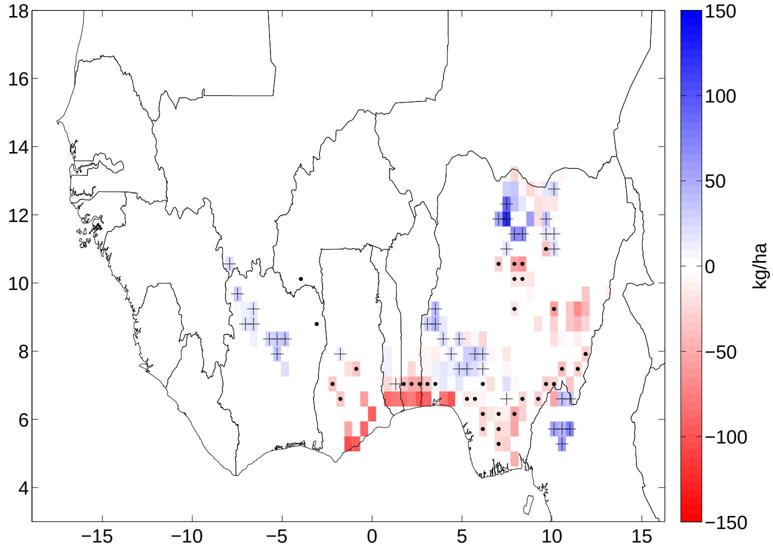

Figure 1. Multi model mean change in maize yield between control and future climates over West Africa in a world 1.5 K warmer than pre-industrial. Where + indicates three crop models agree the change will be positive and · indicates three crop models agree the change will be negative. Sarra-H indicates the model simulating the 90 day variant of maize.

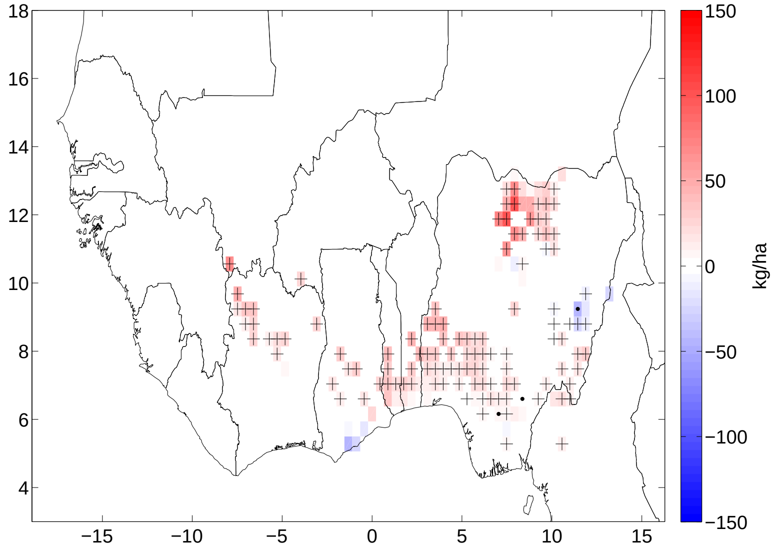

Figure 2. Multi model mean change in maize IAV between control and future climates. over West Africa in a world 1.5 K warmer than pre-industrial. Where + indicates three crop models agree the change will be positive and · indicates three crop models agree the change will be negative. Sarra-H indicates the model simulating the 90 day variant of maize.

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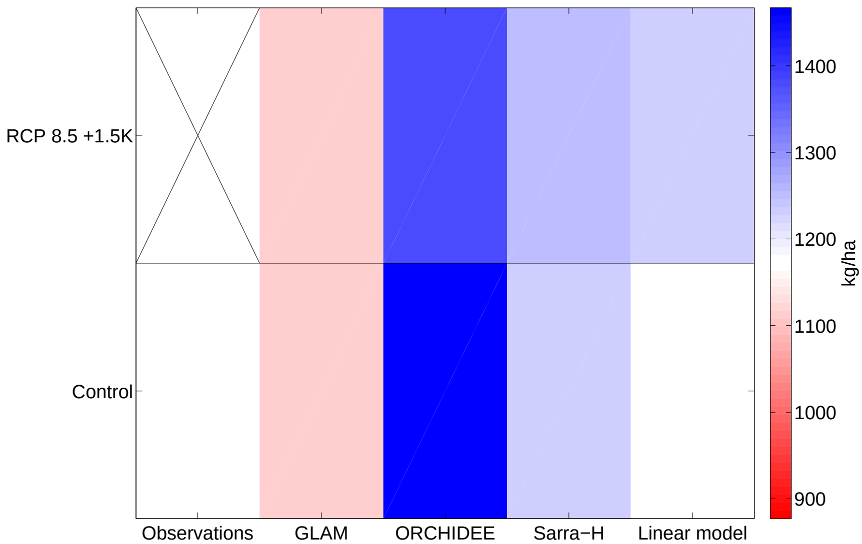

Figure 3. Heatmap of maize yields for four models for the control time period and at 1.5 K.

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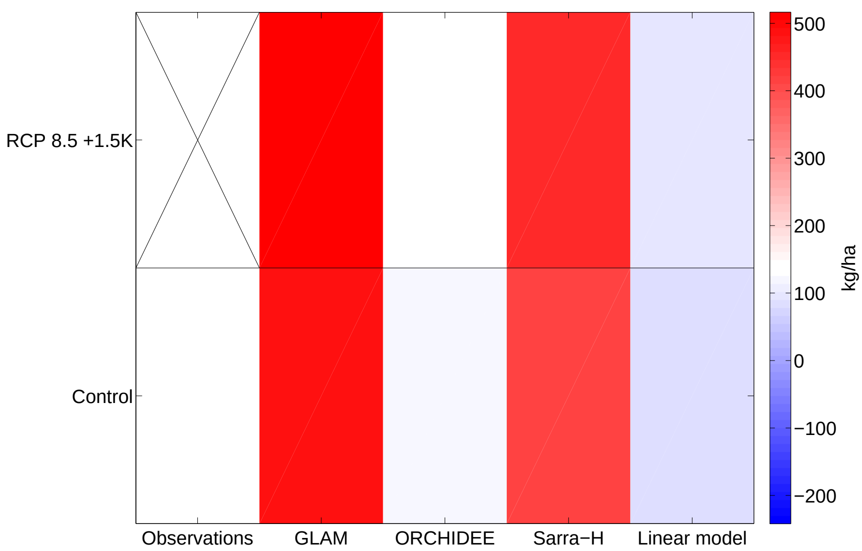

Figure 4. Heatmap of inter annual variability of maize yields for four models for the control time period and at 1.5 K.

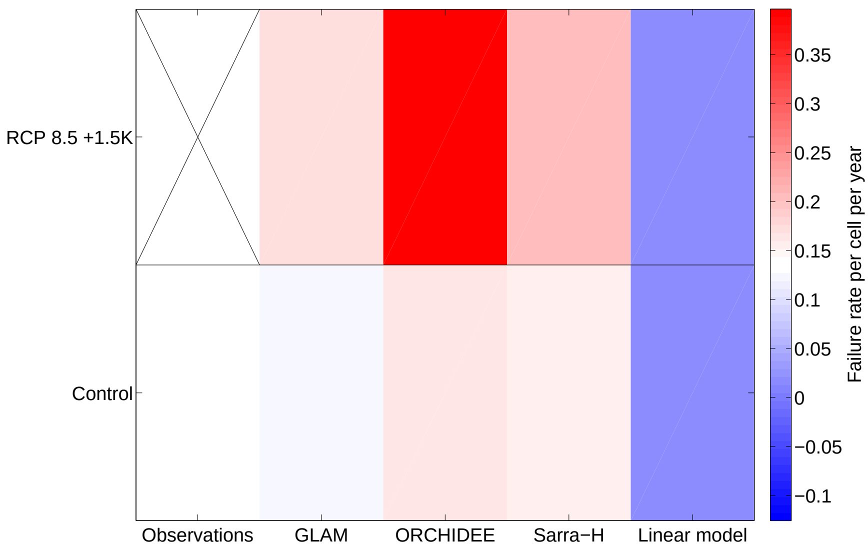

Figure 5. Heatmap of mild crop failure rate of maize for four models for the control time period and at 1.5 K.

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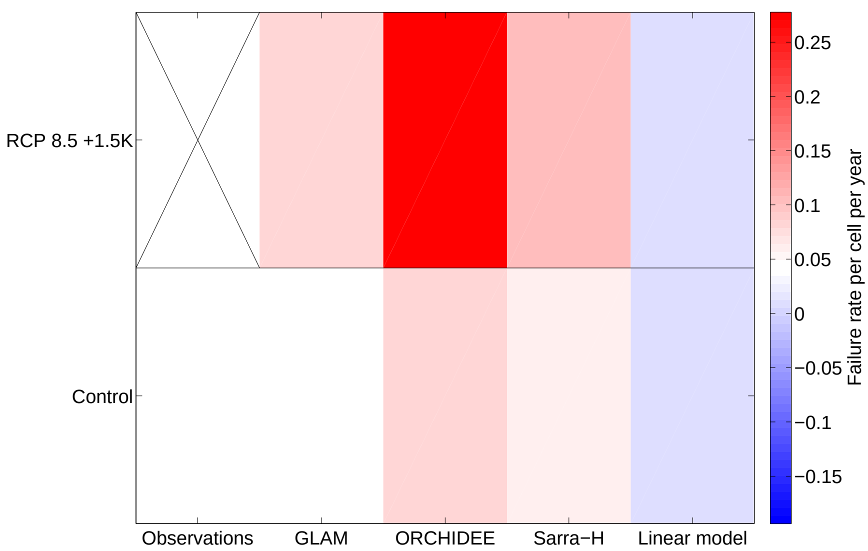

Figure 6. Heatmap of severe crop failure rate of maize for four models for the control time period and at 1.5 K.

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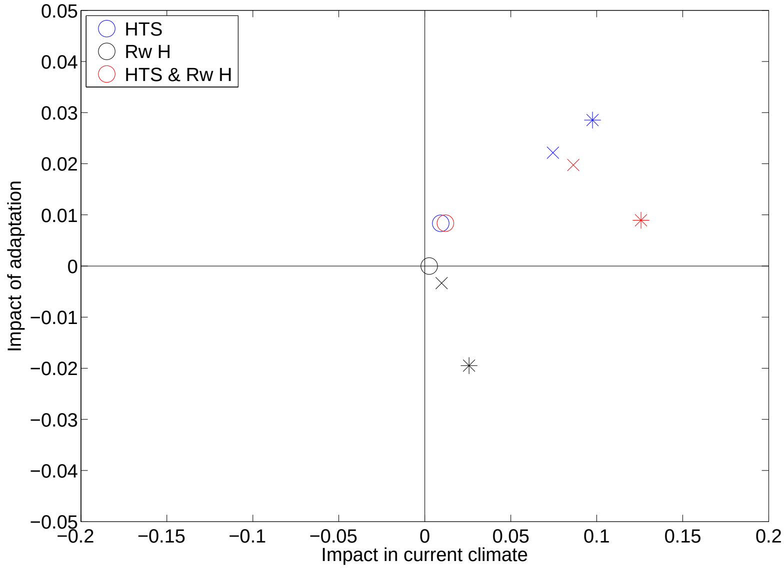

Figure 7. Efficacy of adaptation methods for maize in GLAM. Where circles show mean yield, crosses and stars show average number of years between mild and severe crop failures respectively. HTS is high temperature stress adapted crops, Rw H shows crops with rainwater harvesting, HTS & Rw H shows both adaptation methods in use.

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Table 1. GCMs and RCMs where **X** indicates a RCM-GCM combination used in this study. The RCM description papers are as follows: RCA4 (Chylek et al., 2011), RACMO22T (van Meijgaard et al., 2008), HIRHAM5 (Christensen et al., 2006). The GCM decription papers are as follows: CNRM-CM5 (Voldoire et al., 2013), CM5A-MR (Dufresne et al., 2013), CSIRO-Mk3.6.0 (Rotstayn et al., 2012), NOAA-GFDL-CM3 (Griffies et al., 2011), MOHC-HadGEM2-ES (Jones et al., 2011), ICHEC-EC-EARTH (Hazeleger et al., 2012), MIROC5 (Watanabe et al., 2010), MPI-ESM-LR (Raddatz et al., 2007), NorESM (Bentsen et al., 2013).

	RCA4	CCLM4.8.17	RACMO22T	HIRHAM5
CanESM2	**X**			
CNRM-CM5	**X**	**X**		
CM5A-MR	**X**			
CSIRO-Mk3.6.0	**X**			
NOAA-GFDL-CM3	**X**			
MOHC-HadGEM2-ES	**X**	**X**	**X**	
ICHEC-EC-EARTH	**X**		**X**	**X**
MIROC5	**X**			
MPI-ESM-LR	**X**	**X**		
NorESM	**X**			

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Table 2. GCM time slices at +1.5 K and their corresponding carbon dioxide concentrations.

	Time (years)	CO_2 (ppm)
CanESM2	2000-2029	402.8
CNRM-CM5A	2016-2045	453.5
CM5A-MR	2002-2031	408.2
CSIRO-Mk3.6.0	2018-2047	461.2
NOAA-GFDL-CM3	2020-2049	469.3
MOHC-HadGEM2-ES	2009-2038	429.1
ICHEC-EC-EARTH	2006-2035	419.7
MIROC5	2018-2047	461.2
MPI-ESM-LR	2004-2033	413.9
NorESM	2018-2047	461.2
GCM Mean	2011-2040	438.0
RCM Mean	2010-2039	434.1

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Table 3. Percentage maize yield change by country. The number of grid cells analysis is in brackets and countries where fewer than 10 grid cells were analysed have been omitted. The fraction of West African maize production for the year 2005 from the Food and Agriculture Organization of the United Nations (FAO) (FAOSTAT, 2014) is shown in the rightmost column.

Country	GLAM	ORCHIDEE-Crop	Sarra-H	Linear models	Multi model mean	Production fraction
Côte d'Ivoire (13)	3.65	-3.95	9.05	1.33	2.52	5.52%
Ghana (11)	1.34	-6.82	-3.60	-0.23	-2.33	10.09%
Nigeria (120)	-0.86	-6.11	1.91	5.20	0.03	51.34%

Table 4. Percentage millet yield change by country.The number of grid cells analysis is in brackets and countries where fewer than 10 grid cells were analysed have been omitted. The fraction of West African millet production for the year 2005 from the Food and Agriculture Organization of the United Nations (FAO) (FAOSTAT, 2014) is shown in the rightmost column.

Country	Sarra-H 90	Sarra-H 120	Sarra-H PP	Linear models	Multi model mean	Production fraction
Burkina Faso (93)	-4.21	-12.44	-7.47	0.67	-5.86	8.83%
Chad (24)	11.31	2.42	-1.72	-5.03	0.53	-
Côte d'Ivoire (11)	2.1	0.97	-4.17	3.6	0.63	0.26%
Ghana (10)	-1.16	-4.78	-5.08	8.38	-0.77	1.37%
Mali (94)	-1.6	-16.79	-17.78	3.85	-8.08	8.55%
Niger (114)	11.95	-1.56	-1.8	4.2	3.2	19.59%
Nigeria (232)	7.24	-3.53	-2.44	1.58	0.71	52.93%
Senegal (40)	5.52	-12.32	-16.22	1.62	-5.35	4.49%

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Table 5. Percentage sorghum yield change by country. The number of grid cells analysis is in brackets and countries where fewer than 10 grid cells were analysed have been omitted. The fraction of West African sorghum production for the year 2005 from the Food and Agriculture Organization of the United Nations (FAO) (FAOSTAT, 2014) is shown in the rightmost column.

Country	Sarra-H 90	Sarra-H 120	Sarra-H PP	Linear models	Multi model mean	Production fraction
Benin (20)	-10.55	-18.52	-1.25	-0.37	-7.05	1.27%
Burkina Faso (102)	-11.4	-19.63	-1.62	-7.52	-10.04	11.63%
Cameroon (65)	-10.87	-17.98	-1.51	1.35	-7.25	-
Chad (28)	-3.63	-16.55	-0.36	-3.68	-6.06	-
Ghana (28)	-7.66	-9.69	1.37	-1.94	-4.48	2.28%
Mali (93)	-9.42	-23.5	-9.5	1.69	-10.18	4.71%
Mauritania (11)	-7.54	-14.16	-8.33	11.28	-4.69	0.61%
Niger (94)	9.98	-7.9	2.63	-2.1	0.65	7.07%
Nigeria (313)	-2.7	-14.92	1.51	-0.29	-4.1	68.72%
Senegal (19)	-7.29	-16.62	-15.56	-3.7	-10.79	1.08%
Togo (16)	-6.02	-9.87	2.84	-2.65	-3.93	1.54%