Robust Negative Impacts of Climate Change on African Agriculture

Supplementary Data

Contents

1 Data Appendix

1.1 Yield Data

Our dependent variables are country-level yields (tons/ha) for five staple crops: maize, sorghum, millet, groundnuts and cassava in Sub-Saharan Africa. The yield data as well as total acreage were obtained from the FAO website for the years 1961-2007 (accessed November 2008).[1] Summary statistics of average yields are given in the top row of Figure A1. If a country had several consecutive years with identical yields, it was flagged and excluded from the estimation of the coefficients in our baseline model. Such flagged countries are marked with a dotted surface in Figure A1. While these countries were eliminated in the estimation, we still evaluated the predicted yield changes under climate change for these countries using the estimated coefficients we obtained from the panel data set of the remaining countries (see Section 1.4 below).

1.2 Growing Season

The growing season for each crop and country was taken from [1].

1.3 Weather Data

The yield data set is merged with two weather data sets.

(i) CRU 2.1: The Climatic Research Unit of the University of East Anglica provides a data set of monthly minimum and maximum temperatures as well as precipitations for the years 1901-2002 on a 0.5 degree grid [2] (accessed November 2008).[2]

(ii) NCC: Thanh Ngo-Duc at the University of Tokyo has constructed a corrected data set of the National Center for Environmental Prediction (NCEP). It is a 6-hour time series for temperatures on a 1 degree grid for the years 1949-2000 [4] (accessed November 2008).[3] Each day has four temperature and precipitation readings at midnight, 6am, noon, 6pm. We construct the daily minimum (maximum) as the minimum (maximum) of the four daily observations. These data are reanlysis data, using NOAA's NCEP data base that are calibrated to monthly averages from the CRU data base.

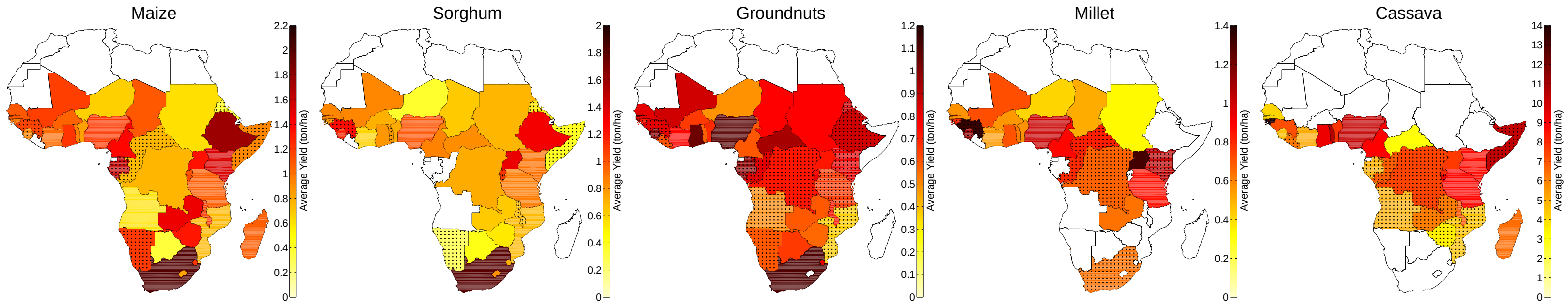
[1] http://faostat.fao.org/site/526/default.aspx

[2] http://www.cru.uea.ac.uk/∼timm/grid/CRU_TS_2_1.html

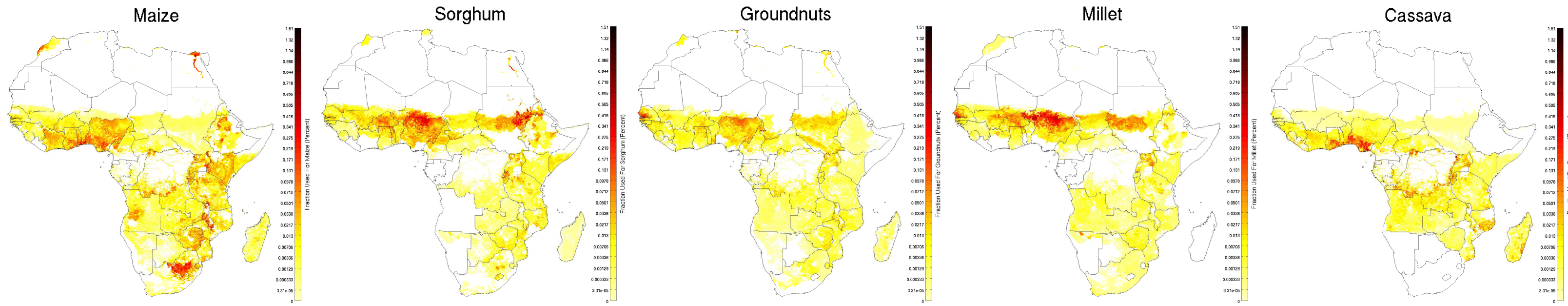
[3] http://hydro.iis.u-tokyo.ac.jp/ thanh/wiki/index.php?n=Main.NCCDataset

Figure A1: Descriptive Statistics: Average Yields and Growing Area in 2000

Panel A: Average Yields



Panel A: Growing Area



Notes: The top row displays average yields. Countries with flagged yield series have black dots superimposed). The bottom row gives the fraction of each 5-minute grid cell that is used to grow a crop [3]. Fractions larger than 1 indicate double-cropping.

We use Geographic Information Systems (GIS) to link the grid-points of the two weather data sets to countries. The weather in a country is then derived in two alternative ways:

(i) Land-cover weighted average: The land cover data from [3] provides the amount of cropland of each crop in each 5-minute grid cell. The weather in a country is the cropland-area weighted average of all grids, where we only count the 5-minute cells that are within a country's boundaries. Note that the weather for maize in a given year and country might be different than the weather for millet in the given year and country, as we use different weights for the weather grids within a country, even if the growing season were to be identical. The growing areas are shown in the bottom panel of Figure A1.

(ii) Country Average: all grid points that fall within a country are averaged uniformly.

The spatial distribution of temperatures for all countries in our data is shown in panel A of Figure A2 under the CRU 2.1 data base, which has the finest grid structure.

Our baseline model uses the area-weighted average of the NCC weather data.

1.4 Climate Change Predictions

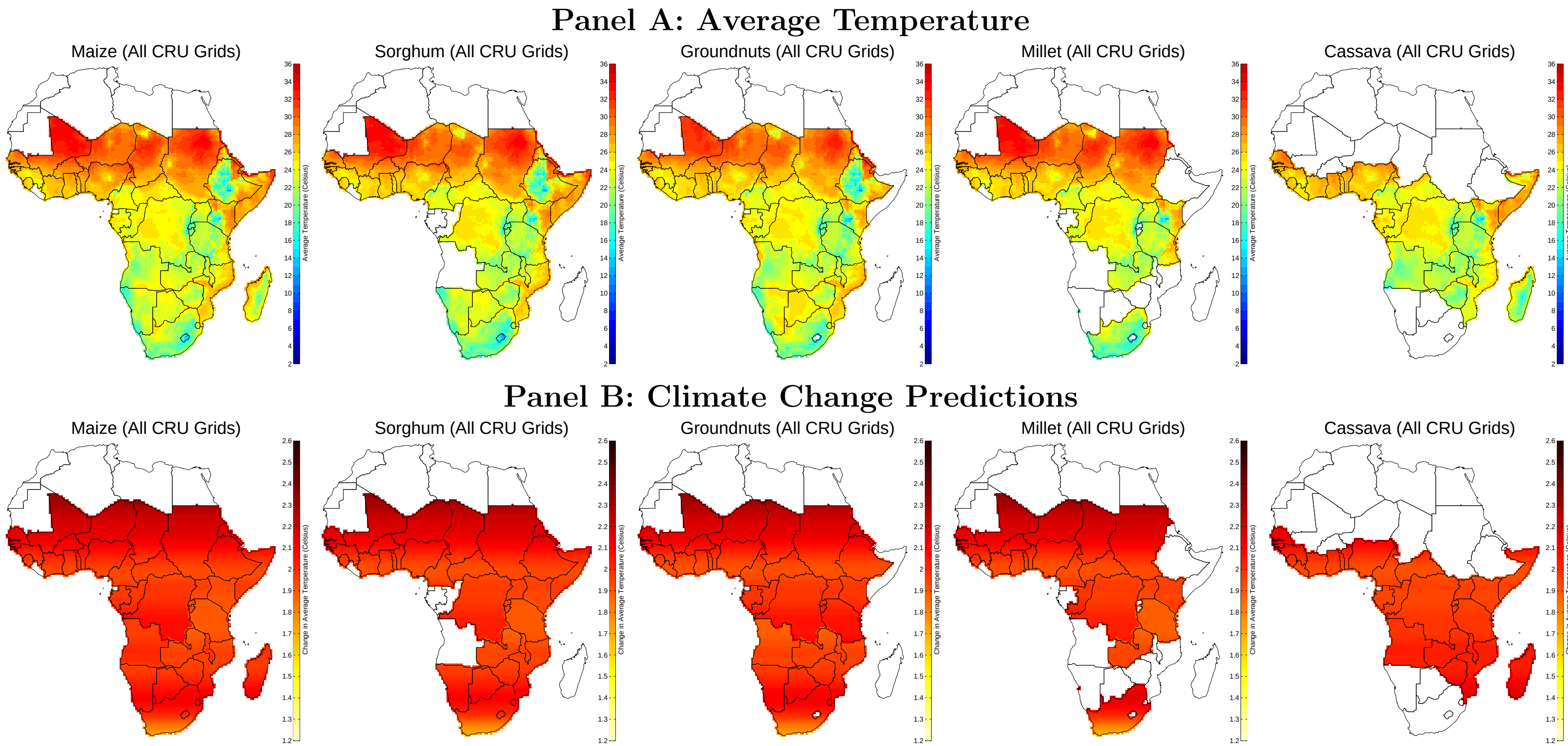
We obtain predictions from 16 climate change models from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) at Lawrence Livermore National Laboratory.[4] Each model gives predicted changes in minimum and maximum temperature as well as relative changes in precipitation for the period 2045-2065 compared to the historic baseline period 1961-2000 under the A1b scenario. The 16 models are: (i) bccr bcm 2.0; (ii) cccma cgcm 3.1; (iii) cccma cgcm 3.1 t63; (iv) cnrm cm3; (v) csiro mk 3.0; (vi) gfdl cm 2.0; (vii) gfdl cm 2.1; (viii) giss aom; (ix) giss model e.r; (x) iap fgoals 1.0g; (xi) ipsl cm4; (xii) miroc 3.2 hires; (xiii) miroc 3.2 medres; (xiv) miub echo g; (xv) mpi echam5; (xvi) mri cgcm 2.3 2a.

Predicted changes at each grid of the historic weather data sets (CRU 2.1 or NCC, see Section 1.3) are weighted averages of the GCM grids. We use a Kernel smoother (normal density) with a bandwidth of 2 degrees. The predicted monthly change in maximum and minimum temperature is then added to the historic baseline series (1961-2000 for NCC and 1961-2002 for CRU 2.1), or for the case of precipitation, the historic baseline series is multiplied by the predicted relative change. The weather variables are recalculated with the shifted historic time series, and the average over all years is taken and compared to the historic average. The predicted change in average temperature is shown in the bottom panel of Figure A1.

Predicted changes are shown in panel B of Figure A2 for the CRU 2.1 grid, which has the finest grid structure.

[4]http://www-pcmdi.llnl.gov

Figure A2: Descriptive Statistics: Historic Average Temperatures and Predicted Changes

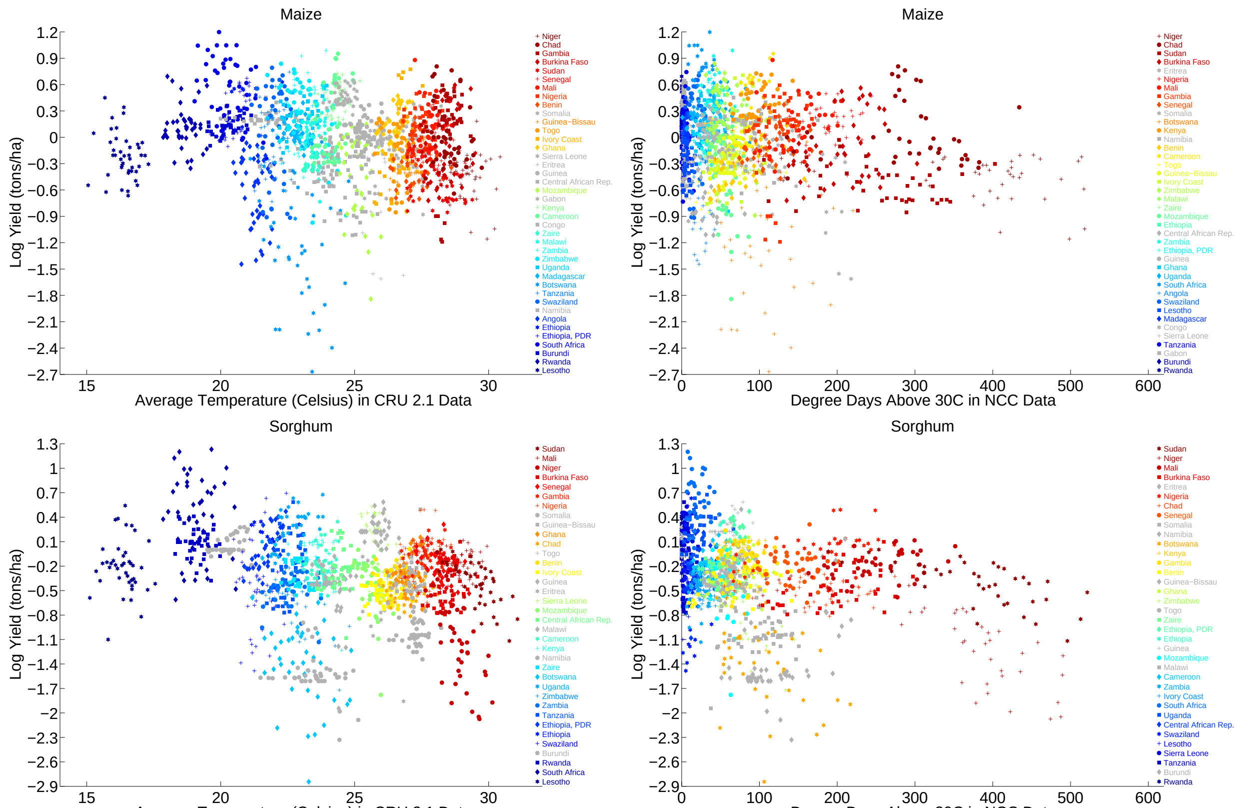


Notes: The top row displays average temperature during the gropwing season. The bottom row gives the mean predicted increase in average temperatures during the growing season among our 16 climate change models. Both panels use the CRU 2.1 weather data set, which features a finer grid than the NCC data sets.

1.5 Scatter Plots

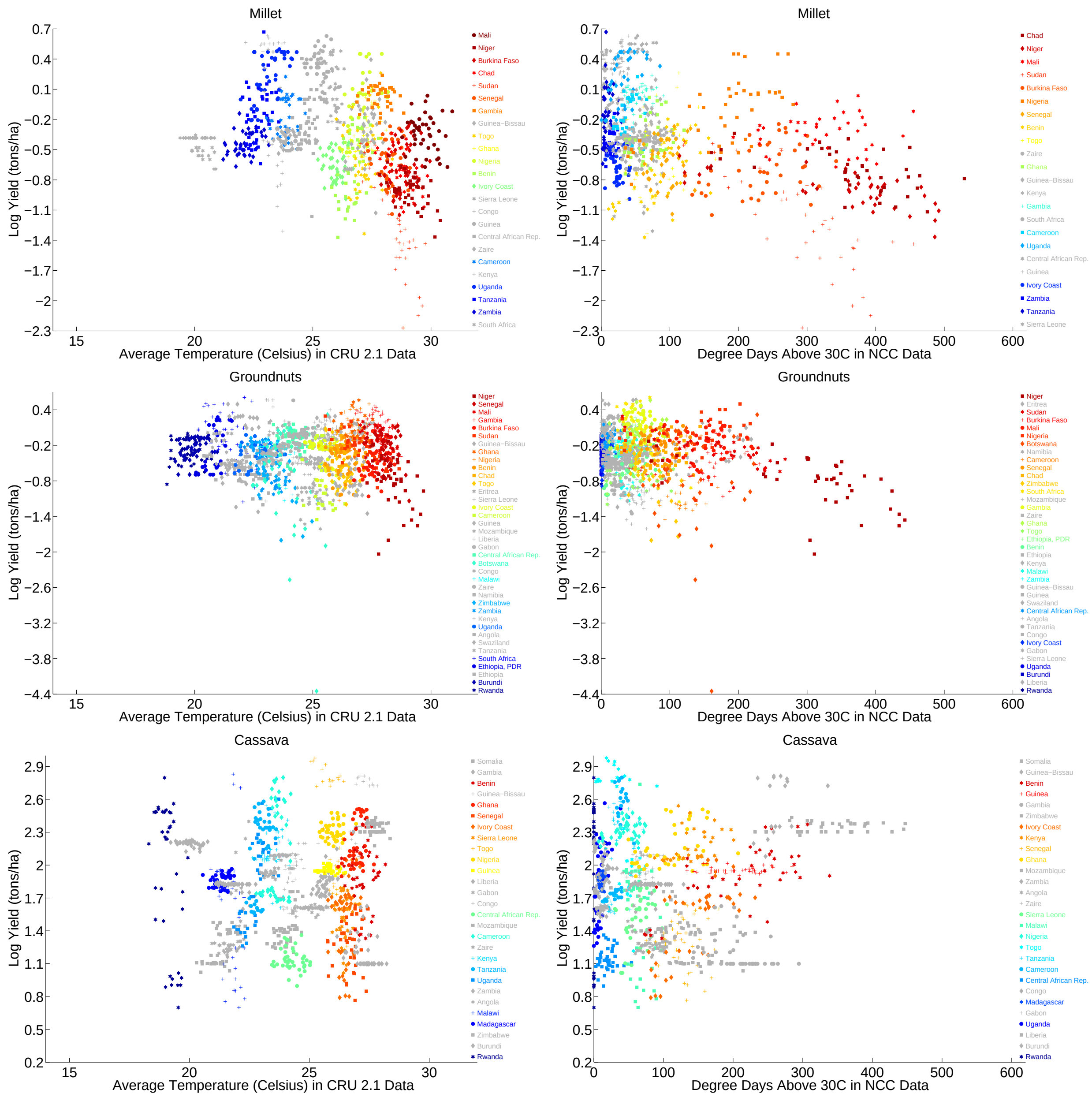
Figures A3 and A4 display scatter plots of our panel data. The y-axis displays log yields, while the x-axis displays a temperature measure (average temperature in the left column and degree days above 30°C in the right column. Observations from one country are displayed in a unique color-symbol combination. Countries with suspect yields (e.g., several consecutive years with identical yields) are displayed in grey. These countries are excluded in the estimation of our main results. The color of a country is determined by the average of the temperature variable over all years in the panel, ranging from the coolest country (blue) to the hottest country (red).

Figure A3: Scatter Plots: Maize and Sorghum



Notes: Panels display scatter plots of log yields against two temperature measures. The left column uses average temperature throughout the growing season (Using data from the CRU 2.1 data base), while the right column uses degree days above 30°C (constructed from the NCC data base). Observations from each country have a unique color-symbol combination. Countries are ordered from coldest average (blue) to warmest average (red). Flagged yields are displayed in grey.

Figure A4: Scatter Plots: Millet, Groundnuts, and Cassava



Notes: Panels display scatter plots of log yields against two temperature measures. The left column uses average temperature throughout the growing season (Using data from the CRU 2.1 data base), while the right column uses degree days above 30°C (constructed from the NCC data base). Observations from each country have a unique color-symbol combination. Countries are ordered from coldest average (blue) to warmest average (red). Flagged yields are displayed in grey.

2 Models

Our regression equation links log yields y_{it} in country i in year t to various specifications of weather $f(w_{it})$ as outlined below. A log-model implies that the effect of temperature on yields is in relative terms, i.e., a certain temperature reduces/increase yields by a given percentage independent of the baseline. All regression include a quadratic time trend (to capture overall technological progress) as well as country fixed effects c_i. I.e.,

$$y_{it} = f(w_{it}) + \gamma_1 t + \gamma_2 t^2 + c_i + \epsilon_{it}$$

2.1 Regression Model

We use four specifications to model the impact of weather

(i) Average weather. We use a linear specification in both the mean temperature during the growing season $\bar{h}_{it}$ as well as total precipitation p_{it}, i.e.,

$$f(w_{it}) = \alpha_1 \bar{h}_{it} + \beta_1 p_{it}$$

(ii) Quadratic in average weather. We use a quadratic specification in both the mean temperature during the growing season $\bar{h}_{it}$ as well as total precipitation p_{it}, i.e.,

$$f(w_{it}) = \alpha_1 \bar{h}_{it} + \alpha_2 \bar{h}_{it}^2 + \beta_1 p_{it} + \beta_2 p_{it}^2$$

(iii) Degree days. Agronomists have stipulated that log-yield growth is piecewise linear. This underlies the concept of degree days, which is a truncated temperature variable. We use two degree days variables: (a) degree days 10-30°C ($d_{10-30,it}$) and degree days above 30°C ($d_{30,it}$). The former measures temperatures above 10°C and below 30°C, i.e., a temperature of 9, 10, 11, 12, 30, and 31°C would result in 0, 0, 1, 2, 20, and 20 degree days 10-30°C, respectively. Degree days above 30°C measures temperatures above 30°C with no upper bound, i.e., a temperature of 29, 30, and 31°C would result in 0, 0, and 1, degree days above 30°C, respectively. The intuition is that temperatures between 10-30°C are generally considered yield-enhancing, while temperatures above 30°C are yield-decreasing. The exact bounds depend on the crop in question. They have been estimated for corn, soybeans, and cotton in the United States using a much larger data set [6]. Given the limited number of observations we have in Africa, we exogenously fix these bounds, but would like to note that the overall results are robust to perturbations of these bounds. For the NCC data base, we follow [6] and construct the temperature distribution within a day by fitting a sinusoidal curve between the daily minimum and maximum temperature. Since the CRU data base only gives *monthly*, and not *daily* values, we use Thom's formula to approximate the distribution of daily temperatures within a month [8, 7] as described in [5]. We again include a quadratic of total precipitation during the growing season to get

$$f(w_{it}) = \alpha_1 d_{10-30,it} + \alpha_2 d_{30,it} + \beta_1 p_{it} + \beta_2 p_{it}^2$$

(iv) Non-parametric in temperature. While the concept of degree days assumes a piecewise-linear function in temperatures, there is some discussion about the optimal breakpoint. [6] derive the time temperatures are exposed to various temperatures, however the sample size of that study was much larger compared to the current panel. In this paper we therefore break the degree-days variables into subcategories of 5°C intervals, estimating a piecewise linear function on the intervals [10°C,15°C); [15°C,20°C); [20°C,25°C); [25°C,30°C); [30°C,35°C); [35°C,oo°C). The model becomes

$$\begin{aligned} f(w_{it}) &= \alpha_1 d_{10-15,it} + \alpha_2 d_{15-20,it} + \alpha_3 d_{20-25,it} + \alpha_4 d_{25-30,it} + \alpha_5 d_{30-35,it} + \alpha_6 d_{35,it} \\ &\quad + \beta_1 p_{it} + \beta_2 p_{it}^2 \end{aligned}$$

2.2 Fertilizer Use - Estimation Subsets

Planted crop varieties and, correspondingly, responses to weather may vary with fertilizer use. There are two countries in Sub-Saharan Africa with historically higher fertilizer usage: South Africa and Zimbabwe. We therefore spilt our sample in two and estimate separate models for (i) a panel of South Africa and Zimbabwe and (ii) a panel of the remaining countries in Subsaharan Africa unless otherwise noted.

Note that Millet and Cassava are either not grown in high-fertilizer countries, or yields for these crops were flagged and excluded. We are hence not able to estimate a separate regression equation for these two crops in high-fertilizer countries.

2.3 Error Terms

To obtain the correct confidence intervals we use a bootstrap where we randomly sample years with replacement. In our baseline panel (NCC weather data) we have 40 years and we hence draw 40 years with replacement and always include all countries for which we have observations in that year. We employ 1000 bootstrap runs. The motivation for using a grouped bootstrap is that weather is highly spatially correlated, while it is less so temporally (except for some some weak weather cycles).

2.4 Climate Change Impacts

The predicted climate change impacts are changes in *total* production keeping the growing area and crops grown constant. We derive the impacts as follows: For each of our 1000 bootstrap runs we calculate the predicted yield under the historic time series (1961-2000 for the NCC weather data base) w_{it}^0 as $y^0 = e^{f(w_{it}^0)+\delta_i+\frac{\sigma^2}{2}}$, where the country-specific constant $\delta_i = c_i + \gamma_1 \bar{t} + \gamma_2 \bar{t}^2$ ensures that the predicted log yield in a country equals the average log yield in the sample. The variance of the error terms σ^2 is included since the exponent is a convex function and hence the expected value is greater than the function evaluated at the expected value (Jensen's inequality). Total production in the baseline is the area-weighted sum of all country-specific yields, where the area is the average production area in the historic yield data (1961-2007).

The predicted yield under future climate w_{it}^1 is $y^1 = e^{f(w_{it}^1)+\delta_i+\sigma^2/2}$, which is again weighted by historic growing areas.[5] The predicted change in total production is $\frac{y_1}{y_0} - 1$.

Since predicted climate change impacts only depend on past and future weather as well as the coefficient estimates (but not on historic yields), we also derive the impacts for countries with flagged yields that were excluded in the estimation sample.

We calculate the relative impact for each of our 1000 bootstrap simulations and each of our 16 GCMs to derive the distribution of impacts.

3 Regression Results

Tables A1 through A4 present the regression results of the weather coefficients in various model specifications outlined in Section 2.1. All regression use our baseline weather data set (NCC) and weight all weather grids within a country by the cropland area from a satellite scan. Separate equations are estimated for high-fertilizer countries (South Africa and Zimbabwe) as well as low-fertilizer countries (remaining Sub-Saharan countries). All regressions include separate quadratic time trends for high and low-fertilizer countries (not reported).

[5]we do not consider shifts in the growing area in this analysis.

Table A1: Regression Results: Model with Average Temperature

	Maize	**Sorghum**	**Millet**	**Groundnuts**	**Cassava**
			Countries with High Fertilizer Use		
Avg. Temperature	-0.246***	-0.188*		-0.208***	
	(0.0761)	(0.0992)		(0.0770)	
Precipitation	0.000900***	0.000618		0.00116***	
	(0.000182)	(0.000390)		(0.000243)	
			Countries with Low Fertilizer Use		
Avg. Temperature	-0.104***	-0.0586**	-0.0901***	-0.0807*	-0.0748**
	(0.0289)	(0.0240)	(0.0287)	(0.0428)	(0.0299)
Precipitation	-0.0000240	0.000314***	0.000116	0.000296***	-0.000100
	(0.0000833)	(0.0000781)	(0.0000758)	(0.000113)	(0.0000757)
R-squared	0.5870	0.6253	0.6756	0.3924	0.5170
Observations	1240	1080	640	912	640

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table reports regression coefficients for each crop response function as well as standard errors in brackets. High-fertilizer countries are South Africa and Zimbabwe (see Section 2.2). All regressions include quadratic time trends.

Table A2: Regression Results: Model with Average Temperature Squared

	Maize	**Sorghum**	**Millet**	**Groundnuts**	**Cassava**
			Countries with High Fertilizer Use		
Avg. Temperature	0.938	0.200		2.377^{*}	
	(0.920)	(0.754)		(1.402)	
Avg. Temperature^2	-0.0269	-0.00804		-0.0575^{*}	
	(0.0217)	(0.0183)		(0.0316)	
Precipitation	0.00384^{***}	0.00535^{***}		0.00457^{***}	
	(0.00148)	(0.00189)		(0.00119)	
Precipitation^2	-0.00000235^{**}	-0.00000461^{**}		-0.00000290^{***}	
	(0.00000114)	(0.00000180)		(0.000000983)	
			Countries with Low Fertilizer Use		
Avg. Temperature	-0.185	0.382^{***}	1.249^{***}	0.674^{**}	-1.220^{**}
	(0.201)	(0.141)	(0.214)	(0.290)	(0.533)
Avg. Temperature^2	0.00184	-0.00878^{***}	-0.0246^{***}	-0.0149^{***}	0.0237^{**}
	(0.00386)	(0.00289)	(0.00431)	(0.00551)	(0.0107)
Precipitation	0.000301	0.000529^{***}	0.000929^{***}	0.000781^{*}	0.000146
	(0.000260)	(0.000204)	(0.000333)	(0.000424)	(0.000216)
Precipitation^2	-0.000000171	-0.000000120	-0.000000486^{***}	-0.000000307	$-8.01e\text{-}08^{*}$
	(0.000000112)	(9.88e-08)	(0.000000185)	(0.000000229)	(4.74e-08)
R-squared	0.5885	0.6336	0.6952	0.4024	0.5257
Observations	1240	1080	640	912	640

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table reports regression coefficients for each crop response function as well as standard errors in brackets. High-fertilizer countries are South Africa and Zimbabwe (see Section 2.2). All regressions include quadratic time trends.

Table A3: Regression Results: Degree Days Model

	Maize	**Sorghum**	**Millet**	**Groundnuts**	**Cassava**
			Countries with High Fertilizer Use		
Degree Days 10-30°C	-0.000310	-0.0000119		-0.000552	
	(0.000582)	(0.000603)		(0.000810)	
Degree Days 30°C	-0.00725**	-0.00624**		-0.00260	
	(0.00321)	(0.00299)		(0.00339)	
Precipitation	0.00306**	0.00437**		0.00360***	
	(0.00148)	(0.00171)		(0.00124)	
Precipitation^2	-0.00000178	-0.00000378**		-0.00000209**	
	(0.00000111)	(0.00000167)		(0.000000984)	
			Countries with Low Fertilizer Use		
Degree Days 10-30°C	-0.000592***	0.0000218	-0.000114	-0.000263	-0.000446***
	(0.000172)	(0.000129)	(0.000173)	(0.000235)	(0.000108)
Degree Days 30°C	-0.000234	-0.00170***	-0.00116***	-0.00130***	0.00188***
	(0.000328)	(0.000291)	(0.000297)	(0.000451)	(0.000450)
Precipitation	0.000287	0.000263	0.000835**	0.000484	0.000279
	(0.000276)	(0.000229)	(0.000394)	(0.000474)	(0.000208)
Precipitation^2	-0.000000166	-8.64e-09	-0.000000437**	-0.000000140	-0.000000100**
	(0.000000118)	(0.000000108)	(0.000000216)	(0.000000255)	(4.68e-08)
R-squared	0.5896	0.6432	0.6883	0.3998	0.5317
Observations	1240	1080	640	912	640

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table reports regression coefficients for each crop response function as well as standard errors in brackets. High-fertilizer countries are South Africa and Zimbabwe (see Section 2.2). All regressions include quadratic time trends.

Table A4: Regression Results: Model with Various Degree Days Ranges

	Maize	**Sorghum**	**Millet**	**Groundnuts**	**Cassava**
			Countries with High Fertilizer Use		
Degree Days 10-15°C	0.00446	-0.00154		-0.0113	
	(0.00578)	(0.00631)		(0.00878)	
Degree Days 15-20°C	-0.00338	0.00165		0.00842	
	(0.00384)	(0.00391)		(0.00583)	
Degree Days 20-25°C	0.000811	-0.00119		-0.00721	
	(0.00267)	(0.00271)		(0.00478)	
Degree Days 25-30°C	-0.000979	0.000621		0.00278	
	(0.00425)	(0.00475)		(0.00674)	
Degree Days 30-35°C	0.00707	-0.00320		0.00527	
	(0.0112)	(0.0105)		(0.0150)	
Degree Days 35°C	-0.0955***	-0.0213		-0.0414	
	(0.0338)	(0.0240)		(0.0337)	
Precipitation	0.00317**	0.00436**		0.00341***	
	(0.00141)	(0.00178)		(0.00122)	
Precipitation^2	-0.00000181*	-0.00000374**		-0.00000185*	
	(0.00000108)	(0.00000173)		(0.000000955)	
			Countries with Low Fertilizer Use		
Degree Days 10-15°C	-0.00602**	-0.00252	-0.00789	-0.00135	0.00289
	(0.00267)	(0.00237)	(0.00592)	(0.0115)	(0.00571)
Degree Days 15-20°C	-0.000418	0.000546	0.00196	0.00349**	-0.00265
	(0.000792)	(0.000722)	(0.00234)	(0.00155)	(0.00162)
Degree Days 20-25°C	-0.000379	-0.000722	-0.0000583	-0.00212***	0.0000309
	(0.000546)	(0.000567)	(0.000659)	(0.000810)	(0.000548)
Degree Days 25-30°C	-0.000698	0.000788	-0.000546	0.000607	-0.000134
	(0.000440)	(0.000600)	(0.000448)	(0.000668)	(0.000401)
Degree Days 30-35°C	0.000532	-0.00160	0.000283	-0.00102	0.000581
	(0.00121)	(0.00117)	(0.00110)	(0.00141)	(0.000971)
Degree Days 35°C	-0.00150	-0.00279	-0.00313*	-0.00313	0.00304
	(0.00175)	(0.00194)	(0.00161)	(0.00254)	(0.00310)
Precipitation	0.000311	0.000274	0.000912**	0.000525	0.000194
	(0.000267)	(0.000232)	(0.000409)	(0.000460)	(0.000221)
Precipitation^2	-0.000000173	5.16e-09	-0.000000480**	-0.000000152	-8.05e-08
	(0.000000112)	(0.000000112)	(0.000000223)	(0.000000244)	(4.98e-08)
R-squared	0.5949	0.6426	0.6884	0.4069	0.5361
Observations	1240	1080	640	912	640

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table reports regression coefficients for each crop response function as well as standard errors in brackets. High-fertilizer countries are South Africa and Zimbabwe (see Section 2.2). All regressions include quadratic time trends.

4 Robustness

We explore the robustness of our results to various specifications checks. Our main finding that Maize, Millet, Sorghum, and Groundnuts yields are negatively impacted by climate change does not change in any of these checks.

4.1 Weather Data

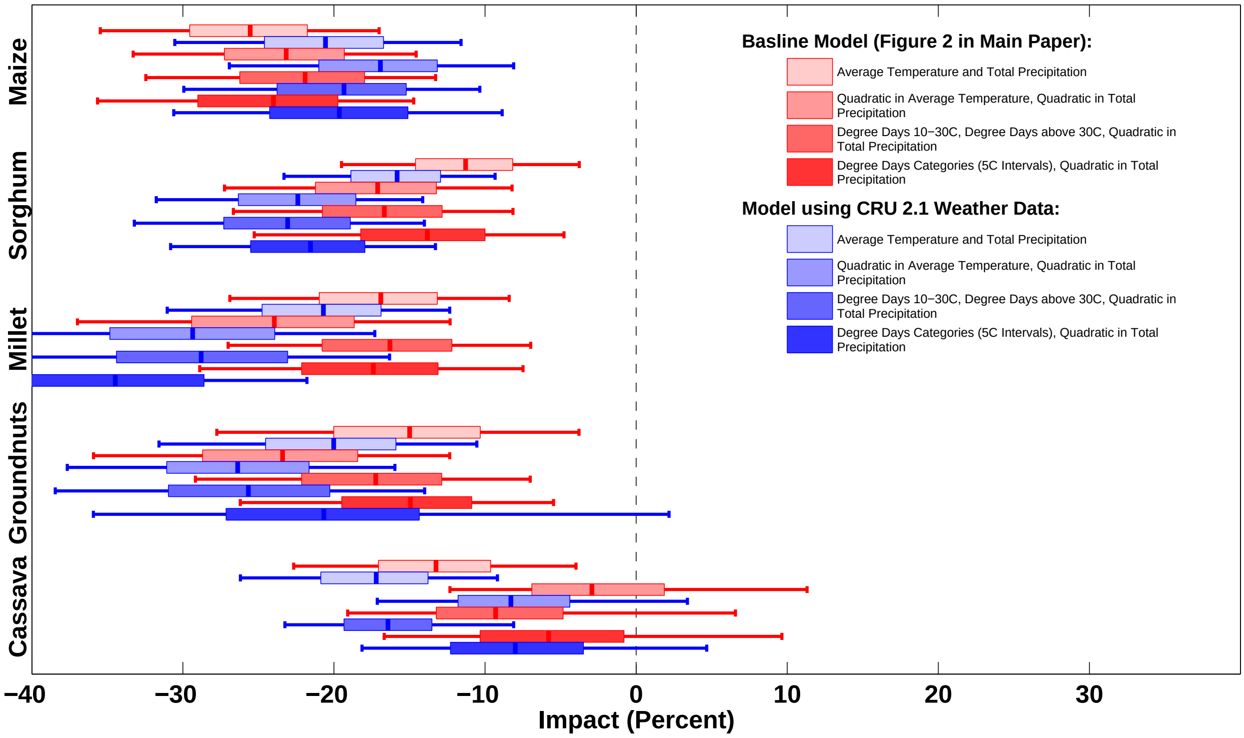
Our baseline data set uses the NCC data set (see description in Section 1.3 above). The main reason why we chose this data set is that it gives four observations per day and hence is better suitable to derive degree days, which depend on daily minimum and maximum temperature. The first robustness check uses the CRU 2.1 weather data set instead. The latter gives monthly averages, but on a finer geographic scale than NCC.

We cross-check our results using a completely different data set. It should be noted that the correlation of average weather outcomes in the NCC and CRU 2.1 data bases is very high. Both models agree which areas are hotter on average and receive more rainfall. However, deviations from means, i.e., by how much was a given year above or below average outcomes is much less correlated. Year specific weather shocks are more difficult to construct given the sparsity of weather data in Africa. As outlined in the main paper, a panel model relies on deviations from mean growing conditions, i.e., by how much is a particular year warmer or colder than the average outcome, where models start to diverge somewhat.

The fact that we get very similar results using a completely different weather data set (NCC is based on NOAA's Centers for Environmental Prediction reanalysis data, while CRU 2.1 smoothes observational weather station data) is reassuring. This suggests that our results are not driven by model-specific measurement error, which will get amplified in a panel that takes out the mean of each variable in each country. Since Africa does not have as good of a weather data coverage as, for example, the United States, this is an important confirmation in our view. Measurement error could potentially be substantial and lead to attenuation bias.

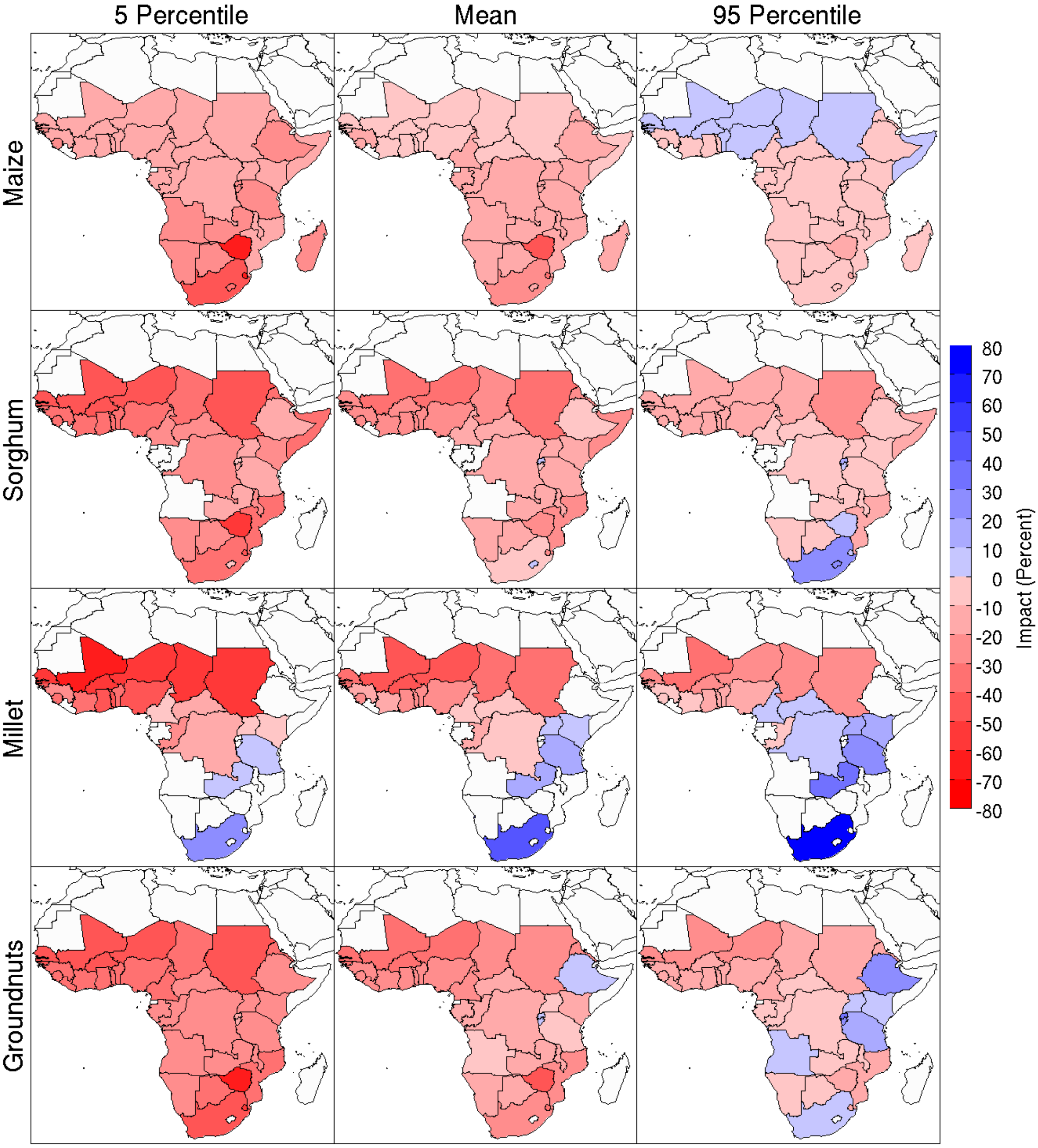
Figure A5 replicates Figure 2 of the main paper with the different CRU 2.1 weather data set. Flagged yields are excluded from the regression and we estimate separate equations for countries with high and low fertilizer use. The original estimates using the NCC data set are shown in red, while the results using the CRU 2.1 weather data set are shown in blue. Figure A6 displays the distribution of impacts among countries, where we again include 1000 bottstrap runs for each of the 16 climate change predictions for the mid-century (a1b scenario).

Figure A5: Aggregate Results using CRU 2.1 Weather Data Set



Notes: Predicted changes in total production (percent) in SSA from climate change in 2046-2065 relative to 1961-2002. Boxplots show the combined distribution of predicted impacts from (i) sampling one of the 16 climate change models and (ii) bootstrapping the model parameters. The median predicted impact is shown as solid line, while the box shows the 25-75 percentile range. Whiskers extend to the 5 and 95 percentile.

Figure A6: Country-Level Results using CRU 2.1 Weather Data Set



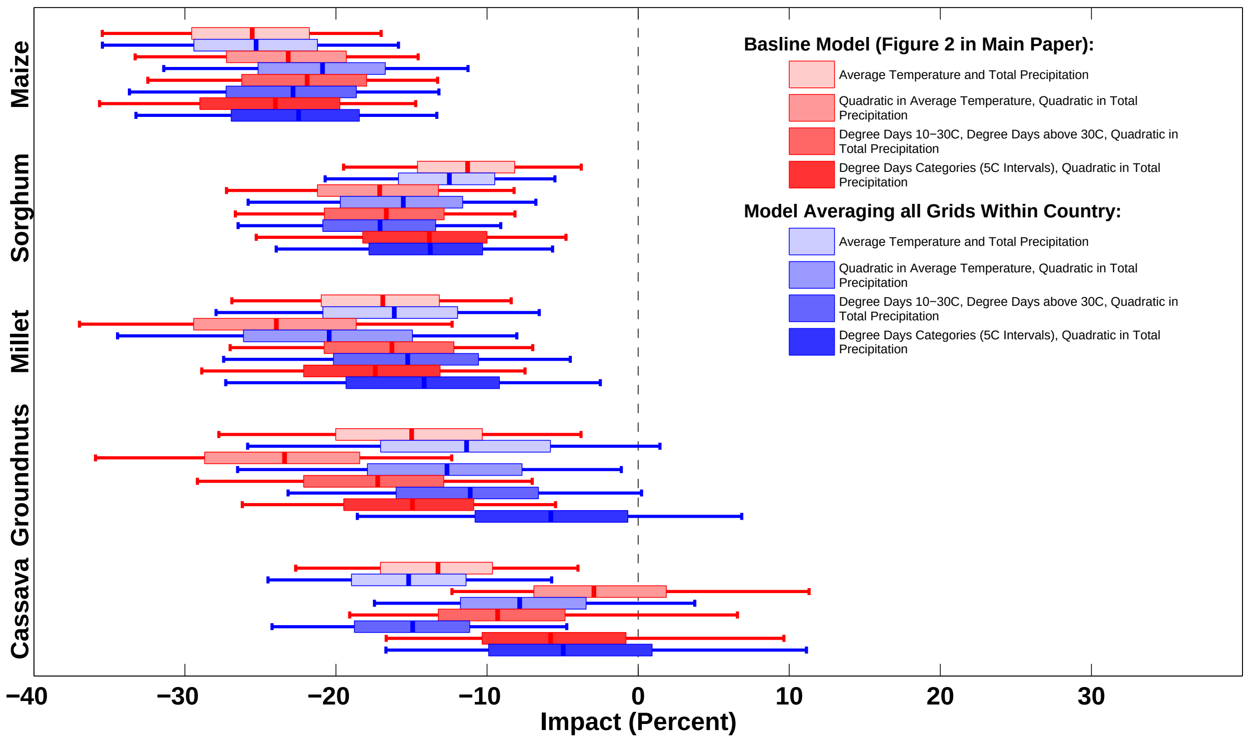
Notes: Distribution of impacts from climate change by country (percent yield change). Mean impacts (middle column) as well as the 5 and 95 percentile (left and right column, respectively) are shown. Each row represents one crop.

4.2 Construction of Country-Level Weather Data Sets

Our baseline model weighs all grid points that fall within a country by the growing area that was contained in each grid cell in a satellite scan in 2000 (see Section 1.3). This growing area might not be representative for early years. In a sensitivity check we simply average all grids in a country. The results are shown in Figure A7.

The underlying weather data set is NCC (Section 1.3). Flagged yields are excluded from the regression and we estimate separate equations for countries with high and low fertilizer use.

Figure A7: Aggregate Results Averaging all Weather Grids within a Country



Notes: Predicted changes in total production (percent) in SSA from climate change in 2046-2065 relative to 1961-2000. Boxplots show the combined distribution of predicted impacts from (i) sampling one of the 16 climate change models and (ii) bootstrapping the model parameters. The median predicted impact is shown as solid line, while the box shows the 25-75 percentile range. Whiskers extend to the 5 and 95 percentile.

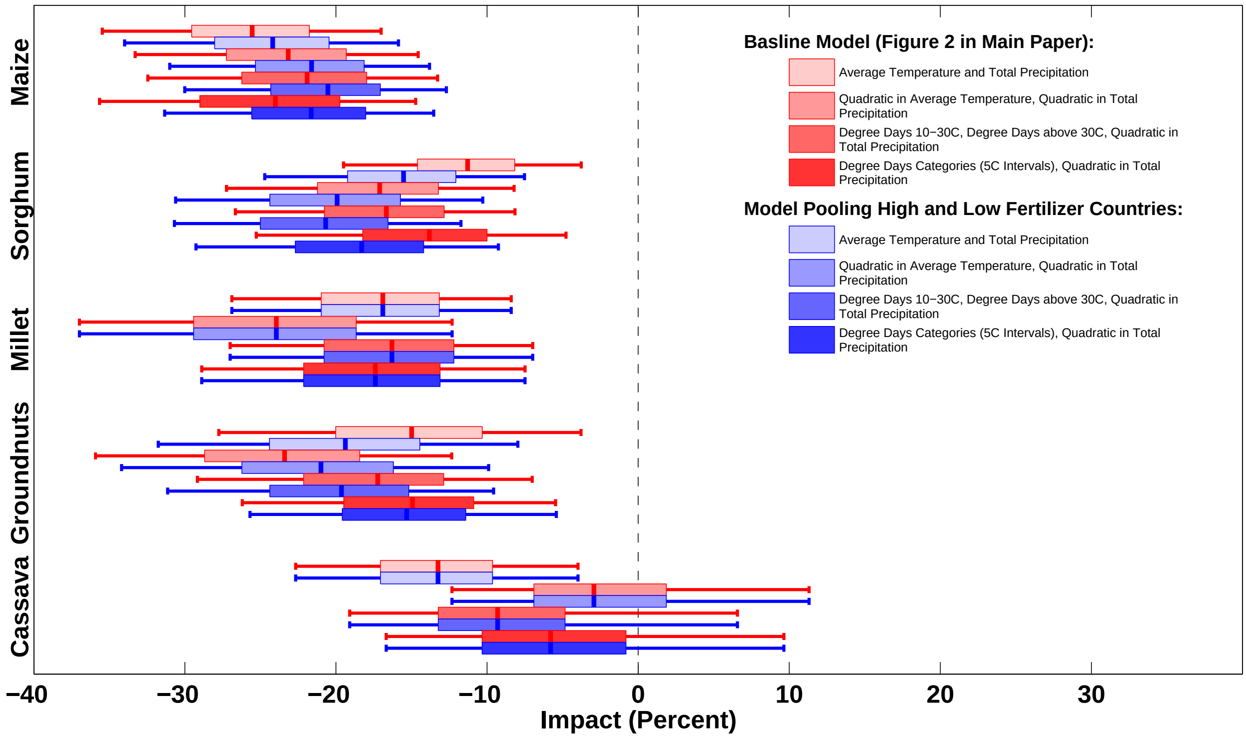
4.3 Pooled Estimation Sample (Irrespective of Fertilizer Use)

Our baseline model fits a separate regressions for countries with traditionally high fertilizer use (a panel of South Africa and Zimbabwe) and a panel of the remaining countries in Sub-Saharan Africa (see Section 2.2). The F-test weather the coefficients on all climate variable are the same in the two subsets fails with a p-value less than 0.05).

In a sensitivity check we pool all countries in the estimation of the coefficients and then evaluated the predicted impacts. Compared to our baseline results in Figure 2 of the main paper, the median impacts are rather robust, but the variance of the distribution decreases in Figure A8 (Recall that we had Millet and Cassava had no high-fertilizer observations and the results are hence identical to the baseline). This is not surprising as the subsample of high-fertilizer countries (South Africa and Zimbabwe) is small and hence the coefficients are estimated less precisely i.e., with larger standard errors. These larger errors, combined with the fact that these countries account for a significant share of overall production implies that the aggregate impacts show wider fluctuations as well.

The underlying weather data set is NCC (Section 1.3), where all grids within a country are averaged using a satellite scan of the growing area in 2000. Flagged yields are excluded from the regression.

Figure A8: Aggregate Results using a Pooled Model of High and Low-Fertilizer Countries



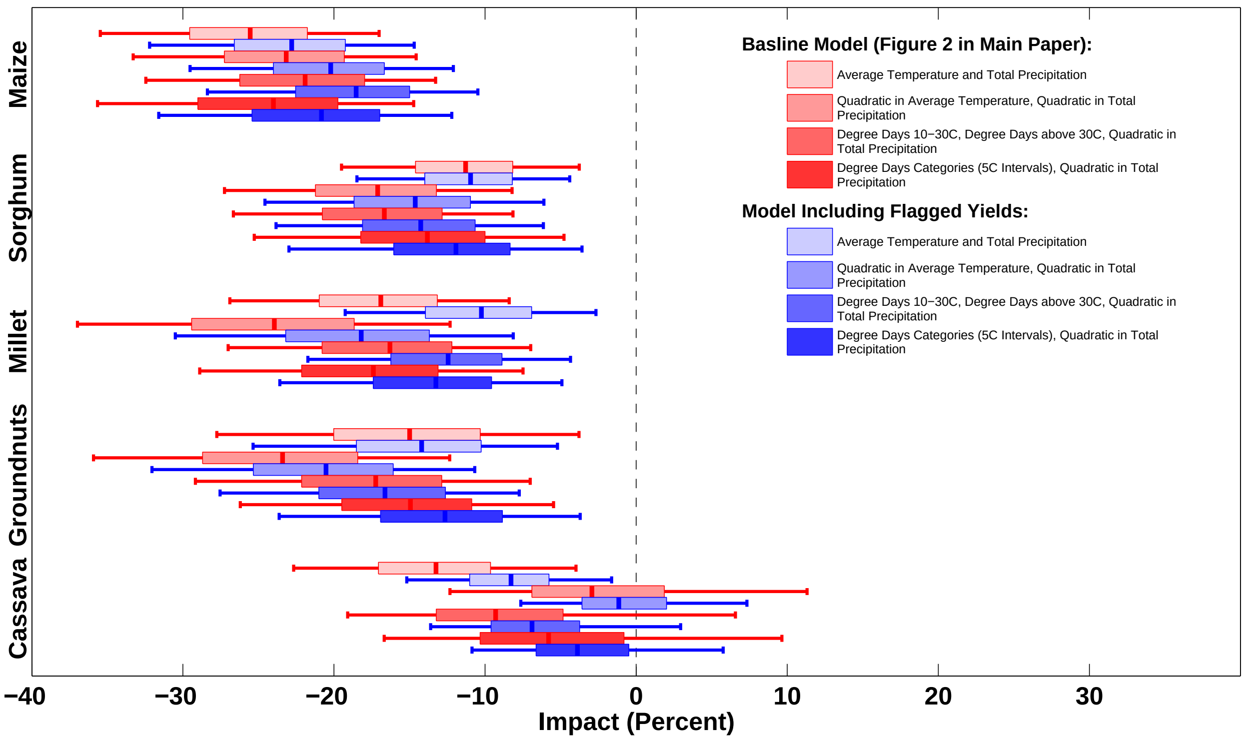
Notes: Predicted changes in total production (percent) in SSA from climate change in 2046-2065 relative to 1961-2000. Boxplots show the combined distribution of predicted impacts from (i) sampling one of the 16 climate change models and (ii) bootstrapping the model parameters. The median predicted impact is shown as solid line, while the box shows the 25-75 percentile range. Whiskers extend to the 5 and 95 percentile.

4.4 Including Flagged Yields

Our baseline model excludes countries that feature some suspicious yields (e.g., several consecutive years with identical yields). As long as these interpolated yields are not systematically related to weather fluctuations, including them will cause no bias. Accordingly, the median impacts do not change much in Figure A9, but the variance increases somewhat.

The underlying weather data set is NCC (Section 1.3), where all grids within a country are averaged using a satellite scan of the growing area in 2000. Separate equations are estimated for countries with high and low fertilizer use.

Figure A9: Aggregate Results using CRU 2.1 Weather Data Set



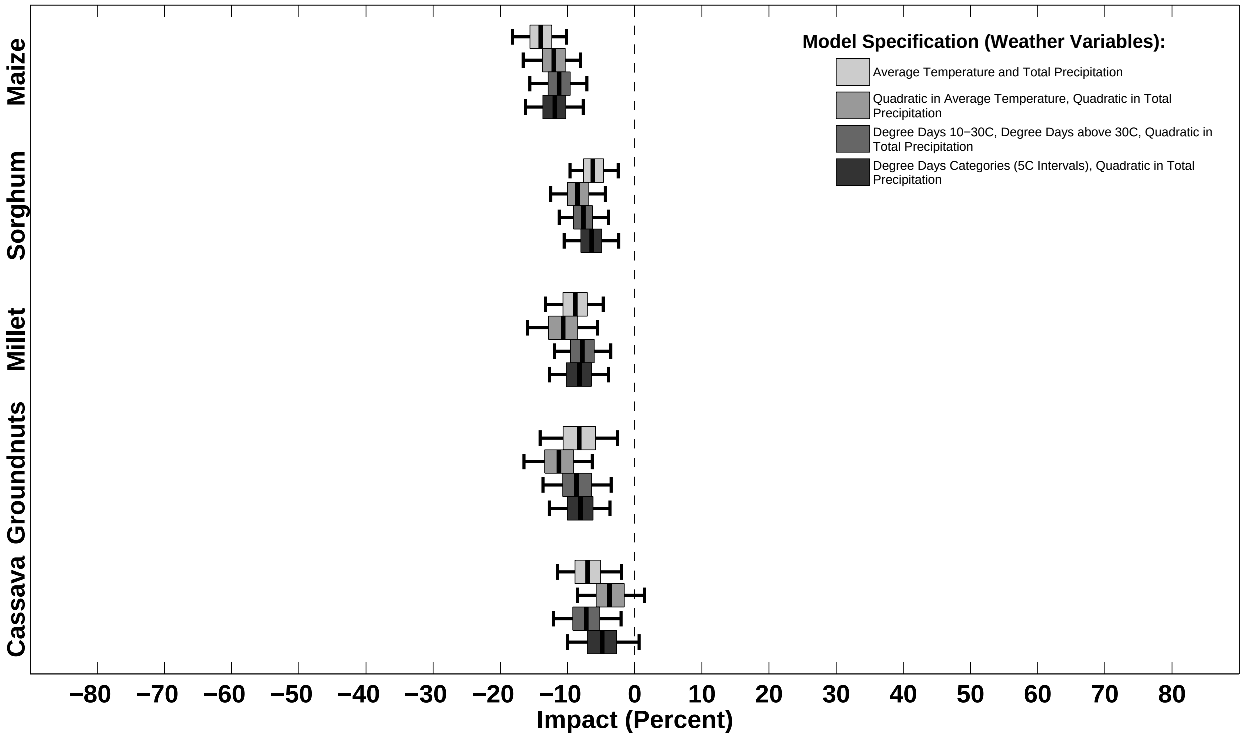
Notes: Predicted changes in total production (percent) in SSA from climate change in 2046-2065 relative to 1961-2000. Boxplots show the combined distribution of predicted impacts from (i) sampling one of the 16 climate change models and (ii) bootstrapping the model parameters. The median predicted impact is shown as solid line, while the box shows the 25-75 percentile range. Whiskers extend to the 5 and 95 percentile.

4.5 Uniform Climate Change Scenarios

Figure A10 through Figure A13 show the distribution of impacts under 6 uniform climate change scenarios. We increase temperatures by 1°C, 2°C, 3°C, 4°C, 5°C, and 6°C respectively while leaving precipitation unchanged. The rows within each panel represent combinations of various specifications as explained in Figure 2 of the main paper.

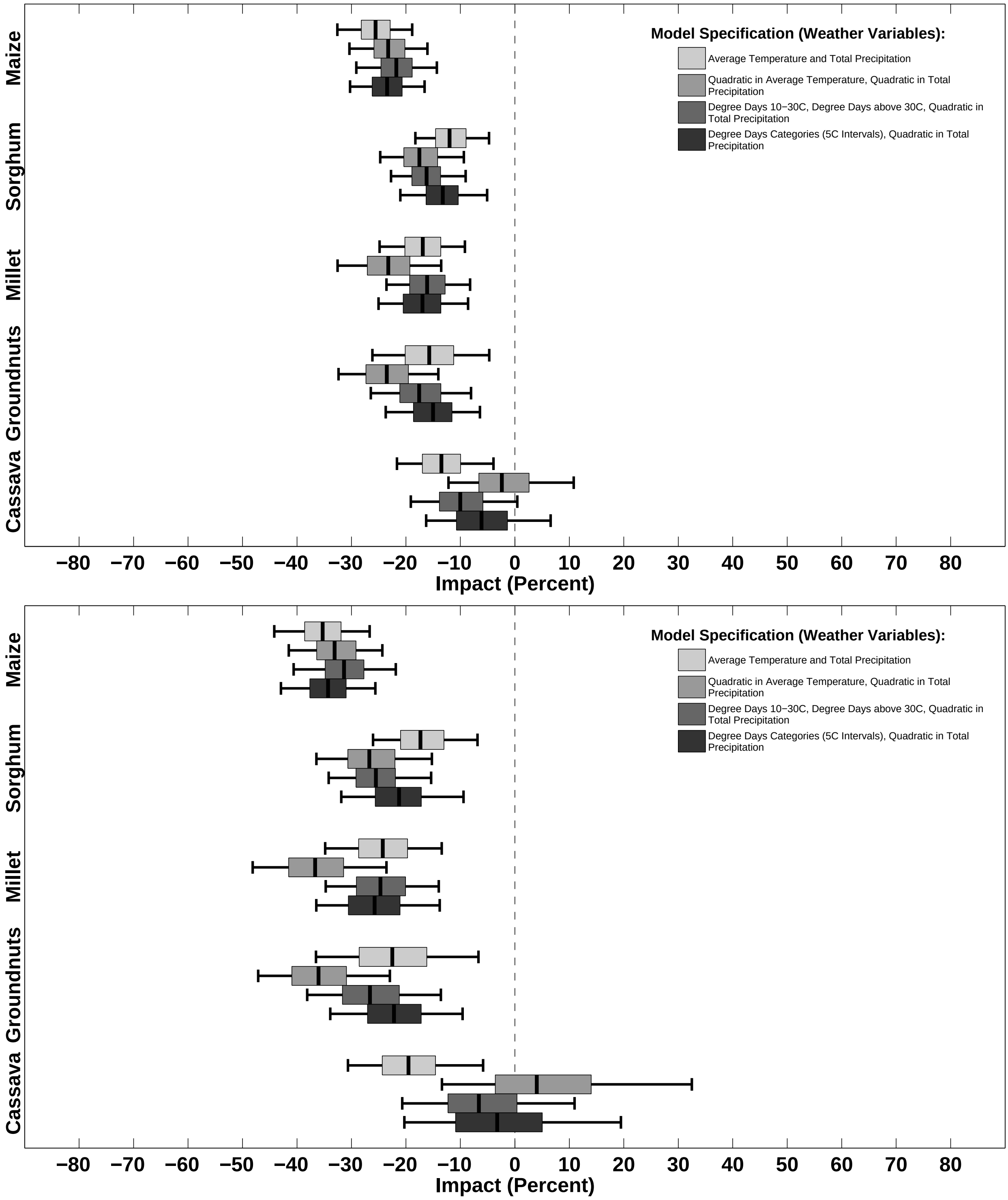
The underlying weather data set is NCC (Section 1.3), where all grids within a country are averaged using a satellite scan of the growing area in 2000. Flagged yields are excluded from the regression and we estimate separate equations for countries with high and low fertilizer use.

Figure A10: Uniform Climate Scenarios (+1°C)



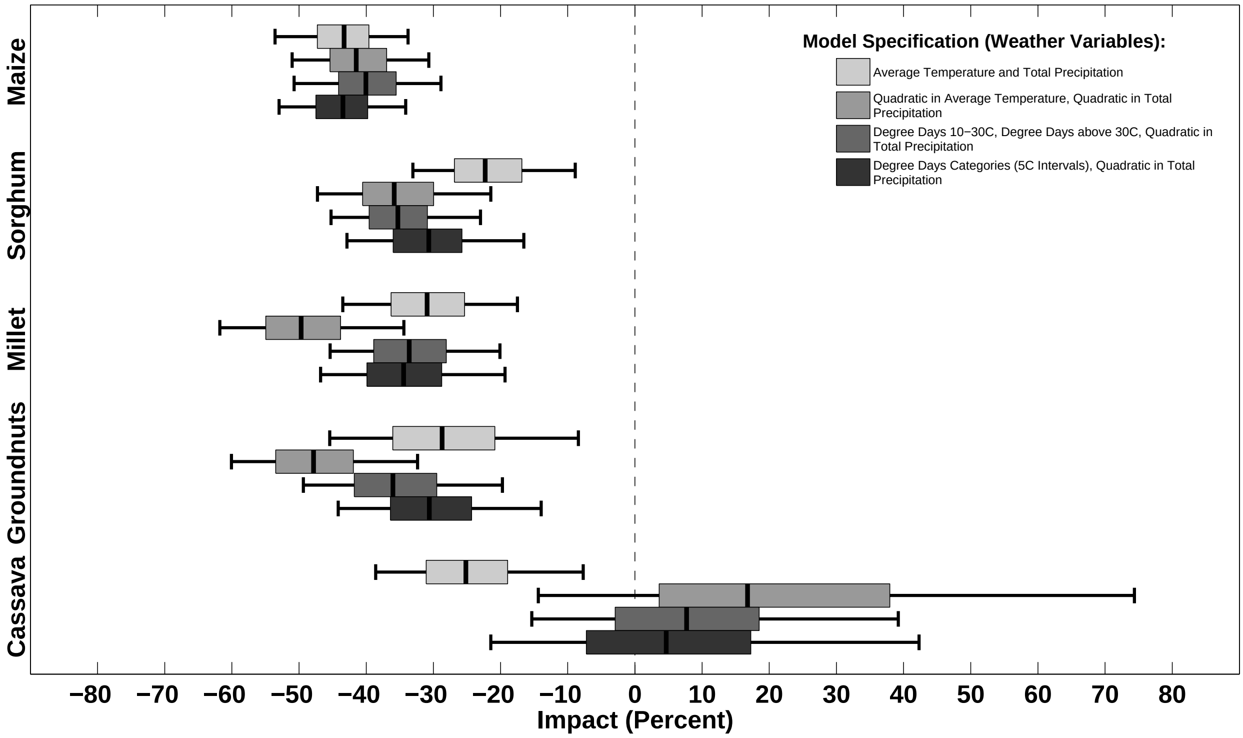
Notes: Replication of Figure 2 in the main paper for a uniform +1°C scenario. Bars show aggregate impact on crop production in Africa in percent. The box marks the 25-75 percentile range, while the inner solid line is the median. Whiskers extend to the 5 and 95 percentile.

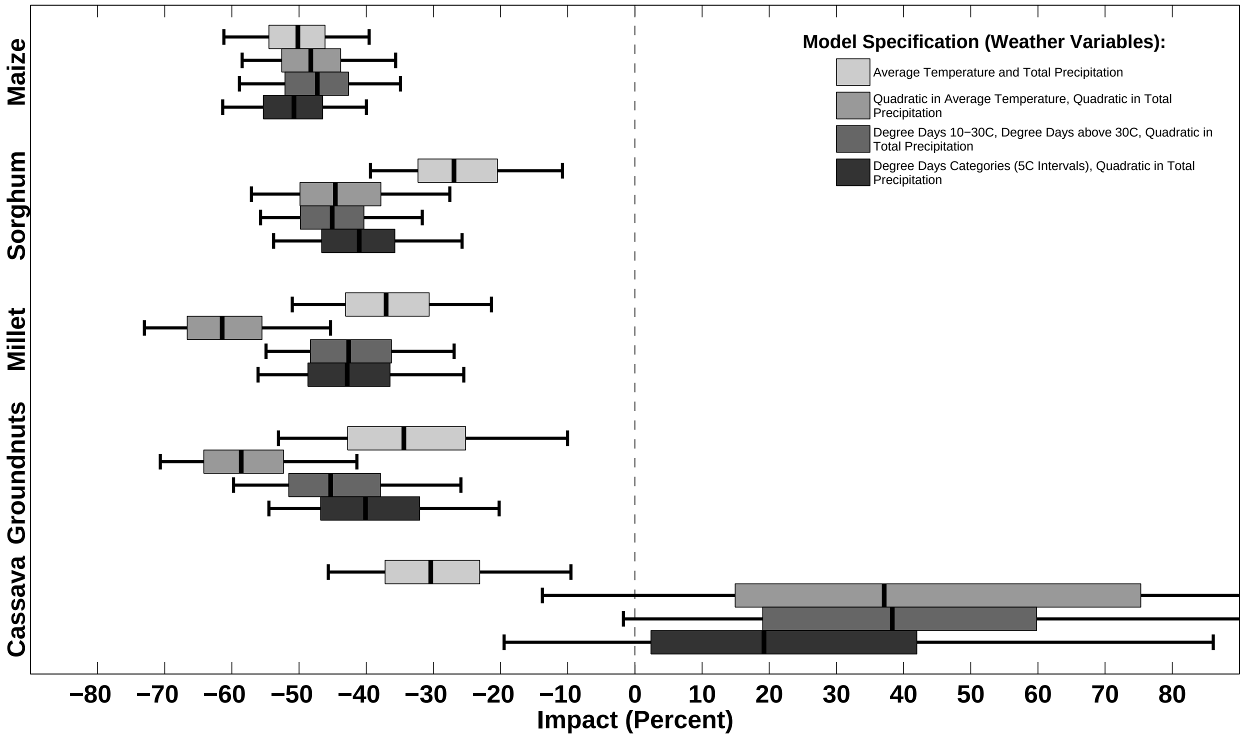
Figure A11: Uniform Climate Scenarios (+2°C and +3°C)



Notes: Replication of Figure 2 in the main paper for a uniform +2°C scenario in the top panel and a +3°C scenario in the bottom panel. Bars show aggregate impact on crop production in Africa in percent. The box marks the 25-75 percentile range, while the inner solid line is the median. Whiskers extend to the 5 and 95 percentile.

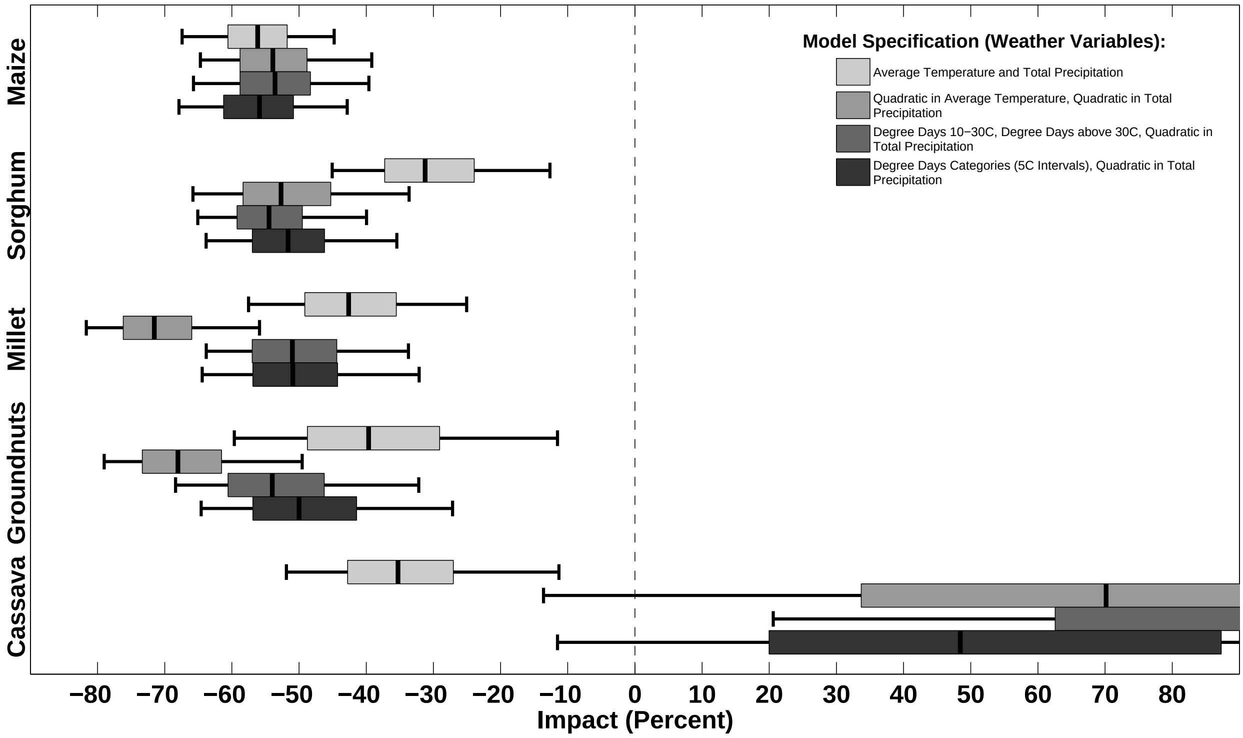
Figure A12: Uniform Climate Scenarios (+4°C and +5°C)





Notes: Replication of Figure 2 in the main paper for a uniform +4°C scenario in the top panel and a +5°C scenario in the bottom panel. Bars show aggregate impact on crop production in Africa in percent. The box marks the 25-75 percentile range, while the inner solid line is the median. Whiskers extend to the 5 and 95 percentile.

Figure A13: Uniform Climate Scenarios (+6°C)



Notes: Replication of Figure 2 in the main paper for a uniform +6°C scenario. Bars show aggregate impact on crop production in Africa in percent. The box marks the 25-75 percentile range, while the inner solid line is the median. Whiskers extend to the 5 and 95 percentile.

4.6 Comparison Of Maize Impacts in Africa and the U.S.

We can compare the predicted impacts we obtained from the panel of maize yields in Africa to the results obtained in the U.S. in [6]. The latter study had many more observations and better weather data records. We hence use the results from the U.S. as a cross-check by calculating predicted impacts in Africa in two ways: (1) The baseline degree days model using the panel of country-level maize yields in Africa (fit differently to high-fertilizer and low-fertilizer countries, see Section 2.2); (2) the same degree days model (degree days 10-30°C and degree days above 30°C) estimated in a county-level panel of maize yields in the eastern United States (east of the 100 degree meridian). The coefficients are then applied to the countries in Africa. Table 4.6 gives the results of both models.

For the countries with high fertilizer use (South Africa and Zimbabwe), the predicted impacts are roughly comparable if we use the coefficients from the African panel of yields or the US panel of maize yields. For all other countries, the impacts seem to be less sensitive towards higher temperature increases. This is line with the claim that crop varieties with higher average yields (that are grown in areas that use more fertilizer and other inputs) are also more susceptible to unfavorable weather conditions.

Table A5: Comparing Regression Estimates for Maize in Africa and the U.S.

.

	+1°C		+3°C		+5°C	
Country	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Angola	-9.70	-6.43	-25.94	-28.42	-38.49	-58.18
Botswana	-8.90	-20.00	-23.79	-57.27	-35.38	-83.07
Benin	-9.13	-20.85	-23.54	-66.43	-33.19	-93.44
Burundi	-10.14	2.56	-27.33	4.52	-40.94	-3.68
Chad	-8.06	-36.58	-21.00	-82.39	-30.39	-97.26
Congo	-10.11	-1.43	-26.67	-21.59	-38.43	-65.85
Zaire	-9.42	-14.67	-24.96	-49.43	-36.55	-80.45
Cameroon	-9.65	-11.21	-25.72	-39.82	-37.92	-70.93
Central African Rep.	-9.63	-11.39	-25.26	-46.52	-36.40	-82.14
Eritrea	-8.53	-28.97	-22.42	-72.58	-32.89	-92.86
Ethiopia	-9.85	-7.05	-26.35	-27.89	-39.27	-53.62
Gambia	-8.68	-28.93	-22.16	-77.11	-30.93	-96.81
Gabon	-10.15	-0.61	-26.67	-21.79	-38.08	-69.69
Ghana	-9.68	-9.69	-25.13	-46.77	-35.32	-86.62
Guinea	-9.85	-7.20	-26.16	-32.06	-38.13	-68.92
Ivory Coast	-9.43	-15.68	-24.70	-54.29	-35.40	-87.06
Kenya	-8.99	-22.23	-23.80	-62.30	-35.09	-87.25
Lesotho	-9.22	-0.38	-25.53	-5.96	-38.96	-19.59
Madagascar	-10.07	-0.37	-26.87	-11.61	-39.63	-42.77
Malawi	-9.38	-13.79	-24.98	-46.02	-36.94	-75.34
Mali	-8.86	-25.72	-23.08	-70.46	-33.17	-93.69
Mozambique	-9.31	-15.23	-24.44	-53.44	-35.36	-85.20
Niger	-7.47	-42.09	-19.66	-87.42	-28.87	-98.40
Nigeria	-8.80	-26.66	-23.01	-71.02	-33.11	-93.81
Guinea-Bissau	-9.35	-17.23	-24.34	-58.94	-34.16	-91.32
Rwanda	-10.17	3.33	-27.50	9.92	-41.43	14.46
South Africa	-14.64	-7.79	-43.72	-29.57	-68.67	-55.19
Senegal	-8.70	-27.55	-22.37	-74.67	-31.57	-95.85
Sierra Leone	-10.16	-0.33	-26.80	-18.69	-37.79	-72.20
Somalia	-8.41	-32.25	-21.73	-78.87	-31.34	-96.17
Sudan	-8.00	-35.62	-20.71	-81.55	-29.86	-97.01
Togo	-9.31	-17.55	-24.08	-61.07	-34.04	-91.48
Tanzania	-10.01	-0.40	-26.69	-12.42	-39.35	-43.56
Uganda	-9.73	-6.37	-26.00	-26.66	-38.44	-56.94
Burkina Faso	-8.50	-30.44	-22.29	-74.88	-32.25	-94.90
Namibia	-8.92	-19.38	-23.93	-56.12	-35.75	-81.65
Swaziland	-13.12	-5.68	-42.39	-27.10	-70.82	-57.96
Zambia	-9.64	-8.58	-25.75	-32.98	-38.01	-64.28
Zimbabwe	-18.98	-12.70	-54.12	-43.30	-80.44	-72.94

Notes: The table compares predicted impact on maize yields under various uniform climate change scenarios. Columns labeled (1) use the country-level panel of African yields to estimate the coefficients, columns labeled (2) use the results for maize from the United States. Rows give the predicted mean impact in percent.

References

[1] David B. Lobell, Marshall B. Burke, Claudia Tebaldi, Michael D. Mastrandrea, Walter P. Falcon, and Rosamond L. Naylor. Prioritizing climate change adaptation needs for food security in 2030. *Science*, 319(5863):607–610, February 1 2008.

[2] Timothy D. Mitchell and Philip D. Jones. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology*, 25(6):693–712, May 2005.

[3] Chad Monfreda, Navin Ramankutty, and Jonathan A. Foley. Farming the planet:2. geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22:1–19, 2008.

[4] T. Ngo-Duc, J. Polcher, and K. Laval. A 53-year forcing data set for land surface models. *Journal of Geophysical Research*, 110:D06116, 2005.

[5] Wolfram Schlenker, W. Michael Hanemann, and Anthony C. Fisher. The impact of global warming on u.s. agriculture: An econometric analysis of optimal growing conditions. *Review of Economics and Statistics*, 88(1):113–125, February 2006.

[6] Wolfram Schlenker and Michael J. Roberts. Nonlinear temperature effects indicate severe damages to u.s. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598, September 15 2009.

[7] H. C. S. Thom. Normal degree days above any base by the universal truncation coefficient. *Monthly Weather Review*, 94(7):461–465, July 1966.

[8] H.C.S. Thom. The rational relationship between heating degree days and temperature. *Monthly Weather Review*, 82(1):1–6, January 1954.