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Robust negative impacts of climate change on African agriculture

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Abstract

There is widespread interest in the impacts of climate change on agriculture in Sub-Saharan Africa (SSA), and on the most effective investments to assist adaptation to these changes, yet the scientific basis for estimating production risks and prioritizing investments has been quite limited. Here we show that by combining historical crop production and weather data into a panel analysis, a robust model of yield response to climate change emerges for several key African crops. By mid-century, the mean estimates of aggregate production changes in SSA under our preferred model specification are -22, -17, -17, -18, and -8% for maize, sorghum, millet, groundnut, and cassava, respectively. In all cases except cassava, there is a 95% probability that damages exceed 7%, and a 5% probability that they exceed 27%. Moreover, countries with the highest average yields have the largest projected yield losses, suggesting that well-fertilized modern seed varieties are more susceptible to heat related losses.

Keywords: food security, degree days, crop response function

S Online supplementary data available from stacks.iop.org/ERL/5/014010/mmedia

1. Introduction

SSA maintains the highest proportion of malnourished populations in the world, with one in three people chronically hungry [1], and an economy that is extremely dependent on agricultural production. Roughly 17% of GDP was derived from agriculture in Sub-Saharan Africa in 2005, with this fraction in excess of 50% in some countries [2]. Given the central role of agriculture, and the unprecedented changes in climate anticipated over the next few decades in the region [3–6], there is a need to understand possible responses of SSA crops to climate change. Yet widely reported statements such as 'reductions in yield in some countries could be as much as 50% by 2020' [7] are often based on little or no empirical evidence, and do not provide any meaningful measures of uncertainty.

Past studies have used a variety of approaches, ranging from simply equating average future impacts to yield losses observed in historical droughts [7] to more quantitative crop simulation modeling [8–10], statistical time series [11] and cross-sectional analyses [12]. To date, simulation studies have been limited by a lack of reliable data on soil properties and management practices, and have provided only 'best-guess' estimates with little to no information on uncertainties that result from choices in model structure, parameter values and scaling techniques [13]. Statistical analyses have been limited by the poor quantity and quality of historical agricultural data relative to other regions, resulting in model estimates with wide confidence intervals [11]. Thus, while there is some expectation that African agriculture is likely to suffer from climate impacts, little can be said about the probability of different outcomes or the relative threats to different places or crops. Whether yields are more likely to be reduced by 5% or 50%, for instance, is critical for prioritizing investments that focus on climate adaptation relative to the many other potential uses of scarce resources for agricultural development.

In this paper we provide statistical evidence for how five staple crops in Africa relate to weather fluctuations using a panel dataset. Such a panel data analysis has several advantages. First, observational studies are preferable to field trials as they measure how farmers react to weather shocks given various other constraints (credit markets, lack of required inputs, etc), while field trials usually have to make assumptions about these parameters. Getting actual responses is more informative to policy makers than results from field trials. Second, country fixed effects capture all additive differences between various countries and hence do not have to be modeled explicitly. Given the lack of data on confounding variables like soil quality in a data poor region like Africa, this is especially important. Fixed effects capture all time-invariant effects and hence make the analysis less prone to omitted variable bias. Third, a statistical analysis gives confidence intervals on the predicted impacts while crop simulation models usually only give point estimates. Below we will separate uncertainty into climate and model related uncertainty. In case of the former, better climate forecasts are crucial, while in case of the latter a more precise response function would narrow confidence bands. Fourth, statistical measures like R-square allow for an assessment of how well the model can predict fluctuations in yields.

The main potential downside of panel models is that they measure responses to weather shocks, which might be different to responses to permanent shifts in climate. However, a panel model can give valuable guidance on what the impacts could be under current production technology and help identify research and adaptation needs. Moreover, many farmers in Africa face cash constraints and find it difficult to adapt new technologies, as evidenced by the fact that a large fraction of growers currently use production technologies that are arguably suboptimal, such as too little fertilizer. A second common concern is that panel models use deviations from country-specific averages in the identification of the yield response function, thereby amplifying measurement error, which can be substantial in data poor regions like Africa. Gridded weather data usually show much higher correlation in average levels across space (i.e., they agree on which places are hot or cold) than in deviations from the mean (was a particular year above or below normal). Accordingly we use two different weather datasets and show that results are consistent between the two, which makes a spurious correlation less likely.

2. Methods

The five staple crops used in this study are maize, sorghum, millet, groundnuts and cassava. These are among the most important sources of calories, protein, and fat in SSA. For example, the top sources of calories for SSA as a whole are, in order, maize, cassava, rice, sorghum, wheat, and millet [14]. Rice and wheat were excluded from the analysis because, unlike the other staples, they are widely irrigated. The use of irrigation is often correlated with weather and can greatly increase yields, and therefore has the potential to seriously bias results without explicitly modeling the effects of irrigation [15]. In this case, data on irrigation by country is

currently sparse and therefore wheat and rice were reserved for future study.

Our dependent variables are country-level yields (tons/ha) for these five staple crops. The yield data as well as total harvested area were obtained from the FAO website for the years 1961–2006 ([14], accessed November, 2008). Some countries were excluded because of suspicious yields, but the results are robust to whether or not we include them (see supplementary data, available at stacks.iop.org/ERL/5/014010/mmedia, for illustration of data, and sensitivity checks to including suspicious yields).

These country-level yields were matched with various weather measurements for 1961–2002. Weather data were obtained from a dataset named NCC consisting of 6 h time series for temperatures (at midnight, 6 am, noon, 6 pm) on a 1° grid for the years 1961–2000 [16]. This dataset recalibrates the reanalysis data by the National Centers of Environmental Prediction (NCEP) to match monthly CRU averages. We compute average temperature as the mean of the four daily observations, and the daily minimum (maximum) as the minimum (maximum) of the four. As an alternative to reanalysis data, we also use the monthly observations of the CRU 2.1 dataset for 1961–2002 from the Climatic Research Unit of the University of East Anglia [17] and obtain similar results. The weather in a country is the land-cover weighted average of all grid centers that fall in a country, with the area of various crops taken from Monfreda et al [18], and the length of the growing season from Lobell et al [11].

Predicted absolute changes in minimum and maximum temperature as well as relative changes in precipitation were obtained for 16 climate change models under the A1b scenario for mid-century (2046–2065) (www-pcmdi.llnl.gov). We apply these changes to the historic weather series in each country and compare the average yield in the new time series with historic averages. Thus, the model is used to evaluate the effects of climate change on yields while keeping all other variables unchanged, not the absolute level of yields in 2050. The latter would require assumptions on trends in technology, infrastructure, and other factors that are outside the scope of this study. Moreover, we do not consider potential shifts in the growing season for each crop, which would be a potential adaptation to higher temperatures.

Our regression equation links log yields y_{it} in country i in year t to various specifications of weather $f(w_{it})$ that have been used in the literature, with the important finding that our results are relatively robust to various weather measures. I.e.,

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

All regression include a quadratic time trend (to capture overall technological progress) as well as country fixed effects c_i. Since the error terms ε_{it} are likely correlated in space, we use a grouped bootstrap where we randomly choose years with replacement and include data for an entire year. We use four specifications to model the impact of weather $f(w_{it})$.

(i) Average weather. A linear specification in the mean temperature as well as total precipitation during the growing season.
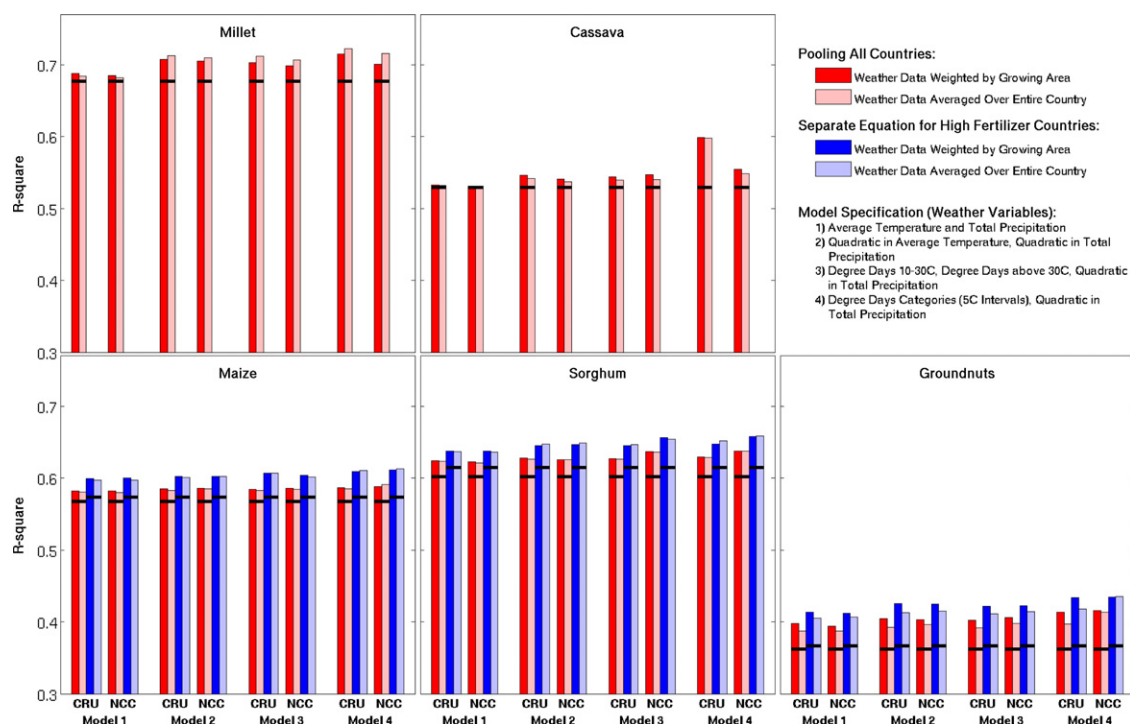
Figure 1. *R*-square of various model specifications excluding all flagged yields: for each crop we run four model specifications (model 1–4) using two different data sources (CRU 2.1 and NCC) and averaging weather over entire country of only crop growing area. Maize, Sorghum, and Groundnuts include results when a separate regression is estimated for high fertilizer countries (shown in blue). The *R*-square for a model using fixed effects as well as time trends (but no weather variables) is added as a black line.

(ii) Quadratic in average weather. A quadratic specification in both the mean temperature as well as total precipitation.

(iii) Degree days: a piecewise-linear function of temperatures captured by the two variables degree days 10–30 °C and degree days above 30 °C (see supplementary data, available at stacks.iop.org/ERL/5/014010/mmedia, for more detail) as well as a quadratic in total precipitation.

(iv) Degree days categories: piecewise-linear functions within 5 °C intervals: [10 °C, 15 °C); [15 °C, 20 °C); [20 °C, 25 °C); [25 °C, 30 °C); [30 °C, 35 °C); [35 °C, ∞ °C) as well as a quadratic in total precipitation.

Since the response might vary by fertilizer use we fit separate models for high fertilizer countries (a panel of South Africa and Zimbabwe) and lower fertilizer countries (a panel of all remaining countries in SSA). The supplementary data, available at stacks.iop.org/ERL/5/014010/mmedia, provides a sensitivity check for a pooled model, where the point estimates remain rather robust, but the confidence intervals narrows somewhat. We prefer the model treating high and low fertilizer countries separately because the weather coefficients are significantly different ($p < 0.05$).

3. Results and discussion

Figure 1 displays the *R*-square statistics if we combine (i) one of our four model specifications with (ii) weather data from the NCC or CRU data base; and (iii) average all weather grids within a country or weigh them by the cropland area in them; and (iv) estimate separate regression equation for countries with high fertilizer use which in general have more advanced

production technologies. The *R*-square of each model run is shown as a colored bar. A model that only has fixed effects and the quadratic time trend (no weather variables) is shown as a black solid line. Given the large difference in average yields, these fixed effects take up a large fraction of the overall variation. (Note: the *R*-square without weather is higher for the model using a separating equation for high fertilizer countries because we include separate quadratic time trends for high and low fertilizer countries.)

Depending on the crop, different models result in the highest *R*-square, with nearly all showing significant improvement beyond a model with no weather. Only for cassava do the weather variables not add much, which is not surprising as it is a root crop with a highly variable growing season and it is hence empirically difficult to match weather data during the growing season to a particular yield. We choose the degree days model (10–30 °C, above 30 °C) as our baseline model. It generally gives lower predicted damages (see below) and we are hence conservative in our damage estimates. Moreover, most of the agronomic literature has used degree days as a theoretical underpinning for crop growth. While research in other countries has shown that degree days models give superior out-of-sample forecast [19] it should be noted that the gridded weather data for Africa is much coarser than the individual weather stations that are available in the developed world. Moreover, neither of our weather datasets is ideal: the CRU data base gives minimum and maximum temperatures on a monthly timescale and hence an interpolation (Thom's formula) is required to derive degree days, which depend on daily minimum and maximum
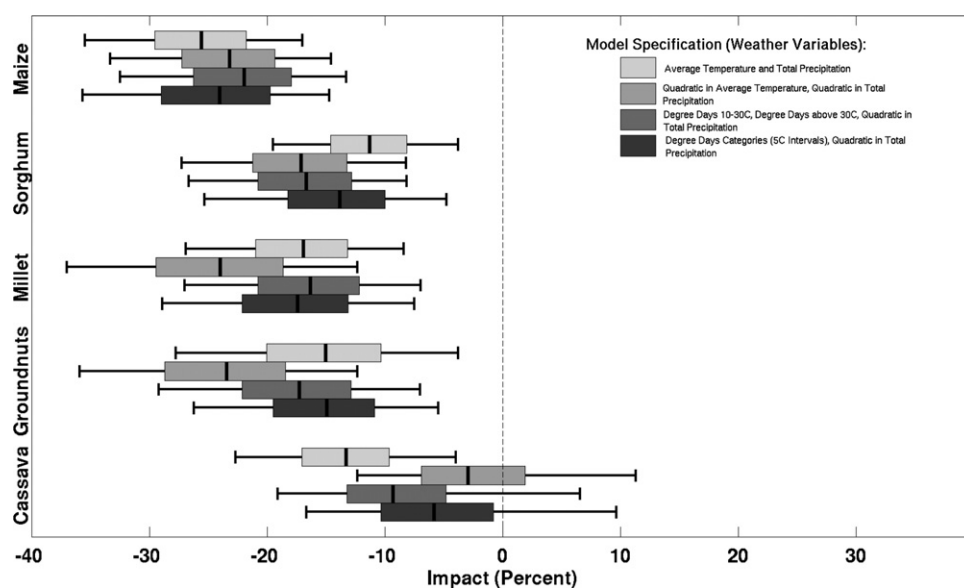
Figure 2. Predicted changes in total production (per cent) in SSA from climate change in 2046–2065 relative to 1961–2000. Results for four model specifications using NCC climate data are shown by crop. Box plots show the combined distribution of predicted impacts from (i) sampling one of the 16 climate 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.
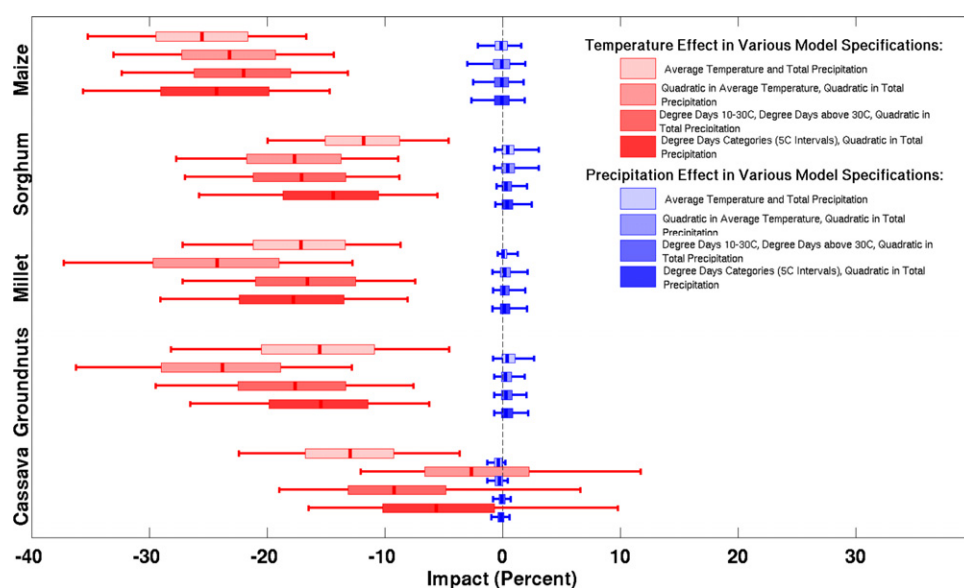

Figure 3. Aggregate impacts of figure 1 separated into impacts due to temperature changes (shown as red box plots) and precipitation changes (blue box plots). The median predicted impact is shown as solid line, while the box shows the 25–75 percentile range. Whiskers extend to the 5 and 95 percentile.

temperature. While the NCC dataset gives four daily values, we assume that the maximum of these four values is the daily maximum, and the minimum of the four is the daily minimum. Averaged weather data will hence include noise, which gets amplified in truncated weather variables. Such noise in the explanatory variables will induce attenuation bias towards [20]. The fact that despite these data concerns we consistently find negative impacts that are large in magnitude demonstrates the utility of these admittedly imperfect climate and crop datasets for understanding crop responses, and suggests that there is a real threat for potentially severe impacts.

Figure 2 displays the predicted impacts for the five major crops under four different model specifications. Damages are predicted changes in total production in SSA, which crucially depends on the major producers. We use the historic time series in our data (1961–2000 for NCC or 1961–2002 for CRU 2.1) and add projected monthly changes to daily maximum and minimum temperatures in our historic weather datasets before we recalculate our temperature variables. Historic precipitation variables are multiplied by the predictive relative changes in precipitation. The advantage of using a 40+ year time series of historic weather patterns instead of examining average growing
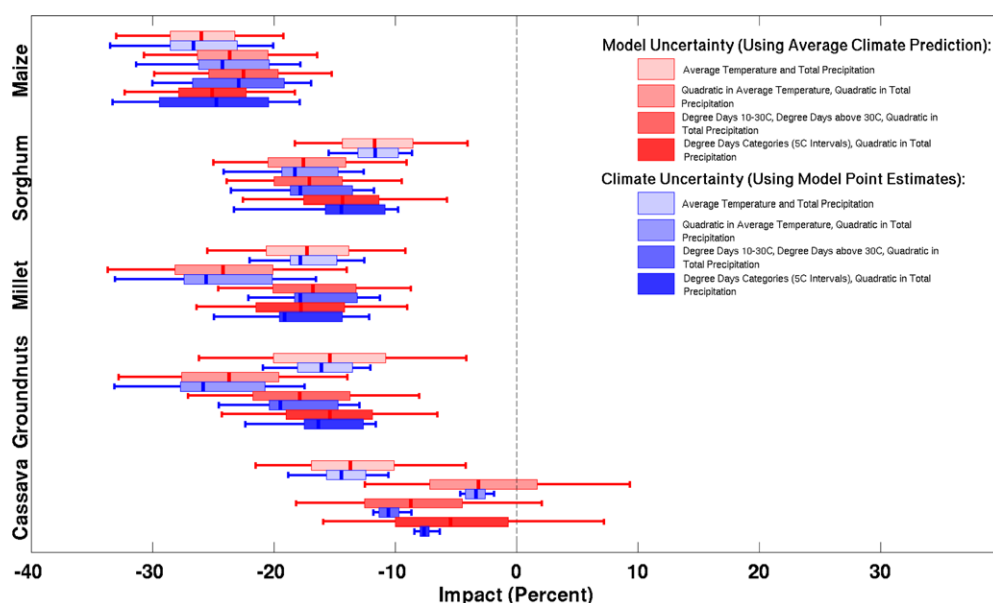
Figure 4. Comparison of parameter uncertainty and climate change uncertainty. Red box plots assume the climate change scenario is known with certainty (approximated as the average of the 16 climate change forecast) and display the parameter uncertainty of the yield response function. Blue box plots use the point estimate of the yield response function with certainty and display the uncertainty of the predicted changes in climatic variables in the 16 climate models. 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 (or the worst and best outcome among the 16 climate change scenarios).
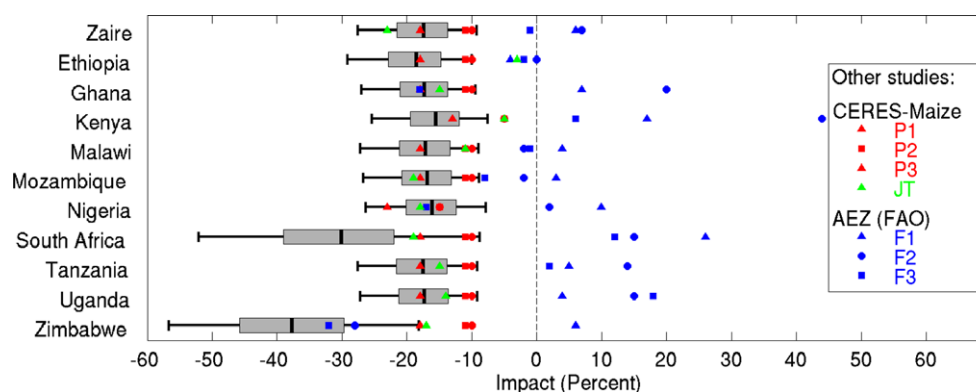

Figure 5. Comparison of predicted impacts on maize yields in various countries to previous studies. Box plots show the combined distribution of predicted impacts from (i) sampling one of the 16 climate change models and (ii) bootstrapping the model parameters for the degree days model. The median predicted impact is shown as solid line, while the box shows the 25–75 percentile range. Whiskers extend to the 5 and 95 percentile. For comparison, point estimates of previous studies are superimposed. P = Parry *et al* [27]. JT = Jones and Thornton [9], F = Fischer *et al* [8]. Estimates for three different climate scenarios were available for P (P1–3) and F (F1–3).

conditions is that we can account for nonlinearities and extreme events that happen infrequently. An underlying assumption of our additive temperature changes is that the year-to-year variance will remain the same as in the past.

While previous studies focused predominantly on point estimates, we present the distribution of predicted impacts that incorporates two sources of uncertainty. First, we evaluate the predicted changes under 16 climate change models to incorporate the uncertainty of future climate change, giving each model equal weight in our distributions of impacts. Second, we rely on 1000 bootstrap runs (randomly drawing years to account for possible spatial correlation) to evaluate the uncertainty of the statistical parameters in our crop response function. Distributions are hence for 16 000 predicted impacts.

With the exception of cassava, which is continuously harvested and therefore has a poorly defined growing season and production year, resulting in a poor model fit, all models predicted negative impacts of warming (figure 2). The median impacts under the degree days specification were −22, −17, −17, −18, and −8% for maize, sorghum, millet, groundnut, and cassava, respectively. The 5th percentile, representing close to a 'worst-case' outcome, indicates severe losses of 27–32% for all crops, except cassava. (Results for other specifications are given in the supplementary data, available at stacks.iop.org/ERL/5/014010/mmedia)

Since our statistical model establishes a link between observed weather shocks and yield outcomes using past data, it does not incorporate the beneficial effect of elevated
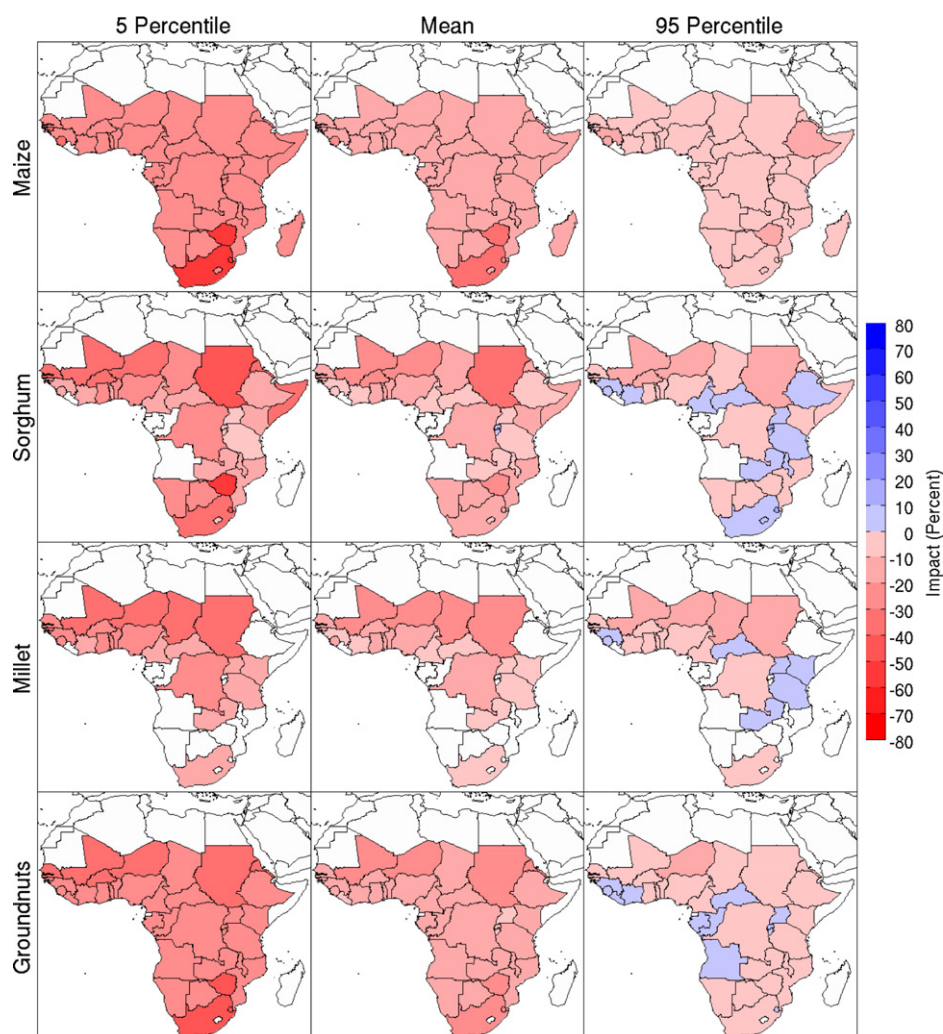
Figure 6. Distribution of impacts from climate change by country (per cent yield change). Mean impacts (middle column) as well as the 5 and 95 percentile (left and right column, respectively) are shown. Each row represents one crop.

atmospheric CO_2, which may improve outcomes particularly in water-stressed environments [21, 22]. The complete lack of CO_2 enrichment experiments in tropical croplands to date makes it difficult to quantify this effect, but maize, sorghum, and millets all possess a C_4 photosynthetic pathway, which has much smaller sensitivity to CO_2 than other crops [23].

Figure 3 separates aggregate yield impacts by weather variable. Red box plots show impacts due to changes in temperature, while blue box plots show impacts due changes in precipitation. Temperature changes have a much stronger impact on yields than precipitation changes. This is driven by two reasons: first, the marginal impact of a one standard deviation change in precipitation is smaller compared to a one standard deviation change in temperature. Second, projections of temperatures increases for the 16 climate models used in this study are much larger relative to precipitation changes, with the latter typically smaller than the historical standard deviation. Thus, both the mean and uncertainty of estimated impacts are driven mainly by temperature, as found in other regions [24]. This conclusion depends on using differences between climate models as a measure of uncertainty in precipitation changes, which is a common but potentially misleading approach [25].

Our projections also omit potentially important changes in the distribution of rainfall within growing seasons [26]. Although we see little evidence that such shifts would be large enough to override temperature impacts, it is a topic deserving of future study.

Figure 4 examines how much of the variance is attributable to parameter uncertainty in the yield response function (shown in red) and the uncertainty of future climate change (shown in blue). Red box plots uses the average of the 16 climate change scenarios as given and evaluate parameter uncertainty in the yield response function. Blue box plots use the point estimate of the yield response function as given, but sample over the 16 climate change models. In all cases the uncertainty about parameters in the yield response function is comparable to uncertainty in future climate change, suggesting that both more precise climate change forecasts as well as improved crop response functions are required to narrow the confidence intervals in our analysis.

Figure 5 compares our predicted impacts under the conservative degree days model to other estimates from crop models by middle of the century. The study using the AEZ model [8] reports only aggregate cereal impacts with CO_2

effects, we therefore assume these numbers are representative for maize and subtract the reported CO_2 effect in their model (4%) to make our estimates comparable. The two studies based on the CERES-Maize model [9, 27] provide estimates for 2050 that generally lie within the probability distributions presented here, though they tend toward the optimistic end of the range. Because those studies used uniformly low fertilizer rates, it is unsurprising that their estimates are considerably different for Zimbabwe and South Africa. The study based on the FAO AEZ model is considerably more positive than any of the other estimates, casting some doubt on that model especially in light of its very limited testing in SSA systems.

Zimbabwe and South Africa are the countries with the highest fertilizer use in SSA. While these countries have higher average yields, they are also more susceptible to temperature increases. The relative effect of temperatures above 30 °C is similar to estimates obtained for maize in the United States (see the supplementary data, available at stacks.iop.org/ERL/5/014010/mmedia). The remaining countries have lower average yields but also show lower sensitivities to higher temperatures.

Figure 6 displays the predicted impacts by country, where the four crops with significant aggregate impacts are shown in the rows (i.e., we exclude cassava), and the three columns give the 5 percentile, mean, and 95 percentile of the impacts. While the impacts are generally less severe for the low fertilizer subsample, they are still statistically significant, i.e., even the 95th percentile of the damage distribution is still negative (has a red color) in the right column for most crops and countries. This occurs despite rainfall increases in several of the climate projections, particularly in Eastern Africa.

We note that impacts at the country-level mask differences between regions and farmers within country, which arise from diversity in access to factors such as land, credit, markets, and technology, as well as differences in the baseline climate. Although these within-country heterogeneities can be considerable [9], the current study is limited by the crop datasets to evaluate only broad scale yields. Future work with finer scale panel data, as well as alternate approaches such as process-based modeling, will help to elucidate fine scale differences that can be important for many adaptation decisions. However, the patterns depicted in figure 6 should be useful for a suite of decisions made at broader scales, such as how much to invest in agricultural development or adaptation in individual countries or SSA as a whole.

There is arguably little scope for substantial poverty reductions in SSA without large improvements in agricultural productivity [2]. The results presented here suggest that this challenge will get even more difficult in a warming climate. Rather than a cause for despair, we view this as an added incentive for serious, immediate, and sustained investments in agricultural productivity in SSA. Varieties with greater drought and heat tolerance, improved and expanded irrigation systems, rainwater harvesting technologies, disaster relief efforts, and insurance programs will likely all be needed to foster agricultural development and adaptation to warming. Increased fertilizer inputs has also long been recognized as a critical factor for productivity growth in SSA, although

the above results indicate that fertilizer alone will tend to increase yield vulnerability to warming even while raising overall average yields. This finding does not necessarily argue against increased fertilizer use, but instead emphasizes the fact that as fertilizer rates trend upward, so too will the benefits of efforts toward climate adaptation.

Acknowledgments

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