Farm-level agricultural productivity and extreme weather events[1]

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Abstract

Rising temperatures and shifting precipitation patterns affect yields and productivity, posing one of the largest threats to future food security. To measure the impact of extreme weather events on yield, we use information on i) water availability, ii) household location, and iii) growing season. This is to ensure that the relationship between extreme events (here defined by water availability) and yield is measured at the time and location where the crop is grown. We match growing-season information with detailed geospatial climate data and household survey data. The final constructed dataset contains information on weather events, yield and household characteristics for 6 crops across 5 countries, totalling 31,085 unique observations. The results indicate that deviations – whether above or below expected climate conditions – tend to reduce agricultural productivity. However, the tolerance level to such deviations before negative effects emerge varies across crops, highlighting heterogeneous climate impacts.

Keywords: agricultural productivity; climate change, extreme weather events

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1. Introduction

Rising temperatures and shifting precipitation patterns affect yields and productivity, posing one of the largest threats to future food security. As the climate changes, the expected frequency and severity of extreme weather events, such as heavy rainfall, extreme heat and droughts, are increasing, causing economic losses in the food system. A report from the World Meteorological Organisation [1] estimates that African countries are losing 2-5 per cent of Gross Domestic Product (GDP), and many are diverting up to 9 per cent of their budgets to respond to climate extremes.

Multiple approaches have been used to examine the relationship between productivity and climate conditions. A long-term relationship between changing temperature and productivity has been modelled using average temperature levels and precipitation [2], while others argue for a non-linear relationship between yield and temperature [4,3]. This non-linear relationship is further emphasized in papers that model the impact of climate change as an increase in extreme weather events, such as days with temperatures above a certain threshold [5] or deviations from expected climate conditions [6].

This paper contributes to the literature by building on and extending previous approaches. It examines the relationship between farm-level productivity – measured by yield – and climate, as explored for Nigeria by [5], but expands the analysis to five African countries. To incorporate a climate variable that is comparable across crops and suitable for this broader geographic scope, the paper adopts the framework proposed by Nes et al [6], capturing the productivity–climate relationship through deviations from expected climate conditions at each farm's location.

To measure the impact of extreme weather events on yield, we use information on i) water availability, ii) household location, and iii) growing season. This is to ensure that the relationship between extreme events (here defined by water availability) and yield is measured at the time and location where the crop is grown. We match growing-season information with detailed geospatial climate data and household survey data. The final constructed dataset contains information on weather events, yield and household characteristics for 6 crops across 5 countries, totalling 31,085 unique observations.

Our results show heterogeneous impacts of extreme weather shocks across crops. We find no impact on rice and wheat, while extreme flooding events – here measured by 2 standard deviations from normal climate expectations – are associated with 11% and 25% reductions in yield, respectively. Drought events are associated with negative production shocks for maize and pulses, leading to 60% and 28% reductions in yield, respectively.

The following paper is structured as follows: we outline an overview of the data sources and methods used to assess the impact of extreme weather events on yield. Lastly, we present the results and discuss their relevance to policy.

2. Data

Our analysis hinges on using information about weather events that affect production outcomes for a specific household during the crop's growing season. The scope of the analysis – both in selection of crops and countries -- depends on the availability of data sources, as well as the ability to combine the information they contain. Specifically, we combine information from:

- The Global SPEI database for global information on climate conditions.
- The household surveys contained in The World Bank Living Standards Measurement Study (LSMS).
- Growing season information obtained from [7].

The final selection of crops and crops, as well as the information used to align the datasets, is listed in Table 1.

Table 1 Commodities with growing season information, by country

Country	Years	Location indicator	Commodities
Ethiopia*	2011, 2013, 2018	Modified GPS coordinates	Wheat, Maize, Millet, Groundnuts
Malawi	2010, 2016, 2019	Modified GPS coordinates	Wheat, Rice, Maize
Nigeria*	2011, 2013, 2016, 2019	Admin level 2	Millet, Maize, Groundnuts, Rice
Tanzania*	2019	Admin level 2	Wheat, Maize, Rice
Uganda*	2011, 2012, 2014, 2016, 2019	Admin level 3	Pulses, Maize, Millet

Source: Authors' own elaboration. * The growing season varies by region for certain products.

2.1 Climate variables

To capture potential weather events, we use the Standardized Precipitation Evapotranspiration Index (SPEI), which is a multiscalar drought and wetness indicator that indicates the balance between water supply (precipitation) and atmospheric water demand (potential evapotranspiration). It is based on monthly precipitation and potential evapotranspiration data from the Climatic Research Unit of the University of East Anglia, starting in January 1901, and it is updated as soon as new data becomes available. The SPEI is normalised to zero, with larger positive deviations indicating wetter-than-normal conditions (increased likelihood of flooding) and larger negative deviations indicating drier-than-normal conditions (reduced water availability or drought). Data are available at a 0.5-degree grid-cell resolution and a monthly frequency.

2.2 Growing season.

Growing season information is obtained from Sacks et al. (2010) for certain crops, limiting the scope of the analysis to these crops. The database contains information about the planting and harvesting months, and the growing season is assumed to occur between them.

2.3 Household surveys

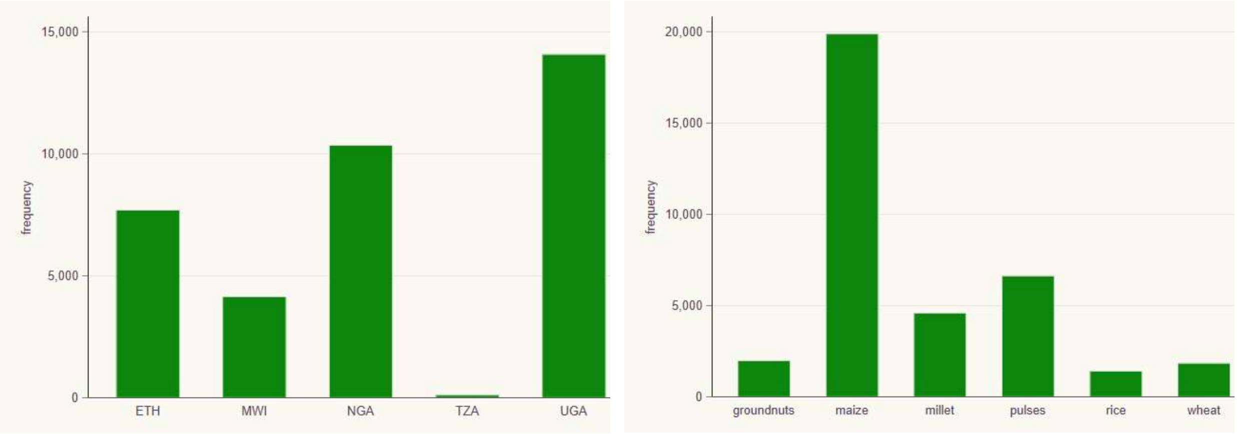
We consider LSMS household survey data from five countries and 15 survey rounds. These datasets contain detailed information on household characteristics, farming outcomes (i.e., area cultivated and quantity harvested), and input use, which can be used to construct yield estimates at the crop-household-year level. It is worth noting that the number of observations varies significantly across crops; thus, we limit the scope to crops with sufficient observations to perform the analysis.

2.4 Aligning household survey location and climate variables

The household location information varies by country, and information used to align the household data with the climate variables is provided in Table 1. For Ethiopia and Malawi, modified GPS coordinates are used to match specific point coordinates to SPEI values at these coordinates. The GPS coordinates are modified to ensure anonymity of the household participating in the survey. For Nigeria, Tanzania and Uganda, the household surveys do not include specific coordinates for the location of the household (or the coordinates are listed as confidential in the survey), and instead we rely on information on the most disaggregated administrative level reported for the household without missing observations, which are matched with the SPEI dataset using shape files from the United Nations Office for the Coordination of Humanitarian Affairs. The SPEI values used are the average SPEI value reported for a month-year combination within the specific administrative level. In Nigeria and Tanzania, we match at amin level 2, while in Uganda, we match at level 3. Note that for some of these countries – in particular Tanzania – more potential survey rounds were available, but we were unable to match the location information with the climate variables.

The final constructed dataset is at the household, crop, and survey-year levels for each country and contains 31,085 observations, though the number of observations varies by crop and country, as seen in Figure 1. Unexpectedly, the countries with the most survey rounds -- Uganda and Nigeria -- have the highest level of observations. Likewise, the products available in most countries – i.e., maize – have the most observations, while rice, wheat, and groundnuts have fewer.

Figure 1 Observation counts by crop and country



Country Crops

Source: Authors' own elaboration.

3. Methods

We use the constructed dataset to estimate the impact of large deviations from climate expectations, as measured by the SPEI indicator, on yield. Because crops differ in their resilience to climate conditions and are often adapted to the environments in which they are grown, the impact of shocks is estimated at the crop level. Ideally, we would also have liked to measure whether these extreme weather events affect crops differently based on the country; however, by definition, extreme weather events are rare, and to obtain sufficient variation in the data to robustly estimate the impacts of these events, the following equation is estimated for crop subsamples:

$$y_{hct} = \alpha + \gamma * x_{hct} + \delta^{low} * \text{SPEI}_{low,hct} + \delta^{high} * \text{SPEI}_{high,hct} + \vartheta * r_c + \tau * t_t + \varepsilon_{hct} \qquad (1)$$

where, y_{ist} denotes the log yield for household h at time t in country *c*., α denotes the constant, x_{hct} represents a vector of control variables and γ their respective coefficients. r_c denotes country indicators, and ϑ denotes their coefficient. Finally, ε_{ist}, denotes the error term.

Our main variables of interest, the climate and weather variables, are constructed using information on i) water availability, ii) household location, and iii) growing season. First, our climate and weather outcomes are represented using SPEI events. We construct this events variable based on values obtained from the Global SPEI database, SPEIbase, dataset. The location of the specific household in the LSMS-ISA survey is matched to its corresponding grid-cell contained in the SPEIbased. Lastly, the household-level water balance SPEI is combined with crop-specific growing season information to capture weather events at the time when the crop is grown.

Using this information, the SPEI variables – our indicators capturing the presence or absence of weather shocks – are constructed as deviations from normal climate conditions during the crop growing season. These variables are defined as indicator variables based on their standard deviation from expected weather conditions for each growing season. To capture the non-linear relationship between productivity and extreme weather events, the SPEI variables are specified as stepwise binary indicators in 0.25 standard deviation intervals. In the equation, this vector is denoted as $SPEI$, with δ representing the corresponding coefficients.

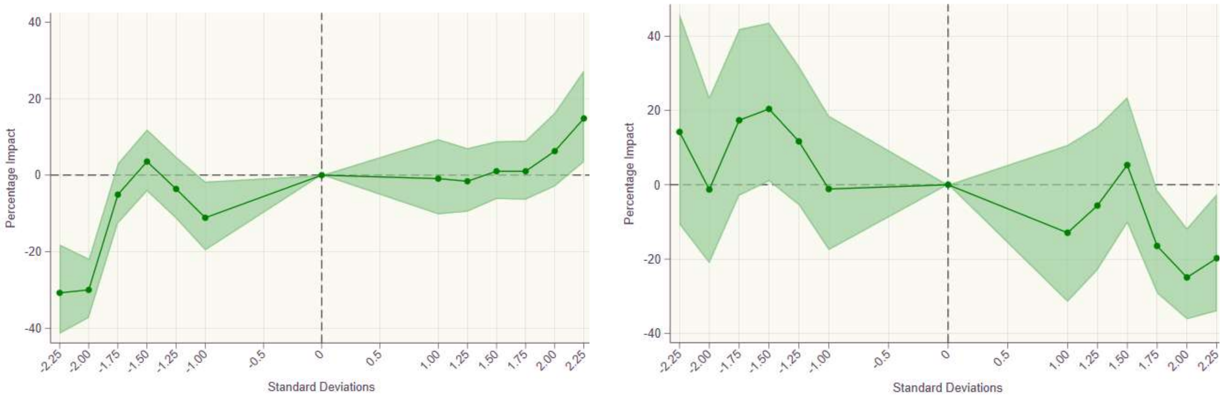
In addition to our variable of interest, we include several control variables, denoted by x_{hct}, r_c and t_t. The vector x_{hct} comprises indicator variables for input use — specifically fertilizer, irrigation, and labor. Fertilizer and irrigation are captured as binary indicators of whether the household uses these inputs on its plots. To consistently measure labor use across countries, we proxy labor by the number of household members aged 16–60. We include time fixed effects, t_t, to control for time-specific factors that may affect yields for all crops in a given period, such as global price movements for the crop and its inputs. Finally, country indicators are included to account for country-specific determinants of yields. Ideally, we would also include regional indicators to capture within-country heterogeneity in growing conditions that may influence yields. However, because the extreme events studied here tend to exhibit spatial dependence – for example, droughts or floods affecting large geographic areas – including regional indicators for countries with fewer survey rounds could absorb much of the variation driven by our variables of interest.

We estimate the equation using ordinary least squares and the errors are clustered at year-lowest administrative level available within each country.

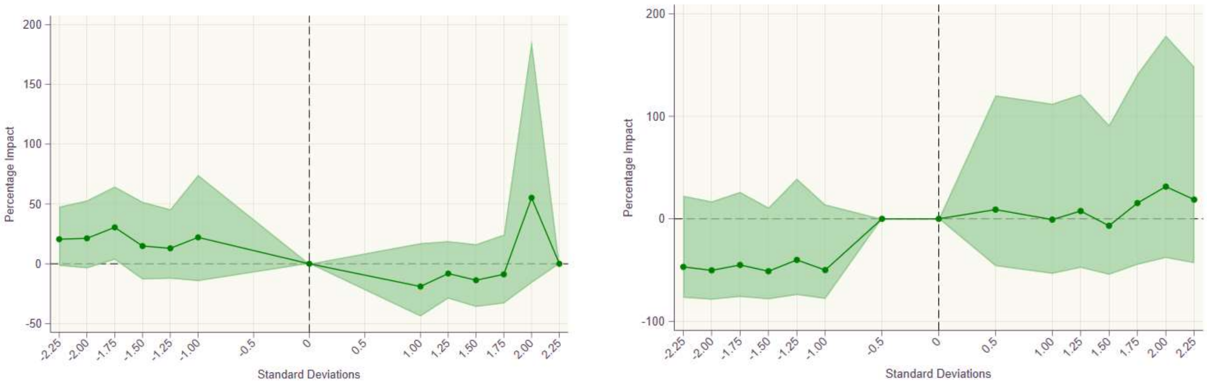
4. Results

The results for the selected crops are provided in Figure 2 and implies a heterogeneous impact of extreme weather conditions on yield. The Figure reports the estimated coefficients of interest from equation (1) across the range of thresholds for our binary SPEI variables (δ^{low} and δ^{high}), using the transformation e($\hat{\delta}$)-1. The panels report the results for the maize, millet, wheat, rice, pulses and groundnuts specifications, respectively. In each panel, the horizontal axis plots the various SPEI thresholds, defined in standard deviation terms. The vertical axis represents the associated impact of a corresponding weather event on yield outcomes (defined in terms of percentage impact).

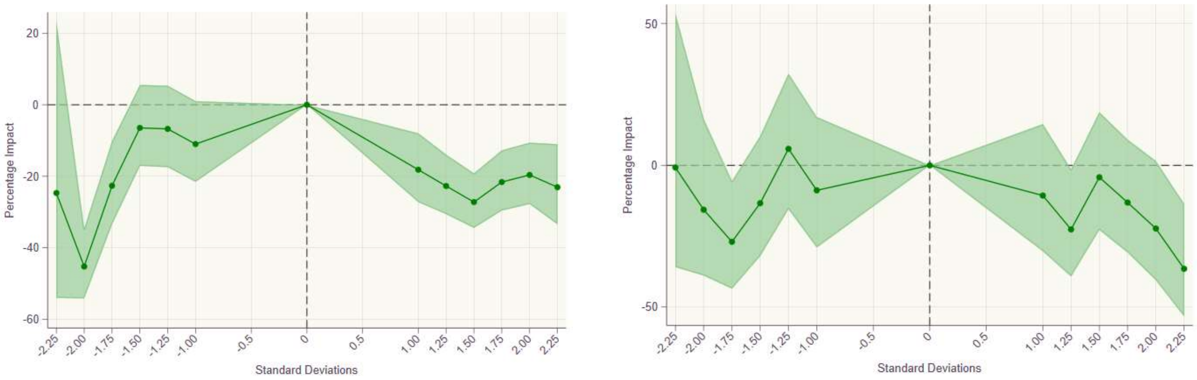
Figure 2 Results of various degree of extreme weather events on yield, by selected crop



Maize Millet



Wheat Rice



Pulses Groundnuts

Note: The Figure reports the estimated coefficients of interest from equation (1) across the range of thresholds for our binary SPEI event variables (δ^{low} and δ^{high}), using the transformation $e(\hat{\delta})$-1. The panels report the results for the maize, millet, wheat, rice, pulses and groundnuts specifications, respectively. In each panel, the horizontal axis plots the various SPEI thresholds, defined in standard deviation terms. The vertical axis represents the associated impact of a corresponding weather event on yield outcomes (defined in terms of percentage impact).

For two of the crops — wheat and rice — no statistically significant results were found. These are also the crops with the smallest sample sizes in our dataset, and we may not have observed enough extreme events to estimate robust effects. It is worth noting that the coefficients for negative SPEI events are negative, but they are not significant at the 5% level.

For the other crops, as expected, weather outcomes closer to climatic expectations exhibit small — and for the majority of crops, statistically insignificant — effects on yield. Weather events that deviate more substantially from expectations are more likely to affect yields, but the type of extreme event that matters varies by crop: hot, dry events (represented in the figure by negative standard deviation values) and flooding events (represented by positive standard deviation values) have different impacts. Maize and groundnuts show negative yield responses to flooding but no detectable impact from drought, whereas pulses are significantly affected by both types of extremes.

For crops with significant impacts on yield, the magnitudes of these effects vary. For millet, groundnuts, and pulses that are negatively affected by flooding, an extreme event — here defined as 2 standard deviations from the mean — is associated with yield reductions of 11%, 25%, and 21.9%, respectively (all statistically significant at the 5% level). Similarly, potential drought events are associated with negative production shocks for maize and pulses, where a 2-standard-deviation departure from climate expectations corresponds to approximately 60% and 28% reductions in yield, respectively (also statistically significant at the 5% level). Production of pulses therefore appears particularly sensitive to drought events, with larger losses from these extremes compared with the other crops.

5. Discussion and conclusion

The results indicate that deviations – whether above or below expected climate conditions – tend to reduce agricultural productivity. However, the tolerance level to such deviations before negative effects emerge varies across crops, highlighting heterogeneous climate impacts. Policy interventions could help mitigate these effects, and a natural extension of this study is to investigate how public support in priority areas – such as fertiliser, seed, pesticide, and irrigation assistance – can strengthen farmers' capacity to adapt to changing climate patterns.

Of course, our analysis is not without limitations. By definition, the datasets include only a limited number of extreme weather events and therefore we do not have a sufficient number of observations of extreme events to perform this analysis at the crop-country level. This lack of granularity in our estimated results prevents us from examining whether location-specific growing conditions may buffer the impact of these events. Likewise, in our analysis we can only capture the effects of observed events and therefore if, for instance, more flooding events occurred in areas where the studied crops dominate than drought events, this could bias our findings toward larger observed effects of flooding on yield than drought.

The results presented in this analysis reflect the short-term impacts of extreme weather events and their potential to negatively affect yields and agricultural production, holding climate expectations constant. As climate change progresses, climate expectations are also likely to evolve as farmers adapt to new conditions. Agriculture production depends on this adaptation continuing as climate change unfolds, and policies should assist farmers in transitioning to a new climate reality. A natural extension of this study is to investigate how public interventions in priority areas – such as fertiliser, seed, pesticide, and irrigation support – can enhance farmers' capacity to adapt to changing climate patterns.

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