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Incorporating the Impact of Climate and Weather Variables in Impact Assessments: An Application to an IFAD Grain Storage Project Implemented in Chad

by
Nancy McCarthy
Josh Brubaker
Athur Mabiso
Romina Cavatassi

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Abstract

The overall objective of the paper is to outline a methodological strategy for incorporating current period weather and long-term climate conditions into impact assessments. To do so, we use an IFAD project that invested in grain storage implemented in grain-growing regions in Chad as a case study. Noting that currently there are no agreed climate and weather metrics to use in crop production estimations, we first explore the explanatory power of a wide range of weather and climate variables from a number of different sources. Once we determine the best indicators of weather conditions and corresponding historical climate conditions, we evaluate the impact of including climatic variables in matching treatment and control households and subsequently their impact on household-level outcomes. During the crop season covered by the survey, rainfall and temperature patterns were remarkably favourable over the study area, with few significant weather shocks. However, households located in areas with lower and more variable rainfall and with a greater incidence of high temperature shocks suffered lower grain yields and lower dietary diversity in food consumption. Such households also stored a greater fraction of their grain, consistent with greater value of increasing resilience in these areas.

1. Introduction

Increasing the resilience of rural households is a key part of IFAD's mandate and of its strategic objectives. The third strategic objective deals explicitly with climate resilience: "Strengthen the environmental sustainability and climate resilience of poor rural people's economic activities" (IFAD, 2016). To reach that objective over the period 2016–2025, IFAD proposed to mainstream climate change throughout the entirety of its portfolio. This means that programming and project implementation needs to incorporate the best available evidence on climate change into their design. To do so, IFAD's strategic framework document highlights the need to generate more and better analyses of climate risks and vulnerabilities, and their impacts on agricultural productivity, to determine which specific activities are best suited to increase farm production while also increasing resilience to the effects of climate change.

In this paper, we focus on how weather and climate variables can be integrated into IFAD impact assessments and the methodological issues that arise in the construction and use of such variables. To highlight the steps involved and potential biases that may arise when not including climatic variables in an impact assessment analysis, we use data collected on the IFAD project "Programme d'Appui au Developpement Rural dans le Guera" (PADER-G). To address food insecurity prevalent in the region, the project was designed to manage risks of food shortages through the construction of cereal banks and by increasing capacity to manage community cereal banks by providing extensive training to cereal bank committee members. Household- and community-level data were collected in both project villages and villages where the project did not operate for an ex-post impact assessment (Cavatassi et al., 2018). We build on that work by incorporating weather shocks and climate conditions into the analysis. Because we refer to this work throughout the paper, we hereafter refer to Cavatassi et al. (2018) as CMAD.

To start the analysis, we note that there is a wide range of different data sources that provide data on potentially relevant climate variables, including multiple sources that produce rainfall estimate data, temperature data, a range of vegetation indices such as the normalized difference vegetation index (NDVI) constructed using different data sources, the standardized precipitation index (SPI) and the standardized precipitation and evapotranspiration index (SPEI) constructed using different data sources. In addition, we look through a large number of variables that have been used in previous work to characterize both climate conditions and weather events affecting current period production, such as long-term mean and coefficient of variation of rainfall, season onset dates, current period rainfall covering the flowering period and rainfall covering the entire growing season. Thus, our first objective is to systematically assess the predictive power of alternative sets of climate and weather variables in estimating grain yields. From this analysis, we arrive at a reduced set of such predictors with which to continue the analysis.

The next step is to include the climate variables into the propensity score matching procedure implemented by CMAD. Most impact assessments will use some type of matching procedure to ensure balance across treatment and control households, as the assessment design is generally based on quasi-experimental methods. In the final step, we introduce weather and climate variables into the regression analysis. We note here that it is important to include both long-term measures of climate conditions as well as the current period shocks into the regressions, to ensure that current period weather variables are conditionally exogenous. This is particularly important for cross-section analyses that cannot employ fixed effects specifications.

The paper proceeds as follows. In section 2, we briefly provide details on key aspects of the PADER-G project and of the impact assessment design, we summarize results of the CMAD impact analysis. In section 3, we provide a brief literature review focusing on the impacts of weather and climate conditions on grain production using household datasets, drawing implications for the data sources and variables to create used in this analysis. In section 4, we present a systematic analysis of the impacts of climate and weather variables on grain production. From this analysis, we select two sets of weather and climate variables to use in matching and in the final regressions. Section 5 gives results of the matching exercise. Section 6 presents final results for grain production, as well as for household consumption outcomes. These are presented using specifications both with and without climatic variables to facilitate comparison. Finally, section 7 concludes.

2. Background

The PADER-G project began in 2011 and was completed in December 2016 (CMAD). Project activities were implemented in the Guera region of Chad, one of the poorest and most food-insecure regions in the country, where over 87 per cent of the population rely on rain-fed smallholder farming (Boutna, 2016). The main objective of the PADER-G project was to address food insecurity through increasing access to safe drinking water, rural road construction, cereal bank operationalization to manage food shortage risks, access to financial services and strengthened farmers' organizations. Following CMAD, we focus on one major project activity, cereal bank construction and operation. Sub-activities included the construction of community cereal banks, provision of cereals for the first operating year, provision of training and other assistance to ensure efficient management of the bank and effective maintenance of the infrastructure, and proactive training of women in the communities. The project's Theory of Change argues that well-functioning cereal banks would lead to greater consumption in the lean season, and potentially to reduced use of money-lenders and lower migration of men leaving the community to seek wage labour in the lean season. The Theory of Change also posits that well-functioning storage facilities would lead to greater grain production and productivity, although exactly how that would occur is not well-articulated. Interestingly, in the Theory of Change figure (CMAD, figure 1), a critical assumption is listed as: "there is no extreme weather shock (e.g. drought)". This assumption is not discussed in the text and is somewhat odd given the project objectives. Perhaps this implicitly assumes that, although the project hopes to build resilience to weather stressors, the area is drought prone and drought is considered a chronic event, whereas extreme events (including extreme drought) are still expected to have negative impacts.

Prior to data collection, the impact assessment team selected villages in the region where there were no PADER-G activities to serve as counterfactuals. The team used information on PADER-G targeting criteria along with a 2009 census of all villages in the region to implement a village-level propensity score. A list of candidate counterfactuals was then reduced in consultation with project implementers to minimize spillover and contamination effects. Data were collected from 2 198 households in 72 villages. However, there were a number of counterfactual villages that had acquired a cereal bank since the 2009 census. We follow CMAD and use only counterfactuals in villages without a cereal bank; this ultimately gives us data from 1 104 treated households and 337 control households.

The CMAD impact assessment results show that PADER-G had significant and positive impacts on dietary diversity, grain production and storage, and may have helped to reduce distress sales of assets during the lean season. As will become apparent further down, there were no extreme weather shocks during the crop seasons covered by the survey, so that impacts of an extreme weather event cannot be tested. Nonetheless, long-term climate conditions also influence farmers' decision-making and thus project outcomes, and this we can and do test.

3. Literature review

There is a growing literature on the impacts of extreme weather events on farm production and consumption outcomes using household-level data, although the evidence tends to be concentrated in relatively few countries and regions, and on grain crops.[1] Most studies in areas where farming is rain-fed show that crop production is highly vulnerable to rainfall shocks, leading to production losses between 20 per cent and 50 per cent on average, depending on the severity of the shock (McCarthy et al., 2018a in Malawi; Amare et al., 2018 in Nigeria; Wineman et al., 2017 in Kenya; Michler et al., 2019 in Zimbabwe; Arslan et al. in Zambia, 2015). Fewer studies using household survey data have generated evidence on the impacts of higher temperatures on crop production, although Asfaw et al. (2016) did find negative impacts of higher temperatures on maize yields in Malawi.

While one certainly expects to find significant negative impacts of weather shocks on crop production – particularly under rainfed conditions – the literature documenting these impacts remained limited until the past decade or so. Until relatively recently, it was difficult to obtain rainfall station data and, when possible, stations were often so sparse they provided limited information on how much rainfall a particular plot received. Researchers would then need to rely on self-reported rainfall shocks, which was often both coarse and noisy data, especially when surveys covered wide geographic regions. Geographic information system (GIS)-based products that produce rainfall estimates and indicators of "greenness" then became more widely available, making it easier to control for climate and weather conditions on farm. But economic theory has nothing to say about which specific variables should be used in agriculture production analyses. Below, we summarize recent literature that includes econometric analyses using GIS-based weather shocks and climate conditions from a number of difference data sources. We focus on empirical results from studies in sub-Saharan Africa, and do not review studies that used either self-reported shocks or rainfall station data.

Michler et al. (2019) estimate impacts of rainfall shocks on smallholders in Zimbabwe using UC Santa Barbara's Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) daily rainfall estimate data, taking average daily rainfall aggregated to the ward level to match households at this level. Matching at ward level was necessitated as household locations were not geo-referenced. In their analysis, they use a rainfall anomaly measure, defined as the difference between current period and mean rainfall divided by the standard deviation of rainfall over the total growing season. They also create two shock measures by dividing shocks between low and high rainfall anomalies. They also run robustness checks using dummy variables to capture more extreme shocks based on standard deviations. Results are consistent across the specifications, with low rainfall shocks having consistently negative impacts on crop outcomes. As the authors use a fixed effects specification, they do not include measures of long-term climate conditions.

Wineman et al. (2017) use CHIRPS rainfall estimate data matched to village centres located in Kenya, using panel data fixed effects that preclude the need to control for historical climate conditions. Weather shocks are defined as the number of dekads during the total rainy season with rainfall greater than 75 mm to capture high rainfall shocks, and the number of dekads during

[1] There is a large body of work looking at rainfall events and heat stress on grain production that uses on-trial data, or is based on crop modelling that tends to use aggregate secondary data, e.g. for the USA (c.f. Akter and Islam, 2017; Auffhammerl et al., 2013; Ortiz-Bobea et al., 2021 and references cited therein). In this literature review, we focus on household-level data analysis as we believe that is a better guide to the data sources and variables created to help explain household-level outcomes, which is our goal here.

the rainy season with less than 15 mm of rainfall to capture low rainfall shocks. These thresholds are based on research done by Guerrero Compean (2013) in Mexico, and are meant to capture absolute thresholds. The authors do not report whether robustness checks using different thresholds, including relative thresholds, were performed. In general they find that high rainfall shocks have positive impacts when significant across a range of household welfare indicators, while low rainfall shocks have negative impacts when significant.

Amare et al. (2018) examine the impacts of rainfall shocks on production and consumption outcomes in rural Nigeria using the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) African Rainfall Climatology version 2 (ARC2) dekadal rainfall estimate data. They use the natural log of the rainfall anomaly (defined as the difference between mean rainfall minus previous period rainfall, divided by the standard deviation (SD)). Similar to Michler et al. (2019), they then create dummy variables to capture low and high rainfall shocks based on whether the rainfall anomaly was less or greater than 1 SD from the mean, respectively. They do not cite any sources to justify threshold choices nor report robustness checks to motivate those threshold choices. They find negative impacts of low rainfall shocks, but positive impacts of high rainfall shocks.

Arslan et al. (2017) use the ARC2 dekadal data, and dekadal temperature data from the European Centre for Medium-Range Weather Forecasts (ECMWF) in an analysis of the impacts of climatic variables on maize yields in Tanzania. For weather variables, the authors include the total season rainfall, a dummy variable capturing whether current period within-season rainfall variability exceeds long-term average within-season variability and a dummy variable capturing whether any temperatures exceeding 28°Celsius occurred during the season. In panel regressions not using fixed effects, the authors use either the coefficient of variation of total season rainfall or the average long-term total season rainfall shortfall covering years when rainfall is below its long-term average. The authors find that high intraseason variability and high temperature shocks both reduce maize yields by 16 per cent and 29 per cent, respectively. Arslan et al. (2015) also use the ARC2 dekadal rainfall data and the ECMWF dekadal temperature data to analyse maize yields in Zambia using a household panel dataset. The authors use total season rainfall, a dummy variable capturing late onset of the rains, average maximal daily temperatures through the season and, in correlated random effects models, the historical coefficient of variation of seasonal rainfall. The authors find a significant positive effect of total season rainfall, but also an unexpected positive effect of delayed rainfall onset on maize yields. Asfaw et al. (2016) use ARC2 and ECMWF variables similar to Arslan et al. (2015), although not a dummy for delayed onset. They find negative impacts of high temperature shocks on maize yields. Alfani et al. (2018) also use ARC2 data to evaluate impacts of a drought on maize yields in Zambia, using a two-period panel dataset in which many households suffered from a severe drought shock in the second year, 2016. As household locations are not geo-referenced, they use ward-level averages to generate weather and climate variables. The authors run a correlated random effects model of maize yield, and include the absolute per cent deviation of total season rainfall, the coefficient of variation of total season rainfall and a dummy for a drought shock to capture non-linear impacts of large deviations from average. The drought shock takes a value of one if, during the total growing season, rainfall was below the minimum of rainfall received over the period 1983–2015. Results indicate that the drought reduced yields between 29 per cent and 41 per cent. The coefficient of variation is also negative and significant, consistent with both theoretical and empirical results that farmers in high rainfall variability environments are less likely to invest in crop productivity.

Pape and Wollburg (2019) use the United States Geological Survey's EROS Moderate Resolution Imaging Spectroradiometer (NDVI_E) data to generate percentage deviation of NDVI in two critical rainy seasons from mean NDVI in three "normal" years preceding the drought (Somalia drought in the second 2016/first 2017 seasons). They also include the average deviation from mean NDVI over the period 2002–2013 to control for propensity to experience a drought. Results show generally negative impacts, although it is difficult to interpret in terms of impacts of current period shocks as the authors use the preceding period NDVI values. Mejia-Mantilla and Hill (2017) use the crop Water Requirement Satisfaction Index (WRSI) matched to households, but it is unclear what time period is covered. The authors use a fixed effect models, so do not directly control for long-term probability of water stress. They find positive effects of higher water satisfaction on agricultural incomes.

As noted, a number of papers included temperature shock variables, and not temperatures per se. In part, this is because agronomic evidence suggests that temperature thresholds best describe negative impacts on grains in particular (the subject of most of the research mentioned above) (Prasad and Djanaguiraman, 2014 for wheat; Prasad et al., 2015 for sorghum; Sánchez et al., 2014 for maize and rice).

In addition to the household survey-based evidence, there are also studies that attempt to compare the performance of different rainfall products, generally by comparing the different rainfall estimates to rainfall gauge measurements (Dinku et al., 2018; Joseph et al., 2020; Logah et al., 2021). Many studies find that CHIRPS outperforms other products such as ARC2, while other studies find that CHIRPS performs more similarly to the Tropical Rainfall Measuring Mission (TRMM) and the Tropical Applications of Meteorology using Satellite data and ground-based observations TAMSAT (Dinku et al., 2018; Joseph et al., 2020; Macharia et al., 2020). However, the above results base performance against rain gauge data, which, by definition, cannot test how well such data sources (and variables created from them) perform for households located far away from such stations. A wide range of studies also determine that dekadal data is more closely correlated with rainfall gauge data than daily data (Ouma et al., 2012; Dembélé and Zwart; 2016; Zwart et al., 2018; Coz and van de Giesen, 2020; Logah et al., 2020). The agreement in the literature on the performance of dekadal versus daily measurements for a wide range of products motivated our decision to collect dekadal data.

While not focusing on weather shocks specifically, a recent study using the World Bank's Living Standards Measurement Study – Integrated Surveys for Africa (LSMS-ISA), used panel data from 17 countries and evaluated a number of climatic variables created from different sources, and found little evidence of difference among products (Michler et al., 2021). It is unclear why the authors chose the actual variables tested, but they did not include variables identified in the agronomic literature (for instance, the flowering period and onset dates, which are critical for grain production), nor did they use economic theory to guide their choice (for instance, expected utility theory states that one should use expected weather metrics, measures of variability of those metrics and current period deviations from those metrics).

In summary, the empirical evidence suggests that households subject to extreme weather events often suffer losses in crop yields and agricultural income. It is difficult to compare results, however, as the studies use a wide range of different definitions of weather shocks using different rainfall and temperature source data. Although the literature on the topic is gaining ground – especially the types of analysis found in Michler et al. (2019) that use household data combined with multiple GIS sources and weather variables – at present, there is not sufficient evidence to use a single data source and specific variables. Best practice would argue for collecting data from a range of sources, while choice of which specific variables to use should be guided by both agronomic evidence as well as economic theory, and using dekadal observations.

4. Analysis of impacts of weather and climate variables on grain production

For the purposes of this note, we will use the term "climate variables" to refer to measures of long-term averages and variability in maximum temperatures and rainfall, while we use the term "weather variables" to refer to temperature and rainfall measures that occurred during the season in which agriculture production data were collected. We use "climatic variables" to describe both weather and climate variables.

We run regressions on grain yield. Grain yields are defined as the combined harvest of sorghum and millet in kilograms, divided by the quantity of seeds used at planting in kilograms. While results are similar using the more standard construction of harvest quantity divided by hectares, explanatory power was much greater for seeds, and so we only report this yield measure in the following analysis. Recent evidence suggests that farmer error in estimating plot sizes can lead to biased results, which also favours reporting on output per quantity of seed (Carletto et al., 2017). Our sample size is 1 327 versus the full sample of 1 471, as 144 households did not grow either sorghum or millet.

4.1. Climatic variable data sources and weather variable construction

To begin the analysis, we must first determine which climate and weather variables to use in our regressions and also determine which climate data source provides the best predictive power in our analysis. For each of our climate datasets, we create a number of variables identified in the previous literature, and systematically test which variables, constructed from which climate dataset, perform best in predicting relevant agricultural production outcomes. Results of systematically testing both variables and data sources will contribute to a sparse literature on identifying the best climate and weather variables to include in production analyses, which should help in generating comparable empirical results across studies.

For temperature, we use data from the ECMWF ERA INTERIM re-analysis model. There are many more data sources for rainfall estimates, and given resource limitations, we had to restrict the number of rainfall data sources used in the analysis. We decided to use NOAA's ARC2 dekadal (10-day) dataset, covering the period 1983–present, and CHIRPS dekadal dataset, covering the period 1981–present. The choice was motivated by a number of considerations. First, many of the existant studies use either CHIRPS or ARC2, and so this choice facilitates comparison. Second, CHIRPS has been found to perform similarly to other products, such as TAMSAT and TRMM (now IMERG), in part because those products use similar inputs and processes for integrating gauge data versus ARC2, which uses fewer inputs and a simpler process for integrating gauge data (Dinku et al., 2018; Coz and van de Giesen, appendix B, 2020). We also use the United States Geological Survey's EROS Moderate Resolution Imaging Spectroradiometer, NDVI-E and the National Oceanic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (NDVI-A). The NDVI measures are capture a wider range of factors affecting local "greenness", just as crop yields are a function of many variables in addition to weather, so interpreting impacts is more difficult. However, there is significant interest in being able to use NDVI variables to predict crop production outcomes, so we include these variables in this step of the analysis. We also use the SPI and SPEI. These indices are not themselves a separate data source, but are rainfall estimate indices constructed using either ARC2 or CHIRPS for the SPI, and either ARC2 or CHIRPS combined with ECMWF temperature data for SPEI. Because SPI and SPEI were highly correlated across the ARC2- and CHIRPS-based variables, in what follows, we only present results for the ARC2-based variables.

4.2. Descriptive statistics: weather shock variables

Following the literature, we construct rainfall variables covering three different time periods. The first period is the total rainy season, which is constructed based on the onset and cessation of rainfall. In the Chad context, onset is defined as any dekad starting from the beginning of April when at least 25 mm of rain falls during a dekad, and then followed by a dekad with at least 20 mm of rain (Tadross et al., 2009). Cessation occurs when three consecutive dekads experience less than 20 mm of rainfall after August (Tadross et al., 2009). The second period is the flowering period, which is defined as cumulative rainfall over the eighth to fourteenth dekads following the onset of rains.

The total season and flowering period variables are obtained by matching GIS data to 99 village centroids as household GPS data are not available. It is unclear how well the village centroid values represent values experienced at farm household and plot locations. From previous work, we know that long-term average rainfall and rainfall variability measures are highly correlated within communities, as are both average and current period temperatures. However, the current rainfall shock variables in this analysis may be relatively noisy proxies of shocks experienced in the field, and we need to bear this in mind as we interpret results.

In Table 1, we present select descriptive statistics for the per cent difference of current period rainfall from long-term mean rainfall, for six weather categories. The second column includes the per cent of households that experienced below-mean rainfall, while the third column includes the average per cent below-mean for those who received below-mean rainfall. Similarly, the fourth column lists the per cent of households that experienced above-mean rainfall, while the fifth column lists the average per cent of above-mean rainfall.

Table 1. Per cent households experiencing below- and above-mean rainfall, and average per cent below- and above mean rainfall.

Rainfall estimate variables	% HH below	|% Diff below, if below|	% HH above	|% Diff above, if above|
ARC2				
Rainy season	8	6	92	13
Flowering period	12	33	88	21
CHIRPS				
Rainy season	54	10	46	7
Flowering period	48	30	52	23
SPI				
Rainy season	43	9	57	9
Flowering period	23	21	77	13
SPEI				
Rainy season	40	5	60	6
Flowering period	19	16	81	17
NDVI-E				
Rainy season	65	7	35	6
Flowering period	53	7	47	9

We first note that the ARC2, SPI and SPEI variables suggest that many more households were subject to above-average rainfall than do the CHIRPS, NDVIA-A and NDVI-E variables. In fact, the NDVI-A and -E variables suggest there were very limited per cent differences for either high or low realizations, given the per cent differences observed. ARC2, CHIRPS, SPI and SPEI also suggest more dramatic per cent differences observed in the flowering period versus the total season.

We also look at the correlations among the variables, which we would hope to be fairly high as high correlations would suggest that different rainfall sources were picking up relatively similar prevailing conditions and, thus, reduce the necessity to evaluate a wide range of variables for each particular analysis. As shown in Table 2, the ARC2, CHIRPS, SPI and SPEI variables are fairly highly correlated with each other, but correlation is limited with NDVI-E.

Table 2. Pairwise correlations, flowering period per cent differences.

	ARC2	CHIRPS	SPI	SPEI	NDVI-A	NDVI-E
ARC2	1.00	0.88	0.91	0.94	0.11	0.64
CHIRPS	0.88	1.00	0.80	0.90	0.11	0.71
SPI	0.91	0.80	1.00	0.93	0.11	0.52
SPEI	0.94	0.90	0.93	1.00	0.04	0.63
NDVI-E	0.64	0.71	0.52	0.63	0.24	1.00

The ARC2 variables, and to a lesser extent CHIRPS, SPI and SPEI, are more in line with observations documented by two early warning systems during the growing season in question. Specifically, in August 2016, the FAO-based Global Information and Early Warning System (GIEWS) noted that “favourable” grain yields were expected due to sufficient rains at the start of the season, and subsequent normal to above-normal precipitation in most areas of the country.[2] Similarly, FEWSNET noted in the June and August 2016 bulletins that rains started early and continued, and that cumulative rainfall totals were above-average and with good spatiotemporal distribution throughout the region.[3]

We have not yet discussed our temperature variable. Consistent with the steady and ample rains, there are no observations in the dataset where noon-time temperatures exceeded 35°C. The calculation of SPEI does incorporate temperatures, and so we can only explore current-period temperature impacts through this variable.

4.3. Climate and weather variables used in the production analysis

Before proceeding to the analysis, we make decisions on which sets of variables to use in the analysis. For weather shocks, we include the absolute per cent difference, which captures impacts of deviations both above and below the mean. Given that many observations are above the mean, we also include a specification that includes the per cent difference for high rainfall events, which takes a value of zero for low rainfall events. We run these specifications for variables created from all six weather sources, although we only report results for ARC2, CHIRPS and SPEI. SPI results are similar to those of SPEI, and the NDVI variables are difficult to motivate and, indeed, are never significant. We also evaluate using anomalies in addition to per cent differences. In our particular case, anomalies are highly correlated with per cent differences with similar results, and so are not reported here.

The second decision relates to climate conditions. Including climate conditions is necessary to ensure that weather shocks are conditionally exogenous in our cross-section analysis (Nizalova and Murtazashvili, 2016). To capture expected weather, we constructed a number of climate indices. We ultimately chose to fully test two indices based on either ARC2 or CHIRPS data, and the temperature data. We ran principal component factor analysis on mean flowering period rainfall, the coefficient of variation (CoV) for rainfall when flowering period rainfall realizations were below the mean, the CoV when flowering period rainfall realizations were above the mean and the average number of days during the flowering period with noon-time temperatures exceeding 35°C. As shown in Table 3, the scoring coefficients on average rainfall are negative, while the CoV for both high and low realizations as well as number of days experiencing critically high temperatures are all positive. Additionally, the scoring coefficients are quite similar across the ARC2 and CHIRPS specifications. Both climate indices thus capture relatively poor underlying climate conditions, increasing with greater exposure to temperature shocks and decreasing in average rainfall.

Table 3. Climate index, principal components factor scoring coefficients.

Variable	**ARC2** Scoring coefficient	**CHIRPS** Scoring coefficient
Avg. rainfall	−0.310	−0.294
CoV-low	0.295	0.246
CoV-high	0.271	0.277
Avg. # high temps	0.273	0.281

For the ARC2 and SPEI regressions, we use the ARC2-based climate index, while for the CHIRPS regressions, we use the CHIRPS-based climate index.

[2] According to the GIEWS website, the GIEWS team use crop models and “ground-based” information from FAO and other local partners, as well as NDVI, and precipitation data for African countries are obtained from FEWSNET, which is likely CHIRPS. Information accessed at: https://www.fao.org/giews/earthobservation/asis/index_2.jsp?lang=en.
[3] According to the FEWSNET website, FEWSNET uses CHIRPS, ARC2, NDVI and SPI data to make assessments, although it is very difficult to know what exact data sources or variables are used, and at least one document seems to suggest these may change by country (c.f. https://fews.net/sites/default/files/documents/reports/Guidance_Document_Rainfall_2018.pdf).

5. Results of production analysis

In the next step, we estimate grain yields using climate and weather variables, as well as standard production function variables. Specifically, we include GIS-based measures of elevation and slope to control for topographical features; the proportion of grain-cropped land that is owned; the total area planted in grains (in natural logs); the quantity of seeds used (in natural logs), number of adults in the household to proxy labour availability (in natural logs); dummies for use of organic fertilizer, inorganic fertilizer, pesticide use, soil and water conservation measures, and whether residue is incorporated into the plot; dummies for whether any plots were managed by a man, a woman or jointly; age of the majority plot manager; a durable goods-based wealth index; an agricultural implements index, the maximum education achieved by any adult in the family; a dummy for whether there is a daily market operating in the village; a dummy for the number of external assistance projects operating in the village; and department (administrative unit) dummies.

Table 4 contains results using variables created from ARC2, CHIRPS and SPEI, respectively. The second and third columns present rainy season results for the absolute per cent difference and the above-mean per cent differences, respectively; and the fourth and fifth columns present those results for the flowering period.

Table 4. Grain yields, weather and climate coefficients.

	Grain yields			
	Rainy season		Flowering period	
ARC2				
|% Diff|	0.703		1.141***	
	(0.973)		(0.380)	
% Diff>0		0.320		0.362
		(0.884)		(0.426)
Climate index	−0.179**	−0.167**	−0.192**	−0.172**
	(0.0754)	(0.0722)	(0.0751)	(0.0686)
Constant	4.922***	4.985***	4.505***	4.914***
	(0.539)	(0.545)	(0.496)	(0.522)
# Obs.	1327	1327	1327	1327
Adj. R^2	0.222	0.226	0.234	0.222
CHIRPS				
|% Diff|	−0.631		0.269	
	(0.818)		(0.366)	
% Diff>0		−1.588		0.169
		(1.127)		(0.330)
Climate index	−0.172**	−0.198**	−0.195**	−0.168**
	(0.0735)	(0.0789)	(0.0742)	(0.0787)
Constant	5.463***	5.755***	5.200***	5.205***
	(0.573)	(0.587)	(0.598)	(0.550)
# Obs.	1327	1327	1327	1327
Adj. R^2	0.222	0.226	0.234	0.222
SPEI				
|% Diff|	2.095		1.856***	
	(1.277)		(0.511)	
% Diff>0		2.659**		0.883
		(1.114)		(0.547)
Climate index	−0.134*	−0.173**	−0.110	−0.145**
	(0.0797)	(0.0784)	(0.0722)	(0.0706)
Constant	4.858***	5.016***	4.503***	4.878***
	(0.534)	(0.512)	(0.483)	(0.520)
# Obs.	1327	1327	1327	1327
Adj. R^2	0.222	0.226	0.234	0.222

Standard errors in parentheses. Asterisks denote significance; p<0.1, **p<.05, ***p<.01.*

As seen in Table 4, very few of our shock variables are significant, and in fact, when significant, the sign of the coefficient is positive. For instance, the flowering period absolute per cent difference and the rainy season above-mean per cent difference variables are both positive and significant using SPEI. The latter indicates that higher than average rainfall conditions had positive impacts on grain yields. On the other hand, the climate index is negative and significant in almost regressions. This suggests that those located in areas subject to low average rainfall, highly variable rainfall and more frequent expected temperature shocks had lower yields, irrespective of current-period weather conditions. The dampening effect of expected rainfall conditions is consistent with both theory and empirical evidence in other settings (Fafchamps, 1999; Chavas & Holt, 1996; Fafchamps, 1992; Roe & Graham-Tomasi, 1986; Feder et al., 1985; Antle & Crissman, 1990; Giné & Yang, 2009; Hurley, 2010).

It is not unexpected that higher than average rainfall conditions would improve yields, especially when relatively few households faced extremely high rainfall. Thus, we next evaluate whether we can identify thresholds below and above which rainfall deviations have significant negative impacts on grain yields. McKee et al. (1993) defined a wet year as occurring at SPI values between 1 and 1.5, a very wet year as occurring between 1.5 and 1.99, and extremely wet years occurring at SPI values at or above 2. Similarly, severely dry years occur at SPI values between −1.5 and −1.99, and extremely dry years occur at or below −2. A similar set of ranges was also developed for the SPEI (Tong et al., 2017; Vincente-Serrano et al., 2105). Even though almost all SPI and SPEI values were above the mean in the 2016 growing season and flowering period, no observations fall into the extremely wet category. Thus, we do not pursue the threshold analysis for the SPI and SPEI indices.

Table 5 includes results for a relevant range of ARC2 and CHIRPS flowering period threshold shocks. The top end of the ranges corresponds to the highest per cent difference observed for at least 5 per cent of households. For ARC2, the range is between 30 per cent and 34 per cent, and for CHIRPS, the range is between 36 per cent and 40 per cent. For ARC2, the only significant threshold is the negative impact at 32 per cent. For CHIRPS, only the highest threshold, 40 per cent, is negative and significant. The ARC2 absolute per cent difference is positive and significant as we expect, although it is not significant using CHIRPS variables. And the climate index coefficient remains consistently negative.

Table 5. Above-mean weather thresholds.

				Grain yields			
		ARC2				**CHIRPS**	
30% Threshold	−0.0919			34% Threshold	−0.0268		
	(0.179)				(0.173)		
32% Threshold		−0.293*		38% Threshold		−0.161	
		(0.175)				(0.165)	
34% Threshold			−0.155	40% Threshold			−0.375*
			(0.175)				(0.222)
|% Diff|	1.331**	1.716***	1.396***	|%Dif|	0.289	0.427	0.417
	(0.565)	(0.535)	(0.513)		(0.392)	(0.402)	(0.401)
Climate index	−0.179**	−0.160**	−0.187**	Climate index	−0.200***	−0.224***	−0.202***
	(0.0700)	(0.0730)	(0.0753)		(0.0740)	(0.0753)	(0.0744)

Standard errors in parentheses. Asterisks denote significance; p<0.1, **p<.05, ***p<.01.*

6. Impact assessment results

In this section, we start by running regressions similar to those found in CMAD, which used an inverse probability weighted regression analysis. First-stage matching variables include gender and age of the household head, a dummy for whether the head ever attended school, a dummy equal to 1 if the marital status is “civil status”, the number of groups operating in the community and the number of external assistance projects operating in the community in the past five years. CMAD also included a parsimonious number of control variables in the second stage outcome regressions. These included household size, the total area of land owned by the household and the age of the cereal bank used by the household (noting that cereal banks exist in both treatment and control locations). Key outcome variables included grain yields defined over seeds used (kg grain/kg seed) in logs; total grain harvest (kg) in logs; the amount of grain stored (kg); FAO’s Food Insecurity Experience Score (FIES); and WFP’s Food Consumption Score (FCS), which is a measure of dietary diversity. In addition, we will also look at the proportion of grain stored.

CMAD did not use any climate variables in the matching procedure used to generate their weights. The CHIRPS-based climate index is in fact well balanced across treatment and controls using either the unweighted or weighted regressions. However, the ARC2 climate index is significantly different under both unweighted and weighted regressions. Thus we create a new inverse probability weight using both climate indices as well as CMAD matching variables.

We run the doubly robust inverse probability weighted regression adjustment (IPRWA) estimations, and results using CMAD explanatory variables are given in Table 6a. Results are quite similar to those in CMAD for production outcomes. For instance, our coefficient estimate for grain yields is .332, while it is .322 in CMAD. However, results for consumption outcomes differ – treatment is not significant in our regressions while they have expected signs in CMAD.

Table 6a. IPWRA results, CMAD explanatory variables, updated weighting.

	Grain yields	Grain harvested	Grain stored	Prop. of grain stored	Food insecurity index	Dietary diversity index
Treat	0.333***	0.467***	0.970***	4.750***	−0.392	0.157
	(0.114)	(0.156)	(0.217)	(1.496)	(0.374)	(0.241)
HH size	0.0149	0.0706***	0.0327	−0.0210	0.0295	0.0384
	(0.0124)	(0.0154)	(0.0315)	(0.236)	(0.0452)	(0.0290)
Land size	−0.0152	0.0390**	0.0556**	0.0536	0.00918	0.00963
	(0.0114)	(0.0168)	(0.0222)	(0.137)	(0.0433)	(0.0213)
Cereal bank, age	0.0432***	0.0246	0.0377	0.115	−0.0530	0.00222
	(0.0153)	(0.0178)	(0.0382)	(0.178)	(0.0431)	(0.0536)
Constant	2.812***	4.846***	1.948***	13.20***	4.112***	4.581***
	(0.132)	(0.193)	(0.267)	(1.851)	(0.428)	(0.283)
# Obs.	1327	1327	1327	1327	1327	1320
Adj. R^2	0.027	0.049	0.031	0.007	0.002	0.001

Standard errors in parentheses. Asterisks denote significance; p<0.1, **p<.05, ***p<.01.*

We next evaluate the impact of weather shocks and climate on production and consumption outcomes. Here, we only present results for the CHIRPS-based shocks, as the ARC2-based shock was never significant. Table 6b presents results for regressions using CMAD explanatory variables as well as the 40 per cent threshold high rainfall shock dummy, the absolute per cent difference in rainfall and the CHIRPS-based climate index. Treatment remains robust, but the climate variables are almost never significant.

Table 6b. IPWRA results, CMAD and climatic explanatory variables, updated weighting.

	Grain yields	Grain harvested	Grain stored	Prop. of grain stored	Food insecurity index	Dietary diversity index
Treat	0.344***	0.483***	0.968***	4.559***	−0.389	0.186
	(0.110)	(0.151)	(0.219)	(1.388)	(0.382)	(0.238)
|% Diff|	0.0294	0.117	−0.0523	6.376	1.592	0.866
	(0.477)	(0.580)	(0.828)	(7.896)	(1.724)	(1.052)
40% Threshold	0.0874	0.272	0.423	0.201	−0.771*	0.0110
	(0.227)	(0.189)	(0.337)	(2.482)	(0.451)	(0.362)
Climate index	−0.0938	−0.131	0.0810	0.590	−0.399	−0.394***
	(0.0598)	(0.0885)	(0.104)	(0.823)	(0.251)	(0.123)
HH size	0.0114	0.0663***	0.0363	0.0308	0.0192	0.0259
	(0.0125)	(0.0152)	(0.0316)	(0.249)	(0.0418)	(0.0244)
Land size	−0.0132	0.0417**	0.0542**	0.0264	0.0137	0.0158
	(0.0116)	(0.0171)	(0.0220)	(0.139)	(0.0419)	(0.0205)
Cereal bank, age	0.0375***	0.0170	0.0423	0.191	−0.0681	−0.0179
	(0.0136)	(0.0187)	(0.0403)	(0.164)	(0.0477)	(0.0492)
Constant	2.827***	4.832***	1.904***	11.13***	3.838***	4.457***
	(0.186)	(0.243)	(0.340)	(2.869)	(0.651)	(0.349)
# Obs.	1327	1327	1327	1327	1327	1320
Adj. R^2	0.033	0.059	0.031	0.011	0.014	0.038

Standard errors in parentheses. Asterisks denote significance; p<0.1, **p<.05, ***p<.01.*

We note that the adjusted R^2 are quite low for all regressions in Tables 6a and 6b, indicating that omitted relevant variables may be biasing results on coefficients other than the treatment variable. In particular, we would expect agricultural inputs and practices to be influenced by climatic conditions. Thus, in our final set of regressions, we return to our production function specifications that use an expanded set of production-related variables as described in section 4.3. Results are presented in Table 7.

Table 7. IPWRA results, production and climatic explanatory variables, updated weighting.

	Grain yields	**Grain harvested**	**Grain stored**	**Prop. of grain stored**	**Food insecurity index**	**Dietary diversity index**
Treat	0.313***	0.340***	0.833***	4.382***	−0.119	−0.0689
	(0.097)	(0.114)	(0.186)	(1.387)	(0.299)	(0.161)
40% Threshold	0.312	0.276	0.59	11.15**	0.611	1.299*
	(0.386)	(0.436)	(0.708)	(5.439)	(1.284)	(0.763)
|% Diff|	−0.239	−0.233	−0.422	−2.981	−0.213	−0.902***
	(0.153)	(0.167)	(0.304)	(1.906)	(0.411)	(0.224)
Climate index	−0.194**	−0.202**	0.145	2.472*	0.437*	−0.429**
	(0.077)	(0.095)	(0.155)	(1.269)	(0.259)	(0.164)
Constant	5.046***	5.358***	2.180**	10.11	2.183	7.351***
	(0.515)	(0.607)	(1.047)	(10.270)	(2.116)	(1.027)
# Obs.	1327	1327	1327	1327	1327	1320
Adj. R^2	0.235	0.251	0.148	0.089	0.161	0.204

Standard errors in parentheses. Asterisks denote significance; p<0.1, **p<.05, ***p<.01.*

As seen in Table 7, the treatment impacts remain robustly positive for all of the production outcomes. However, more of our climatic variables are significant, and explanatory power has increased significantly, especially for the grain yields and harvest models. We observe a positive impact of a 40 per cent above-rainfall shock on the proportion of grain stored, indicating that storage was relatively more valuable in areas receiving extremely high rainfall and therefore at greater risk of post-harvest disease losses. The climate index also has a positive impact on the proportion of grain stored, indicating that those in areas subject to poorer and more variable climate conditions place additional value on grain storage. Furthermore, the climate index coefficient is negative and significant on grain yields, harvest, food insecurity and dietary diversity. Those living in relatively low expected rainfall areas and subject to rainfall and temperature shocks thus have worse production and consumption outcomes, even after controlling for treatment effects, updated weighting and a rich set of additional covariates.

To summarize, by all measures, the impact assessment team did an excellent job selecting counterfactual villages and collecting necessary time-invariant or pre-project household data to ensure balance on covariates across treatment and control households. This is consistent with the robust impacts of project treatment across most outcome variables when comparing our results with those found in CMAD. However, the limited set of regressors used in the CMAD specification also suggests that omitted relevant variable bias may well affect the interpretation of coefficients on included regressors other than treatment, particularly given generally low explanatory power. While the emphasis of impact assessment is to uncover project impacts, in most cases, there are ample opportunities to exploit the data to learn about other relevant contextual factors affecting outcomes that are relevant to the design of future projects. This is particularly important with climatic variables, as evidenced in this analysis. Without a richly specified, theoretically grounded, regression specification, just including climatic variables generally leads to insignificant results. However, when including a wide range of regressors that are standard to agriculture production models, we see that poor underlying climate conditions have negative impacts on grain yields and harvest, increase food insecurity and reduce dietary diversity. There is a positive impact on the proportion of grains stored, however, indicating that storage is of relatively greater value in these environments. Consistent with most empirical evidence, poor climate conditions lead to lower (although possibly more stable) production and to lower livelihood outcomes even in “normal” rainfall years. Future projects need to directly address incentives to invest in agriculture under these circumstance, for example by considering opportunities to diversify on- and off-farm, and opportunities to increase access to risk-reducing inputs such as heat- and/or drought-tolerant varieties.

7. Concluding comments

We started by evaluating the performance of a wide range of weather and climate variables, from a number of different climatic data sources, in terms of predicting grain yields. Descriptive statistics suggest that the same variables constructed with different sources give different percentages of households estimated to have received either below- or above-mean rainfall. The contrast was particularly striking between NDVI-E versus ARC2, CHIRPS, SPI and SPEI, where the NDVI-E variables suggested that more households experienced relatively low rainfall instead of moderately high rainfall. Estimates of relatively low rainfall are also at odds with FAO and USAID famine early warning systems documentation, which reported relatively favourable conditions in the region in 2016, so we dropped variables based on this data source from further consideration. The descriptive statistics also suggest that only a few households experienced extremely high rainfall that could potentially damage crops. And there were very few observations of damagingly high temperatures. In this particular dataset covering this particular year, then, we were limited in the types of weather shocks that could be evaluated.

Looking next at impacts of weather shocks and climate conditions on production outcomes, the analysis showed that using the absolute per cent or above-mean differences yielded limited significant results, but suggested that the ARC2 and SPEI are picking up positive impacts of above-mean differences for the rainy season. Next, we evaluated whether identifying threshold values may better pick up impacts of shocks on yields. The ARC2-based shock was negative and significant at 32 per cent, but not at 30 per cent or 34 per cent, casting some doubt on the robustness of this impact. The CHIRPS-based shock at 40 per cent was significant and negative. It was also at the very top of the range evaluated, and so we used this variable going forward in the analysis.

We then ran regressions similar to those found in the CMAD impact assessment analysis. We added the ARC2 and CHIRPS climate indices to variables used by CMAD to match treatment and controls and generate an inverse probability weight. We then ran IPWRA analyses on grain production, storage and consumption outcomes, first using the CMAD explanatory variables and then using a richer production function specification. While the treatment coefficient is robust to alternative specifications as we would expect given the matching procedure, the climatic variables are not robust. In particular, the parsimonious set of explanatory variables used by CMAD did not sufficiently control for other variables expected to be correlated with climatic variables. Evaluating the impact of climatic variables requires a richer production specification. This specification generated three key results: 1) very high rainfall shocks – those exceeding 40 per cent of expected rainfall – had significant negative impacts on grain production and dietary diversity, 2) the climate index is robustly negative on grain production and consumption outcomes, strongly suggesting that households in this region are under-insured and thus quite vulnerable to increasingly high temperatures and more frequent weather shocks and 3) those living in unfavourable climatic environments store a greater fraction of their grain, indicating that storage facilities are of relatively more importance than those living in more favourable climatic environments.

Overall, the analysis shows that including weather and climate variables into project impact assessments can provide information on how these variables affect the overall outcomes of interest, generating valuable insights into future project design. They may also be important in matching treatment and controls households, although the latter was not important in this case. Importantly, introducing a richer set of production-related covariates, which increased explanatory power of the regressions significantly, revealed significant negative impacts of weather shocks and climate conditions on production and consumption outcomes. The latter reflects potential missed opportunities in many impact assessments, which focus almost exclusively on estimating programme impacts. A lot more evidence can be generated about the conditioning factors that also affect outcomes, which can provide key insights for future project design. But uncovering important conditioning factors means explicitly developing a conceptual framework that outlines which variables must be included to avoid omitted relevant variable biases on the conditioning covariate coefficients. Luckily, data collection efforts almost always do collect data necessary to run well-specified production and consumption regressions.

Our results also suggest that choosing what data sources to use and which exact variables to create will continue to be a difficult task confronting researchers. The same variables created from different sources generate quite different descriptive statistics on per cent of households experiencing either below- or above-mean weather conditions, as well as the average size of that difference. Our analysis also suggests that non-linear thresholds did a better job of explaining impacts on grain production rather than the simple per cent difference, either alone or split into below and above differences. But, much more work remains to be done to corroborate this result.

We tentatively conclude that using dekadal data is likely to generate variables with greater predictive power, mainly because our analysis supports a relatively large body of evidence that suggests that dekadal data is more highly correlated with rain gauge data than daily data, as described above. Choice of rainfall estimate data sources remains difficult. At present, it makes sense to collect data from sources that fundamentally differ. Coz and van de Giesen (2020) give an excellent description of many products as well as summarize the literature on how variables created from different sources perform, both of which can help guide selection of data sources. And, in the future, it is likely that more studies like Michler et al. (2021) will provide evidence that will also help guide data source selection, at least by region and/or by major commodity group. For the choice of variables to create, these choices should be based on economic theory and on agronomic evidence.

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