The impacts of Nigeria's 2012 floods on agricultural households

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Abstract

Nigeria experienced severe flooding during the rainy season of 2012 which cost $17 billion USD in macro-economic terms. This paper provides a complementary micro-level accounting of the flood using panel survey data across 2,500 agricultural households before and after the flood. I examine multiple definitions of flood exposure (self-reports and satellite imagery) and agricultural outcomes (production and value) to better understand local impacts and their distribution. On average, affected farmers lost around 20% of crop production and 40% of crop value after the flood. But not all households in flooded areas were impacted the same: those who were doubly exposed (live in a flooded area and self-reported a flood) lost up to 75% of crop value. Conversely, households living in flooded areas who were not individually affected reported an increase in crop value around 20% without any change in output. Suggestive evidence is presented that food prices increased in flooded areas, benefitting unaffected farmers selling to local markets. The findings of this paper provide a more nuanced and comprehensive understanding of the local impacts of extreme events and can help inform the design and targeting of post-disaster relief.

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Introduction

From July to October 2012, Nigeria experienced unprecedented floods which affected 30 of the country's 36 states, led to more than 431 fatalities, displaced around 1.3 million people, and cost $16.9 USD billion in damages (Unah, 2017). While damage estimates are commonplace after an extreme event and describe the large aggregate costs to the economy, they may not capture the full impacts on livelihoods, or inform about their distribution (Hallegatte et al., 2016). The focus of this paper is on the micro-level distributional impacts of Nigeria's 2012 flood and is examined by exploring the outcomes for 2,500 agricultural households across the country. The paper makes three main contributions: (1) it provides a more comprehensive accounting of Nigeria's 2012 flood on agricultural livelihoods, (2) it informs on how these impacts were distributed across households and interact with local market factors, and (3) it assesses exposure to weather shocks using multiple modalities in the same context.

I find that impacts are large and depend not only on whether a household is flooded, but also on if their neighbors are flooded. On average, affected farmers lost around 20% of crop production and 40% of crop value after the flood. But not all households in flooded areas were impacted the same: those who were doubly exposed (live in a flooded area and self-reported a flood) lost up to 75% of crop value. Conversely, households in these areas who were not individually flooded benefitted and reported an increase in crop value around 20% without any change in output. Suggestive evidence is presented that food prices increased in flooded areas, benefitting unaffected farmers selling to local markets. The findings of this paper provide a more nuanced and comprehensive accounting of the local impacts of extreme events and can help inform the design and targeting of post-disaster relief.

Context and Related Literature

Nigeria, often referred to as the "Giant of Africa", is a large country located in West Africa that spans over 350,000 square miles and is home to over 200 million people, making it the continent's most populous nation. The climate ranges from tropical rainforest in the south at the Niger Delta (where the Benue and Niger rivers drain into the Atlantic Ocean), topical savannah which covers most of the country, and arid desert in the north and east. Despite being Africa's largest economy, Nigeria is classified as a lower-middle income economy according to the World Bank, with a GDP per capita of $2,375 in constant 2010 USD as of 2019, with almost 40% of the population living below $1.90 per day (World Bank, 2021). The country has been urbanizing in recent decades, with 51% of the population living in urban areas as of 2019. Agriculture still plays a major role in the economy, accounting for 22% of GDP and 35% of total employment.

Floods are a regular occurrence during the rainy season, which typically lasts from May to October each year. In recent decades, flooding has become the most common weather shock, responsible for more displacement and property damage than any other hazard (Osumgborogwu & Chibo, 2017). In recent decades, the proportion of the population exposed to floods has grown with 70% at risk of flooding in 2014 (Agada & Nirupama, 2015; Tellman et al., 2020). Despite the importance of flooding across the country and an increase in precipitation expected due to climate change, comprehensive flood risk maps and a national flood risk management strategy remain absent (Echendu, 2020; Oladokun & Proverbs, 2016; Olaore & Aja, 2014).

The lack of a comprehensive flood risk strategy was exposed during the rainy season of 2012. In March, months before the rainy season, the Nigerian Meteorological Agency predicted massive flooding (NIMET, 2012). Despite this warning, there was little preparation and when the floods hit they were termed the "worst in 40 years" by the National Emergency Management Agency resulting in damages of $16.9 billion USD (Federal Government of Nigeria, 2012; Osumgborogwu & Chibo, 2017; Unah, 2017). The major cause was heavy rainfall across the country and was exacerbated by dam releases (OCHA, 2012). In terms of post-disaster aid, $180 million USD of federal and private funds were allocated to affected states by the end of 2012, accounting for only 1% of the total damage (OCHA, 2012; Unah, 2017).

Cutter's (1996) hazard-of-place model identifies vulnerability to a certain flood hazard as a combination of existing social vulnerability, geographic context, and lack of government support. Applying this model to the study area of this paper, Nigeria's high agricultural reliance, low income per capita, lack of investment of flood infrastructure, and absence of a safety net mean any large-scale flood event is likely to have severe consequences, especially on the livelihoods of the poorest. Given the increases in precipitation expected in the future linked to climate change, there is value in studying the impacts of past flood events to inform future decision-making surrounding disaster risk management in the country.

The literature on the economics of natural disasters is extensive. One strand of the literature focuses on macroeconomic impacts, for instance by estimating the impact of hurricanes in the recent past on country-level GDP (Hsiang & Jina, 2014). Two review papers examine 89 empirical studies before 2014, all on macroeconomic impacts (Klomp & Valckx, 2014; Lazzaroni & van Bergeijk, 2014). One message from these reviews that motivates this paper is that climatic shocks are found to have the most significant adverse impact on aggregate economic growth in lower-income countries. Focusing on these areas, Hallegatte et al. (2016) finds that globally, floods, droughts and storms push an estimated 26 million people into poverty every year. In sub-Saharan Africa, households are especially vulnerable to the effects of weather shocks due to high poverty and agricultural reliance (Beegle & Christiaensen, 2019).

While these macroeconomic and global studies are helpful in estimating the impact of environmental disasters on wider outcome variables, they can ignore geography, lack spatial detail, and may not have a causal interpretation (Botzen et al., 2019). Studies of the impacts of weather shocks on national outcomes may not include detailed information on the disaster intensity or spatial extent, what the impacts were on the local economy and livelihoods, and whether these impacts were positive or negative in the short and long-run.

Due to spatial advances in remote sensing and the availability of geo-located household surveys (to link household outcomes with exposure to a weather shock), recent work has conducted more detailed micro-level analysis. In these analyses, households are surveyed before and after a major event. For example, after major events like Cyclone Aila in Bangladesh and Tropical Storm Agatha in Guatemala, poverty rates were found to increase by 15% (Akter & Mallick, 2013; Baez et al., 2017; Bandyopadhyay et al., 2018).

Two more recent papers have examined the micro-level impacts of weather shocks in an African context. After the 2009 floods in Tanzania and after the 2015 floods in Malawi, crop production decreased by around 30% for affected farmers (McCarthy et al., 2018; Tiague, 2021). A post-disaster needs assessment conducted by the Nigerian government (with support from international agencies) found that the event cost the economy $16.9 billion USD in economic damages and losses, or around 1.4 of country-level GDP (Federal Government of Nigeria, 2012). Focusing on same 2012 event, Agada & Nirupama (2015) examine the origins and history that shaped the socio-economic vulnerability to the disaster in Benue State, an area especially hard-hit by the event. Despite this work, an analysis of the micro-level impacts of this flood on household livelihoods and outcomes over time remains unstudied, and is the focus of this paper.

Research questions and contributions

While the Post-Disaster Needs Assessment identified which states experienced the largest economic impacts from the 2012 flood, these aggregate estimates may not tell the full story of the impact on people's livelihoods. Economic impacts are calculated by summing up damages (monetary replacement value of damaged durable assets) and losses (changes in the flows of goods and services) (Federal Government of Nigeria, 2012). The poorest households own or produce relatively little, which would not show up in the aggregate economic impacts; however, the livelihoods of these households are likely to be severely affected (Hallegatte et al., 2016). The focus of this paper is on the household impacts at the micro-level, and is structured around two research questions. First, what were the direct impacts of the flood on agricultural production? While "normal" floods during the rainy season can be beneficial for area under cultivation and agricultural productivity (Banerjee, 2010), "extreme" floods are likely to submerge cropland and destroy the harvest. This was observed after two extreme events: the 2009 flood in Tanzania and the 2015 flood in Malawi, where crop production decreased by around 30% (McCarthy et al., 2018; Tiague, 2021). Given the extreme nature of the 2012 event, I expect a substantial drop in crop production similar to the results found in other sub-Saharan African countries.

Second, are the impacts of the flood on agricultural households also dependent on whether your neighbors are also affected? Many studies in the literature examine direct impacts only – either on poverty or agricultural productivity, as described above. In this paper, I examine the how the second-order impacts of the flood might depend also on the level of affectedness of your neighbors. Specifically, I am interested in how local market factors may exacerbate (or potentially mitigate) impacts on agricultural households through the channel of crop prices. After Tropical Storm Agatha in Guatemala, (Baez et al., 2017) documents that the main driver of increased poverty rates was due to higher food prices. On the production side, if agricultural households in severely affected areas can retain some portion of their harvest, they may be able to sell their harvest at higher prices. Given the limited literature examining these second-order effects for producer prices, I have no prior of the expected impact.

The paper makes three main contributions: (1) it provides a more comprehensive accounting of Nigeria's 2012 flood on agricultural livelihoods, (2) it informs on how these impacts were distributed across households and interact with local market factors, and (3) it assesses exposure to weather shocks using multiple modalities in the same context.

Data and methodology

The primary dataset used is the Nigeria General Household Survey Panel[1] (GHS-Panel), which collects data on the same 3,052 agricultural households before and after the flood: once in 2010-11 (Wave 1) and once in 2012-13 (Wave 2)[2]. For each Wave, the household is visited twice: once post-planting (September-November) and once again post-harvest (February-April of the following year). The survey provides detailed information on household socio-economic conditions, agricultural data, and exposure to shocks. In addition, the surveyors make their best attempts to track households that have moved. Of the 3,052 agricultural households surveyed in Wave 1, 2,777 are re-surveyed with complete data in Wave 2 resulting in an attrition rate of 9% across the 2 waves. For context, attrition rates for household surveys in developing countries range anywhere from 1-23% (Hagen-Zanker et al., 2015). Of these 2,777 panel households, 2,563 have complete data and comprise the sample used in this paper.

Geographic information is collected in the survey which gives an estimate of the location of the household. Due to confidentiality reasons, the exact coordinate location of the households is not provided; rather, the average of household coordinate locations in each survey cluster (primary sampling unit) is provided. There are around 10 households in each cluster. The centroid of these 10 household locations is calculated, and then offset by 0-2 kilometers in urban areas and 0-5 kilometers in rural areas.

[1] This household survey is part of the World Bank's Living Standards Measurement Survey – Integrated Surveys on Agriculture, which is a coordinated set of publicly available panel surveys run in 8 countries in sub-Saharan Africa (Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda)

[2] For each Wave, the household is visited twice – once post-planting (Aug-Nov) and once post-harvest (Feb-Apr of the following year). Data is also available for Wave 3 (2015-16) and Wave 4 (2017-18). Given the interest in the impact of the 2012 flood, only Waves 1 and 2 are used for cleaner identification.

Flood exposure data

I use these offset coordinate locations to obtain two indicators of exposure to the 2012 event at the household level – one from the survey (linking household self-report of flood with the coordinate location) and one by linking the survey coordinates with the spatial flood extent collected by satellite imagery.

For the first exposure metric (household self-report), one module of the household survey asks the household head to recall economic shocks experienced in the recent past. The exact question asked is *"Has your household been affected by [SHOCK] in the past 5 years?"* There are 22 different shock categories that each household provides a "Yes" or "No" response to, ranging from death of a household member, job loss, to weather shocks like floods for each of the previous 5 years before the survey interview (Figure 1). The main sub-question of interest is Shock Code 13 which asks if the household has experienced "Flooding that caused harvest failure"[3]. Households who respond "Yes" in 2012 are identified as flooded (x=1), and those who respond "No" are identified as not flooded (x=0).

I'D LIKE TO ASK YOU ABOUT EVENTS THAT MAY HAVE AFFECTED YOUR HOUSEHOLD OVER THE LAST 5 YEARS.

SHOCK CODE	1 Has your household been affected by [SHOCK] in the past 5 years? YES..1 NO...2(► NEXT SHOCK)		2 How many times has this occurred in the past 5 years?	3 In what years did this event occur?				
				2009	2010	2011	2012	2013
1	Death or disability of an adult working member of the household							
2	Death of someone who sends remittances to the household							
3	Illness of income earning member of the household							
4	Loss of an important contact							
5	Job loss							
6	Departure of income earning member of the household due to separation or divorce							
7	Departure of income earning member of the household due to marriage							
8	Nonfarm business failure							
9	Theft of crops, cash, livestock or other property							
10	Destruction of harvest by fire							
11	Dwelling damaged/demolished							
12	Poor rains that caused harvest failure							
13	Flooding that caused harvest failure							
14	Pest invasion that caused harvest failure or storage loss							
15	Loss of property due to fire or flood							
16	Loss of land							
17	Death of livestock due to illness							
18	Increase in price of inputs							
19	Fall in the price of output							
20	Increase in price of major food items consumed							
21	Kidnapping/Hijacking/robbery/assault							
22	Other (specify)							

Figure 1. Shock questionnaire from household survey conducted in Wave 2.

[3] Shock Code 15 asks if the household experienced "Loss of property due to fire or flood". Since I cannot separate property damage from fire from property damage from flood, I decided against using data from this sub-question.

The survey definition of exposure has the advantage of being as close to household's experience of the event as possible. However, these survey responses may not be accurate for several reasons.

First, the exact wording of the survey asks if the household experienced a flood that *caused* a harvest failure. Specifics are not provided in the survey documentation as to what defines a "harvest failure", and each respondent's understanding of this term can vary widely. Additionally, households who may have experienced a flood but not a harvest failure (for example, due to farm-level water management) or households who experienced large non-agricultural losses from the flood would not be identified as flooded using this survey question. For these reasons, I focus only on agricultural households in this paper, and use an additional dataset based on satellite imagery to identify households living in flooded areas.

Second, there is a long duration of recall in the survey questionnaire, which asks households to remember shocks which occurred in the past 5 years. The question of how long people can reliably remember an item of information is unknown, as very few psychological studies of memory have dealt with timescales longer than a year (Fanta et al., 2019). Emotional events such as a natural or human-caused disaster are more likely to be remembered (Berntsen & Rubin, 2006), but memories of traumatic events can become inconsistent within one year (Hirst et al., 2015). While it is unclear how accurate the responses provided are, the finding that many more households report being flooded in 2012 compared to other years suggests this event to be extreme and likely to be remembered.

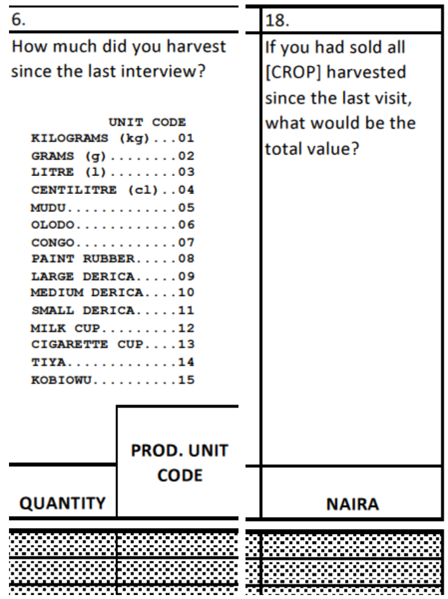
Third, the responses themselves may not be accurate. Households who did not experience a flood in 2012 may tell interviewers that they did experience a flood, and vice-versa. For example, if households believe that saying "Yes" to being exposed to the flood shock may be tied to support from either the government or an NGO, they may be more likely to report being flooded when they did not actually experience a flood (Erman et al., 2018). However, in this context, I do not expect a bias in strategic reporting. Reporting bias is likely higher when the weather shock is more salient during the survey interview: many studies in the literature conduct an ex-post disaster-specific survey to examine the impacts of a flood or drought (Akter & Mallick, 2013; McCarthy et al., 2018; Patankar, 2015). In these cases, investigating the impacts of the shock itself is the main reason for the survey and the salience to potential support is more prominent. In this paper, I use a large-scale nationally representative general household survey that has been going on since 2010, with multiple questionnaires per visit and over 15 modules per questionnaire. The questions of interest for this paper relating to the impacts of the 2012 flood are only a small component of the overall interview, which suggests reporting bias is unlikely. This is something I will test for in the empirical analysis, by correlating survey exposure with observed losses: if the two are well-correlated, reporting bias may not be present.

Forth, a household's historical exposure to floods may affect their perceptions of whether they were flooded (Guiteras et al., 2015). If a farmer's plot is flooded often, they may perceive the 2012 event as "normal" and not self-report a flood in that year. Alternatively, for the same level of water (or crop damage), farmers without such experience of floods may term the 2012 event as "extreme" and might be more likely to report a flood. Combining a historical risk map with the household coordinates, I am estimate historical exposure to floods and explore heterogenous effects in the empirical analysis.

For the second exposure metric, I link the coordinate locations from the survey with satellite imagery on the flood extent of the 2012 event from NASA's NRT Global Flood Mapping product, which is based on images collected by the Moderate Resolution Imaging Spectroradiometer (MODIS). The MODIS instrument, based onboard NASA's Terra and Aqua satellites, collects daily images of the earth's surface at 250m resolution (NASA, 2022). Using an algorithm developed by the Dartmouth Flood Observatory (Dartmouth Flood Observatory, 2021), areas with surface water are identified at 2-day intervals globally. Each of these individual maps (e.g. July 1-2) are aggregated across the study period (July-November) to provide a flood extent that spans the entire event duration (Federal Government of Nigeria, 2012). By combining this flood extent with the cluster location, I classify each household as being exposed (x=1) or not exposed (x=0), based on whether the coordinate lies within the flood zones. Given the uncertainty regarding the exact location of the household, I buffer the cluster coordinates by 5km to identify the locations that intersect the flood extent from MODIS. The primary advantage of the spatial exposure metric is that it detects flooded areas from space and is inherently less prone to human biases in reporting. A limitation of the MODIS product is that it cannot see through clouds, so it is unable to determine surface water when an area is cloudy (NASA, 2022). In order to account for clouds, each MODIS product is built upon using 2 days of data.

Agricultural and socio-economic data

To measure agricultural outcomes, I use two questions from the survey that estimate the total quantity of crop production (kg) and value of crop production (in Naira). For quantity, the interviewer asks each agricultural household how much they harvested this season, and for value, the farmer is asked how much they would receive (in Naira) if they were to sell all crops harvested this year (Figure 2). For quantity, I examine kg produced for all crops, and separately for the 7 major crops grown among farmers in the sample (maize, sorghum, cassava, beans/cowpea, millet, yams, and rice).


6.
How much did you harvest since the last interview?

UNIT CODE
KILOGRAMS (kg)...01
GRAMS (g)........02
LITRE (l)........03
CENTILITRE (cl)..04
MUDU.............05
OLODO............06
CONGO............07
PAINT RUBBER.....08
LARGE DERICA.....09
MEDIUM DERICA....10
SMALL DERICA.....11
MILK CUP.........12
CIGARETTE CUP....13
TIYA.............14
KOBIOWU..........15

QUANTITY	PROD. UNIT CODE

18.
If you had sold all [CROP] harvested since the last visit, what would be the total value?

NAIRA

Figure 2. Snapshots from the survey on the two agricultural outcome variable of interest: production (left) and value (right)

Agricultural survey data in developing countries can be very noisy, often with outliers whose reported value is many standard deviations above the mean and does not appear realistic from a qualitative sense (Fraval et al., 2019). The GHS-Panel data for Nigeria is no exception, as the distribution of the quantity and value outcomes are highly skewed (Figure 3). Following standard practice (BenYishay et al., 2020; Meles, 2020), I winsorize the top-end of outliers, at the 99th and 95th percentiles. This process retains all of the observations of the data, but assigns all values above the percentile to be equal to the percentile itself. For instance, 99th percentile for the raw data on quantity is 28,300 Kg: for this threshold, all 30 observations above would be assigned 28,300 in the data.

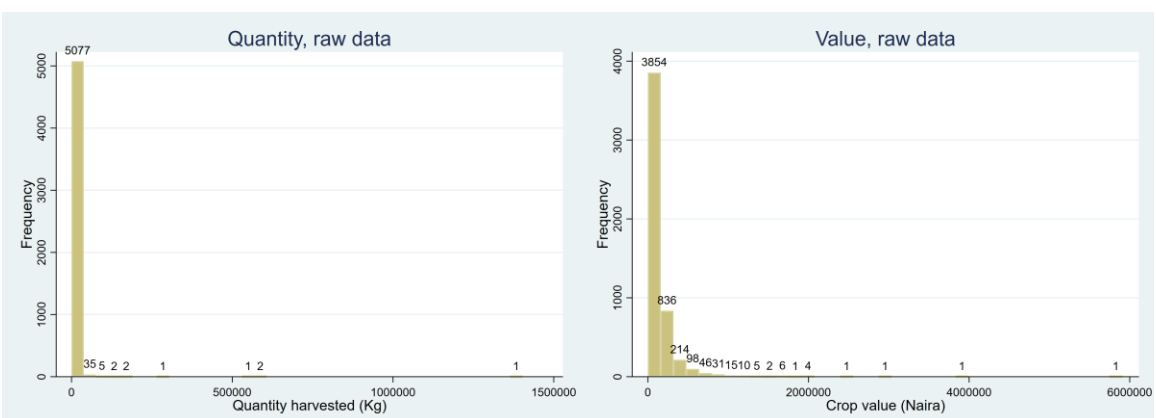


Figure 3. Distribution of raw data for crop production and crop value outcome variables.

Several factors may affect the relationship between exposure to floods and agricultural outcomes, and I control for a number of these variables using data from the survey. I proxy for household structure and level of farmer experience (McCarthy et al., 2018) using the number of adults within each household and the age of the household head.

Households with some level of risk-sharing and market integration might be able to reduce losses from a flood (Le Cotty et al., 2017), and I proxy for this using the presence of a bank account and distance to market. I also collect data on plot-level characteristics that may affect the flood-agriculture relationship (McCarthy et al., 2018) including slope, elevation, and size of landholdings. For households in the sample, the farm is located close by to the household location. I also include data on food prices at the community-level, which is also included as part of the household survey.

The relationship between floods and agricultural outcomes is examined using a panel regression framework. Household-fixed effects are included to control for unobserved factors that do not change over time (e.g. soil quality) and time-fixed effects are included to account for external characteristics occurring during Wave 1 (2010/11) and Wave 2 (2012/13) – for instance, elections or government policies. This framework estimates the within-household effects of experiencing the 2012 flood on agricultural outcomes. I run separate regressions on each outcome variable (quantity and value) and using each explanatory variable (survey flood, satellite flood) and use the combination of these variables to uncover insights on how floods affect agricultural households at the local level. The full specification is presented in Equation 1.

$$Y_{it} = \gamma_i + \delta_t + \alpha D_{it} + \beta X'_{it} + \varepsilon_{it}$$

Y_{it} is the agricultural outcome (production/value) for household i in survey wave t
γ_{i} represents the household-fixed effects,
δ_{t} the time-fixed effects,
D_{it} indicates whether the household was flooded in 2012 (Survey/Satellite),
$\mathrm{X'}_{\mathrm{it}}$ includes covariates (number of adults, age HH head, bank account, distance to market, slope, elevation, and landholdings)

Equation 1. Specification to examine the agricultural impacts of the 2012 flood

Descriptive statistics

The descriptive statistics for the outcome variables of quantity and value for the panel of 2,563 agricultural households is provided in Table 1, top-end windsorized at the 99th and 95th percentile (hereby W99 and W95). In terms of quantity produced, the average for each farmer was around 2,800 kg and increased from Wave 1 to Wave 2. Despite the windsorization, the data is highly skewed: the standard deviation is around 1.5-1.8x the mean for the W99 sample, and still larger than the mean for the W95 sample. In terms of value, the mean is around 120,000 Naira (~$750 USD), and appears to have reduced slightly from Wave 1 to Wave 2. The data exhibits a similarly large standard deviation, which lowers in the W95 sample.

Quantity Produced (Kg)							
	Obs	**W99**			**W95**		
		Mean	Std	Max	Mean	Std	Max
Wave 1	2,563	3,066	4,511	28,300	2,669	2,976	11,020
Wave 2	2,563	3,568	6,472	45,100	2,909	3,599	13,820
Value of Production (Naira)							
	Obs	**W99**			**W95**		
		Mean	Std	Max	Mean	Std	Max
Wave 1	2,563	128k	167k	947k	116k	124k	470k
Wave 2	2,563	123k	154k	926k	110k	110k	397k

Table 1. Descriptive statistics for two outcome variables: quantity produced and value of production, for both waves of the survey, top-end windsorized at the 99th and 95th percentile. Across the survey years, 1 USD = ~160 Naira.

Households are asked to recall their exposure to floods for the last 5 years in the post-harvest visit of each survey wave (conducted in early 2011 and 2013, for Wave 1 and Wave 2). The results are presented in Figure 4 for the panel of 2,563 households interviewed in Wave 1 and Wave 2, with data for the most recent years used. From 2007-2009, fewer than 1 percent (around 25 households in the survey) report flooding that caused harvest failure, this figure rises to 2.5% in 2010 (63 households), and drops back to 1% in 2011. In 2012, the share dramatically increases, with almost 10% of households self-reporting a flood that caused a harvest failure, with 244 "Yes" responses. These descriptive findings provide empirical support to the qualitative evidence presented earlier suggesting the floods in 2012 were a uniquely extreme event.

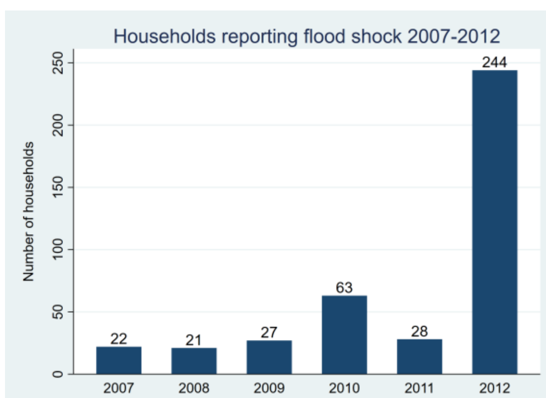


Figure 4. Number of households reporting a "Flood that caused harvest failure" from 2007-2012 (of the panel of 2,725 households).

The second exposure metric combines the GPS location of each household with the satellite-based MODIS flood inundation map in 2012. Given the uncertainty regarding the exact household location, I calculate the intersection between flood and household at different buffer levels. The household location provided from the survey is buffered by 1km, 2km, 3km, 4km, and 5km, and is then intersected with the MODIS satellite map. An example of the buffer methodology is shown in Figure 5 and the results are presented in Table 2. Without buffering the household coordinate, only 38 households are in the satellite flood area. As the buffer gets larger, more households are classified as flooded, with the number rising to 151 at 2km and 394 at 5km. As the exact household location is buffered by 5km by the surveyors, I use the 5km buffer method in the results presented below.

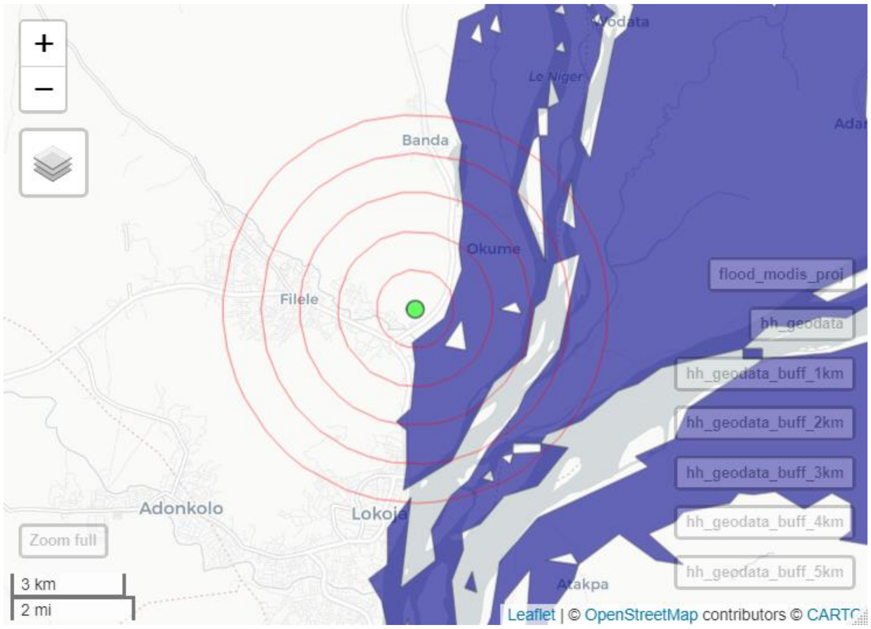


Figure 5. Buffering method used, red circles represent the buffered boundaries of the HH coordinate, at 1km, 2km, 3km, 4km, and 5km. In this example, the HH would be considered flooded at the 1km, 2km, 3km, 4km, and 5km buffer but not without the buffer (at 0 buffer, there is no intersection with the flood map in blue).

Method	**Number exposed**
MODIS (no buffer)	38
MODIS (HH location buffered 1km)	102
MODIS (HH location buffered 2km)	151
MODIS (HH location buffered 3km)	207
MODIS (HH location buffered 4km)	332
MODIS (HH location buffered 5km)	394

Table 2. Number of households exposed to the 2012 floods calculated by intersecting the MODIS satellite with the HH location (at different buffers)

The results on flood exposure are also presented spatially in Figure 6. The dots colored yellow to red represent the survey exposure metric: that is, share of households within each cluster that report experiencing flooding that caused harvest failure in 2012. There appears to be higher concentrations of flood reports in the south west and north east of the country, but self-reports to the 2012 event seem to be widespread in the survey data. The satellite data, alternatively, appears to represent overflow associated with the two main rivers of the country (Niger and Benue) and their confluence in the south west. There is some flood inundation in the north and north east, likely representing flood from smaller rivers. The survey and satellite (5km buffer) are positively correlated, but only slightly, with a correlation coefficient of 0.20. While this low correlation may appear surprising, these two metrics differ based on the source (human self-report or satellite) and measure different aspects of the flood (with the satellite likely capturing large river overflow). In general, the flood exposure metric from the survey can be interpreted as an individual-level metric, while the satellite exposure metric can be inferred as an area-based indicator of flood.

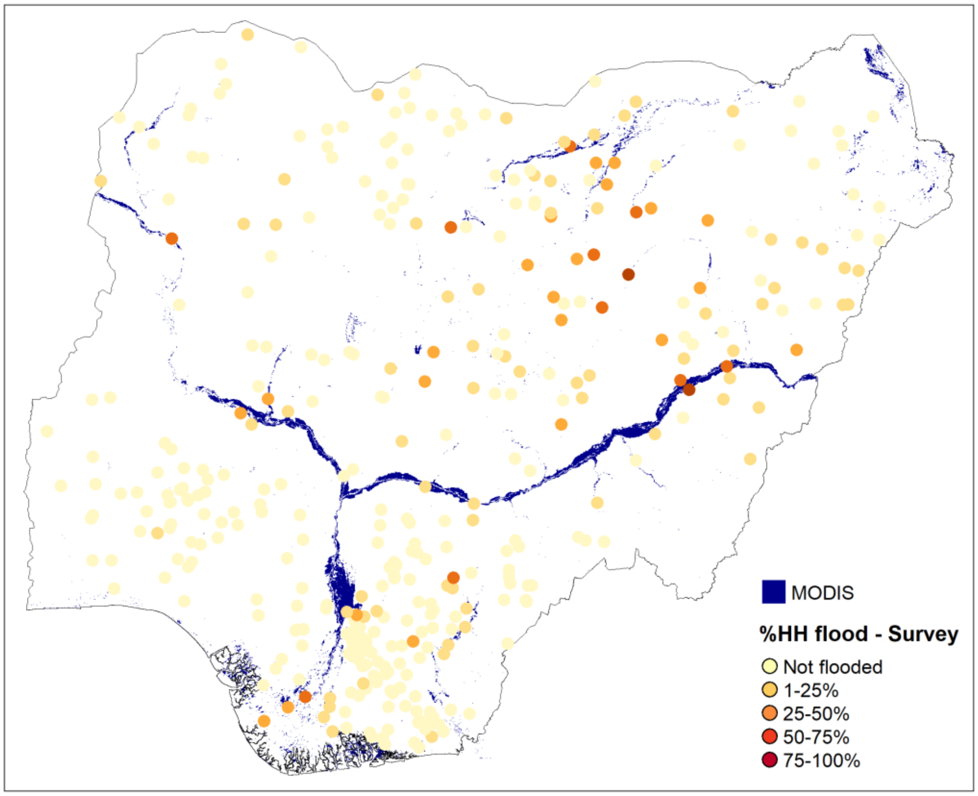


Figure 6. Overlay between household survey data and flood extent from the MODIS satellite during the 2012 rainy season (July-October). Due to privacy reasons, all 10 households in each survey cluster has the same GPS coordinate, and this coordinate is offset by 0-5km. The "share of HH cluster flooded" presents information on how many of the 10 households report experiencing a flood that caused harvest failure within each cluster.

Results

Direct impacts of the flood on agricultural production

The results for the impact of the flood on crop production are presented in Table 3, for total and crop-specific production for the 3 major crops[4]. Separate regression results are presented for the survey and satellite metrics. For the survey metric, agricultural households who were flooded in 2012 experienced a statistically significant decline in total crop production by around 23% for the W95 sample. Crop-specific results find consistent drops in maize, sorghum, and cassava. For the satellite metric, a smaller drop in agricultural production is observed (around 13%) and is statistically significant at the 10% level for the W95 sample. The crop-specific results do not find statistically significant drops in maize and are inconsistent across W99 and W95 samples for

[4] Results for other main crops – Cowpea, Millet, Yams, and Rice – can be found in Appendix 1.

cassava. For sorghum, the survey metric finds a significant decrease, while the satellite metric finds the opposite. One hypothesis is that sorghum may be planted at different times for the areas that are covered by the satellite flood map versus the places where households report a harvest failure.

	(1) Total W99	(2) Total W95	(3) Maize W99	(4) Maize W95	(5) Sorghum W99	(6) Sorghum W95	(7) Cassava W99	(8) Cassava W95
Flood (Survey)	-464.0 (453.1)	-634.5*** (245.5)	-137.4 (131.5)	-145.9* (76.64)	-149.5 (97.01)	-188.9*** (63.81)	-718.9** (357.6)	-335.8** (134.4)
Flood (MODIS)	-438.4 (316.6)	-329.0* (184.5)	-119.7 (100.1)	-98.07 (61.60)	292.2*** (90.32)	202.8*** (62.89)	-613.0*** (217.4)	-83.48 (104.8)
Obs	5,126	5,126	2,592	2,592	2,418	2,418	1,438	1,438
N of HH	2,563	2,563	1,296	1,296	1,209	1,209	719	719
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	HHID	HHID	HHID	HHID	HHID	HHID	HHID	HHID

*Table 3. Effect of flood on agricultural production, for all crops and for there main crops (maize, sorghum, and cassava). Each column represents a separate regression – with the survey flood metric presented above the satellite flood metric. W99 indicates the dependent variable is top-end windsorized at the 99th percentile, W95 indicates the same method at the 95th percentile. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

The results for crop value are presented in Table 4. Households reporting flood in the survey experience a large and statistically significant drop in crop value by around 40,000-50,000 Naira (~250-315$ USD), or 35-40% of the mean value. For the satellite metric, the results are not statistically significant, with the point estimates close to zero for the W95 sample. Taken together, the results from Table 3 and Table 4 suggest that households who self-report flood experience a large and statistically significant decline in crop production. For those living in a flooded area (using the satellite metric), the results on production are inconsistent and are insignificant for crop value.

	(1) W99	(2) W95	(3) W99	(4) W95
Flood (Survey)	-50,577*** (12,294)	-38,505*** (8,259)		
Flood (Satellite)			-7,719 (11,087)	1,507 (7,089)
Obs	5,126	5,126	5,126	5,126
N of HH	2,563	2,563	2,563	2,563
Controls	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	HHID	HHID	HHID	HHID

*Table 4. Effect of flood on agricultural crop value, for all crops. W99 indicates the dependent variable is top-end windsorized at the 99th percentile, W95 indicates the same method at the 95th percentile. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Distributional effects of the 2012 flood

The survey flood metric is an estimate of individual-level exposure, while the satellite metric can be informative on the level of flooding in a particular area. In this section, I explore how an agricultural household's impact from the 2012 flood may be determined by both the individual-level exposure and that of their neighbors (e.g. the surrounding area). The results are presented in Table 5 and Table 6. For agricultural production (Table 5), households who live in a flooded area and individually report being flooded (Columns 2 and 5) experience a statistically significant drop (for the W95 sample) accounting for a third of the mean value. This is larger than the 20% effect found for the individual-level metric alone (Table 3). The effect of living in a flooded area is quite different for households who do not individually report being affected (Columns 3 and 6), with the point estimate insignificant and dropping close to zero.

For agricultural value (Table 6), households who live in a flooded area and individually report a flood experience negative impacts larger than only individually reporting a flood (Table 4). This subset of doubly-affected households (Column 2 and Column 5) experience a drop equivalent to 50-70% of the mean crop value. Columns 3 and 6 provide estimates of the effect of living in a flooded area on crop value, if the household does not itself report an individual-level exposure. Here, I find that the crop value increased for this subset, which is statistically significant at the 1% level for the W95 sample and economically meaningful. These individually-unaffected households may have benefitted from living in a flooded area, with an increase in crop value of around 20,000 Naira (~$125 USD), or a 20% compared to the mean.

	(1) All W99	(2) Survey=1 W99	(3) Survey=0 W99	(4) All W95	(5) Survey=1 W95	(6) Survey=0 W95
Flood (Satellite)	-438.4	-1,463	-165.7	-329.0*	-926.5*	-104.7
	(316.6)	(957.3)	(342.7)	(184.5)	(491.8)	(201.6)
Obs	5,126	488	4,638	5,126	488	4,638
N of HH	2,563	244	2,319	2,563	244	2,319
Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	HHID	HHID	HHID	HHID	HHID	HHID

*Table 5. Effect of living in a flooded area on total agricultural production, for households who also report being individually affected (Columns 2 and 5) versus those who do not report being individually affected (Columns 3 and 6). W99 indicates the dependent variable is top-end windsorized at the 99th percentile, W95 indicates the same method at the 95th percentile. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

	(1) All W99	(2) Survey=1 W99	(3) Survey=0 W99	(4) All W95	(5) Survey=1 W95	(6) Survey=0 W95
Flood (Satellite)	-7,719	-84,445***	17,449	1,507	-52,440***	20,162***
	(11,087)	(27,251)	(11,525)	(7,089)	(16,878)	(7,464)
Obs	5,126	488	4,638	5,126	488	4,638
N of HH	2,563	244	2,319	2,563	244	2,319
Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	HHID	HHID	HHID	HHID	HHID	HHID

*Table 6. Effect of living in a flooded area on total agricultural value, for households who also report being individually affected (Columns 2 and 5) versus those who do not report being individually affected (Columns 3 and 6). W99 indicates the dependent variable is top-end windsorized at the 99th percentile, W95 indicates the same method at the 95th percentile. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Why might households living in affected areas benefit from an extreme event like the 2012 floods? One hypothesis is that the price of food increases after a local production shock (Barrett, 2010). For example, Baez et al. (2017) documents a 17% increase in food prices after Tropical Storm Agatha hit Guatemala in 2010. If flooded areas experience an increase in food prices, households who have retained their harvest may be able to benefit from higher sales prices at the market. To test this hypothesis in Nigeria, I collect food price data from the community interview as part of the same household survey. The data is not comprehensive and provides market prices for 321 communities (or 1/3 of all communities in Nigeria) for all staple crops: maize, sorghum, cassava, cowpea, millet, yams, and rice. Similar to the agricultural data, the price data are highly skewed. In this case, since there are no zero values, I take the natural log of the price, and compare changes from Wave 1 to Wave 2.

Of these 321 communities, I provide two classifications of flooded/non-flooded, either based on the survey or satellite. For the survey method, communities are classified as flooded if at least one household in the community individually reported a flood in 2012. For the satellite method, I classify the community as flooded if at least one household in that community lives in the flood zone. The results are presented in Table 7 using the same regression framework presented in Equation 1, without community controls.

	(1) Log Food Price	(2) Log Food Price
Flood (Survey)	.302**	
	(.147)	
Flood (Satellite)		-.011
		(.174)
Obs	2,057	2,057
N of HH	1,031	1,031
Controls	No	No
Community x Crop FE	Yes	Yes
Time FE	Yes	Yes
Cluster	Community	Community

Table 7. Change in log food prices before and after the flood, for both flood definitions (Survey and Satellite). Food prices for major crops: maize, sorghum, cassava, cowpea, millet, yams, and rice.

Using the survey definition, communities that were flooded experienced an increase in log food prices by .302, which is statistically significant at the 5% level. This translates to a 35% increase in local prices (measured by Naira/kg). However, when using the satellite definition, no changes in food prices are observed. As these two definitions classify very different areas of the country as being flooded (Figure 6), it is no surprise the two diverge. Furthermore, the other 2/3 of the country are omitted, which may or may not yield similar results to the non-representative sample of 318 communities presented here. Taken together, there is suggestive (but not concrete) evidence that food prices may have increased in flooded areas.

Conclusions and policy implications

The 2012 floods in Nigeria were unprecedented, led to over 431 fatalities, displaced almost 1 million people, with economic damages estimated at $16.9 billion USD. However, this does not tell the full story on the impact on the livelihoods of the poorest, which is a focus of this paper. This paper makes three main contributions: (1) it assesses exposure to weather shocks using both survey and spatial data in the same context, (2) it investigates agricultural impacts along two dimensions – production and value, and (3) it examines how impacts of the flood depend on the level of affectedness of your neighbors and market factors.

By combining household survey data with spatial data on the flood's extent, I find affected farmers lost around 20% of crop production. Furthermore, I find that impacts on livelihoods also depend on whether the surrounding area is affected. Households who live in flooded areas and experience harvest failure experience a decline of around $280 USD in crop value, which is around 40% of the mean value. However, households who live in flooded areas but retain some portion of the harvest experience increases in crop value by around $125 USD. Suggestive evidence is presented that these farmers may have benefitted due to higher food prices for staple crops in flooded areas.

The results of this paper show that the same flood event can be measured very differently, with outcomes similarly varying. When studying extreme events, it is important to clearly define and state how exposure is classified, and to collect as many local details as possible to understand heterogenous effects and distributional impacts.

In terms of policy implications, despite the significant impacts on the livelihoods of affected households, there is little evidence of government support. Of the 250 households who report experiencing harvest failure due to flooding in 2012, less than 10 report receiving assistance from the government. The is in stark contrast to a majority of households who report doing nothing. As one household recounted, "Farmers cried bitterly, and nobody helped us" (Unah, 2017). With only 4% of Nigerian households are covered by a safety net, the findings of this paper suggest a stronger role for post-disaster support from the government. Future research on the institutional setting can help inform which mechanism of support – whether it be a cash transfer, release of grain reserves, or food price stabilization – is most effective in Nigeria.

In addition to post-disaster support, there are also opportunities to plan for more extreme floods expected with climate change. Some of the institutional infrastructure is already in place: The Nigerian Meteorological Agency warned in March 2012 of severe floods during the rainy season, but little action was taken to prepare (NIMET, 2012). An immediate policy change could be to better communicate early warning signals to reduce the loss of life and property damage. Improved methods of risk communication and agricultural extension could also encourage and support farmers to plant flood-resistant crops and build on-farm infrastructure to reduce flood impacts. Such adaptation measures can mitigate the impacts of future floods on the livelihoods of the poorest.

Appendix 1

Effects of the flood (survey and satellite) for other crops: Beans, Millet, Yams, and Rice

VARIABLES	(1) Bean W99	(2) Bean W95	(3) Mill W99	(4) Mill W95	(5) Yams W99	(6) Yams W95	(7) Rice W99	(8) Rice W95
Flood, Survey	-25.15	14.59	35.14	9.006	873.9	461.5	22.65	43.81
	(40.10)	(25.75)	(112.1)	(76.69)	(1,018)	(436.2)	(118.2)	(42.86)
Observations	1,968	1,968	1,494	1,494	1,712	1,712	966	966
R-squared	0.009	0.016	0.047	0.078	0.081	0.100	0.036	0.047
Number of hhid	984	984	747	747	856	856	483	483
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	HHID	HHID	HHID	HHID	HHID	HHID	HHID	HHID

VARIABLES	(1) Bean W99	(2) Bean W95	(3) Mill W99	(4) Mill W95	(5) Yams W99	(6) Yams W95	(7) Rice W99	(8) Rice W95
Flood, Satellite	-4.533	-5.399	281.8***	171.0***	-489.6	-303.9	63.38	22.79
	(40.11)	(27.68)	(102.0)	(63.45)	(539.8)	(254.3)	(154.0)	(53.67)
Observations	1,968	1,968	1,494	1,494	1,712	1,712	966	966
R-squared	0.009	0.016	0.058	0.086	0.081	0.100	0.037	0.046
Number of hhid	984	984	747	747	856	856	483	483
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	HHID	HHID	HHID	HHID	HHID	HHID	HHID	HHID

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