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Risky Environment: How Extreme Weather Conditions in Nigeria Lead to Harvest Failure

Julius Berger[†*]

2nd August, 2024

Abstract

This paper investigates the relationship between extreme weather conditions and the risk of flooding-induced harvest failure in Nigerian agriculture using a probit model. I use household-level survey and gridded weather data to exploit weather variation across time and space. Risk of harvest failure increases for agricultural households with more extreme weather conditions. The effect is especially pronounced for a subsample of households in high-risk areas. Overall, extreme weather conditions more than double the risk of flooding-induced harvest failure. Educational attainment acts as a resilience strategy by enabling individuals to shift into other economic sectors and actively choose a less risky location of residence. Internet access per se does not seem to have a significant impact.

Keywords: Flooding Risk, Nigeria, Agriculture, Resilience Strategy, Education, Communication

JEL Codes: Q12, Q54, I25, D83, N57

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1 Introduction

Floods are the most frequent natural disasters worldwide, affecting more than 2.8 billion people over the past three decades (Pielke, 2013). They are also the most devastating weather extreme, accounting for 80% of deaths and 70% of economic losses linked to natural hazards with the agricultural sector affected in particular (Jacobsen et al., 2012). Especially developing countries such as Nigeria suffer severely from extreme weather conditions due to their geography and lack of appropriate resilience strategies (Dell et al., 2012; Loayza et al., 2012).

Economic and health impacts of such extremes are well-studied (e.g. Dell et al., 2012; Salvucci and Santos, 2020; Jacobsen et al., 2012). However, causes of flooding, the involved risk structure, and the impact of an expected intensification of extreme weather events due to climate change still need to be assessed (Auffhammer and Schlenker, 2014; Adger et al., 2003). There is also a need to identify socio-economic groups bearing most of the risk in order to develop effective resilience measures to protect them. This paper investigates environmental effects by modeling the impact of extreme weather conditions on the agricultural sector in Nigeria by quantifying the risk of harvest failure due to flooding. It contributes to the growing literature on the effects of climate change on households in developing countries.

The most immediate economic impact of climate disasters is seen in the agricultural sector due to its ubiquity particularly in developing countries and its natural exposure to such events (Auffhammer and Schlenker, 2014; Bosello et al., 2018). Agriculture usually makes up an above-average share of GDP and employment of 20-40% in developing countries (Dell et al., 2012). Shocks to the agricultural sector are especially disastrous as they affect both the farming households directly through harvest failures as well as non-agricultural households indirectly via spillovers of food shortages and associated price increases (Dell et al., 2014; Noy et al., 2019). The effect is particularly pronounced in countries like Nigeria that are predominantly defined by subsistence farming.

Following the global trend, the most common of such climatic shocks in Nigeria are extreme flooding events, having overtaken droughts in frequency and intensity over the past decades (World Bank, 2023). Furthermore, the country is set to suffer most of all African nations from harvest failures caused by natural hazards due to climate change (Mendelsohn et al., 2000). Cervigni et al. (2013) estimate harvest losses of 20-30% for

Nigeria until 2050 and Tiague (2023) finds a significant drop of 34% in the value of crop production for households affected by flooding in a similar setting in Tanzania. Urama et al. (2019) show that a major flooding event in Nigeria 2012 affected households rather heterogeneously and highlight the need for effective adaptation strategies and resilience building.

Auffhammer and Schlenker (2014) discuss already prevailing implicit adaptation to climate change. Such adaptation is often focused on crop adjustments or changes in land use (Dell et al., 2014). Del Ninno et al. (2001) and Blankespoor et al. (2010), however, highlight the need for more explicit resilience measures from the institutional level against individual extreme events. The literature identifies education (Mavhura et al., 2013; Striessnig et al., 2013) and communication (Smith et al., 2018; Field et al., 2012) as vital resilience measures. However, these analyses lack a quantification of the potential these measures have in reducing the risk from natural disasters, which I address in this paper.

Existing literature mostly evaluates isolated flood events and takes a retrospective view on economic impacts (e.g. Noy et al., 2019; Del Ninno et al., 2001). By contrast, this paper rather aims to provide a more general risk assessment in order to identify highly threatened households. Recognising these at-risk groups facilitates the development of more effective support efforts towards them in coping with the expected consequences of climate change. In particular, targeted resilience policy can alleviate some of the consequences by enabling individuals to take protective measures against them.

Using a micro-approach, this paper studies the risk associated with the ever increasing occurence of flooding and its impact on the socio-economic development of agricultural households in Nigeria. Furthermore, two potential resilience strategies, educational attainment and access to communication, are explored in order to reach policy recommendations to improve the robustness of developing countries against the ramifications of future floods.

I measure weather extremes as short-term deviations from a long-term average. To achieve this, I use the Standardized Precipitation Evapotranspiration Index (SPEI), which is a well-established measure for such deviations in the literature (e.g. Muttarak and Dimitrova, 2019; Azzarri and Signorelli, 2020). Its broad availability for most countries worldwide and its flexibility towards various time frames make it very accessible for a

variety of applications. I assess the impacts of flooding and potential resilience strategies using a survey panel of Nigerian households with a focus on the agricultural sector between 2007 and 2016. The survey provides a broad range of household characteristics as well as information on agricultural activities.

The identification strategy exploits the exogenous variation in extreme weather conditions across time and space using a probit estimation model. The main hypothesis evaluated in this paper assesses the causal relationship between weather volatility and the risk of flooding-induced harvest failure. The analysis identifies the relevant time frames of twelve and six months during which extreme weather conditions have the most devastating effect. The careful definition of relevant subgroups of the population reveals differing risk structures between households in agriculture and other sectors and identifies high-risk groups. Overall, the risk of harvest failure due to flooding more than doubles for years with extreme weather conditions, a result which is very robust across different specifications.

I find the largest absolute effect for high-risk households. Subsequent resilience policy strategies should therefore aim to protect these households in particular. Both, educational attainment and communication access are examined in their qualitative effect on managing risk. The results show that education functions as a resilience strategy both by enabling individuals to shift from agriculture into other economic sectors and by facilitating an informed choice of residence towards safer regions of the country. Internet access per se as a vehicle for knowledge provision does not have a significant impact in making households more resilient.

The remainder of this paper proceeds as follows. Section 2 describes the datasets used for this study. While Section 3 spells out the methodology and empirical strategy applied, Section 4 lays out the results and discusses implications. Section 5 concludes.

2 Data

The data used in this paper consist of two distinct datasets. Climatic developments are approximated using weather variation data at specified grid coordinates. Data about the meteorological impact and economic outcomes are taken from a survey panel conducted on the household level in Nigeria. The weather and household data are matched by

aggregating household location coordinates to the available grid resolution of weather data. The corresponding datasets as well as the most relevant variables are discussed in turn below. Variable definitions and summary statistics can be found in Table A.1 in the Appendix.

2.1 Weather Data

2.1.1 Methods of Measurement for Weather and Climate

Methodologically, one of the challenges in the climate-economy literature is the relationship between climate and weather. While climate rather describes long-term trends, weather constitutes short-term conditions that arise locally (Dell et al., 2014). Hsiang (2016) argues for the use of weather data covering a large time frame in order to approximate climatic long-term trends. These long-term trends in turn provide the basis for a comparison to short-term weather conditions or specific events. In the context of climate analysis, weather changes matter not in the absolute sense but in proportion to a region's usual variation. This concept resulted in a recent shift from cross-sectional to panel weather data to account for heterogeneity in impact sensitivity of different areas (Dell et al., 2014). This shift furthermore enables the exploitation of specific variations in temperature, precipitation and other relevant variables over time in measuring their effect on economic outcomes.

Previously, the production function and the Ricardian approaches were the estimation strategies predominantly used in the climate-economy literature with an agricultural context (Deschênes and Greenstone, 2012; Guiteras, 2009). While the former is based on the fact that the climate is beyond a farmer's control and therefore exogenous, it does not allow for adaptation over time as a response to it. The latter measures the effect of weather variation on current hedonic land value in a cross-sectional dataset, therefore implicitly capturing the potential for adaptation and most efficient use, but makes it difficult to exclude confounding factors and attribute fluctuations to climatic events alone.

Taking these problems and the above mentioned features into account, Deschênes and Greenstone (2012) propose a new year-to-year within-region fixed effects estimation strategy using panel data. By evaluating presumably random short-term deviations of precipitation and temperature from a long-term average for specific locations, they aim

to rule out an impact of other confounding variables. This way weather can be interpreted as an exogenous shock, while adaptation over the medium term is still possible.

2.1.2 Standardized Precipitation Evapotranspiration Index

To apply these ideas to the setting at hand, this paper relies on a dataset of relative weather indices by Mistry (2019). The underlying temperature and precipitation data are taken from the Global Land Data Assimilation System (GLDAS)[1] by NASA, combining satellite-based and ground station data. These data are available at a high resolution of 0.25° x 0.25°[2]. Such so-called reanalysis data, interpolated from multiple sources using a climate model, are especially useful in the context of developing countries, where comprehensive data from a single source are often unreliable or not available (Dell et al., 2014).

The resulting dataset covers the period from 1970 to 2016. Weather trends can usually be considered to reflect climatic variation when covering a time frame of roughly 30 to 40 years (Deschênes and Greenstone, 2012). The available period is therefore optimal as a long-term baseline against which short-term variations can be evaluated. The weather parameters are modelled into such an index variable measuring deviations from long-term climate using the ClimPACT2 software package by Alexander and Herold (2016).

The relevant measure of weather variation that is used for this paper is the Standardized Precipitation Evapotranspiration Index (SPEI) introduced and refined by Vicente-Serrano et al. (2010) and McKee et al. (1993). The crucial advantage of the SPEI compared to other potential measures is its multiscalar setup in modelling the climatic water balance, which primarily incorporates both precipitation (potential 'wetness') and temperature (potential evaporation and transpiration) data. The SPEI itself is designed to be normally distributed and standardised to an average value of 0 with a standard deviation of 1, making it comparable over time and space, always considering the specific local conditions (WMO, 2012). Negative deviations from the long-term average can be interpreted as a higher potential for drought, while positive deviations point towards flooding.

[1]The dataset combines the datasets GLDAS-2.0 (1970-2010) and GLDAS-2.1 (2000-2016), resulting in a break in the time series in 2010. Extensive bias correction was conducted to ensure climatologial consistency.

[2]This approximately corresponds to a 27 km x 27 km grid for Nigeria.

SPEI data points are provided on a monthly basis in the format of time frame deviation per month. This means that the SPEI with a time frame of three months before December (SPEI-3m-Dec) can be interpreted as the comparison of weather in this period, October to December, of a given year with the same period of all years on record, i.e. the period's long-term average. For example, the SPEI-6m-Jun of 2016 indicates to what extent the weather during the first half of 2016 deviated from the average weather between January and June of all years on record. Time frames available from Mistry (2019) are 3, 6, 12, 24, 36 and 48 months. The different versions of the SPEI can therefore be used very flexibly and can be adjusted to specific needs.

Panel A of Figure 1 exemplarily shows the distribution of the SPEI measure for the twelve months before December for the households and years in our sample. The fact that it is roughly normally distributed confirms that the period of study is representative for longer-time horizons. The shift of the mean to the right implies a slight deviation of the weather observations between 2007 and 2016 from the long-term average to more (positive) extreme values, which likely has its roots in climate change over the past decades.

Panel B of Figure 1 provides a first indication for the subsequent analysis. The SPEI-12m-Dec is split up for household-years in which harvest failure happened. As expected, the weather is slightly shifted towards positive values, i.e. is more extreme, in years with harvest failure compared to years without such losses.

2.2 General Household Survey Panel

The Living Standards Measurement Study (LSMS) is a long-running project by the National Bureau of Statistics (2020) that aims to provide researchers with household-level data from countries worldwide. As part of the LSMS, in cooperation with the Nigerian National Bureau of Statistics, the General Household Survey Panel (GHSP) is conducted periodically in Nigeria. It focuses on households, their characteristics, welfare and especially agricultural activities. For this paper the study's panel waves one to three covering the years 2007 to 2016 are the most relevant.[3] Wave four featured a new set of house-

[3]As there is an overlap of waves one and two for the years 2009 to 2011, only one of the available observations is retained. The observations for 2009 and 2010 come from 2011's wave one, as this is the closer survey date. Observations for 2011 are from wave two, as wave one was conducted in early-2011 already, to cover potential events after the survey date.

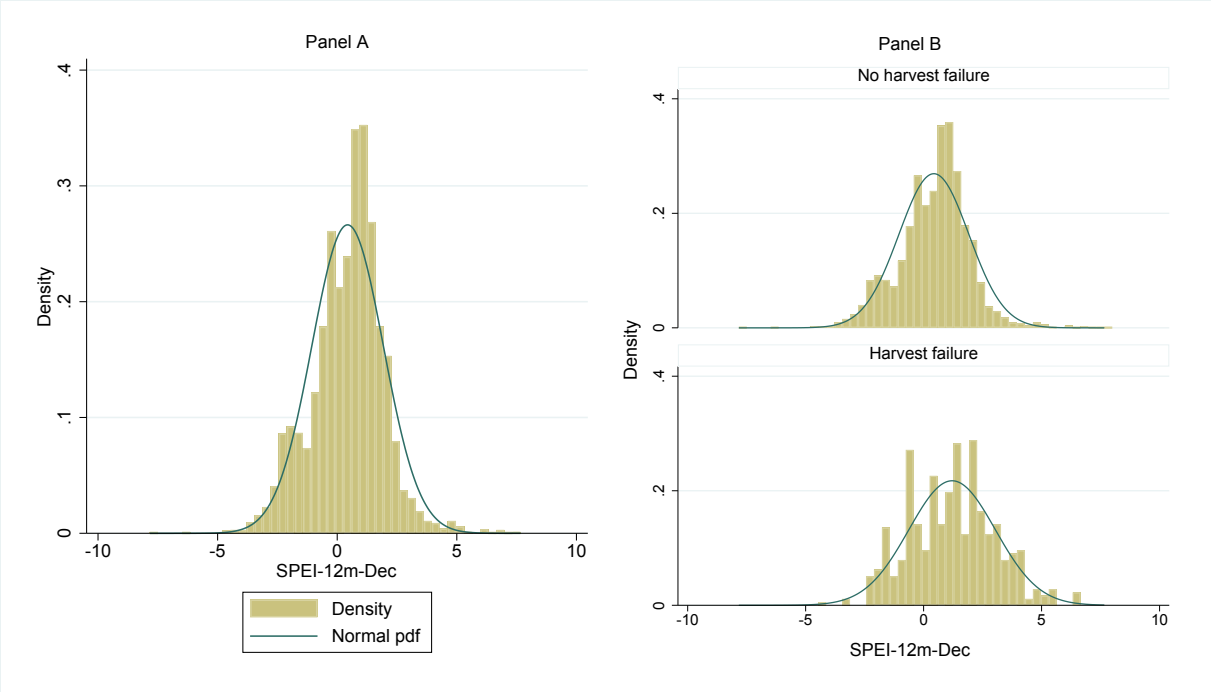

Figure 1: Distribution of SPEI-12m-Dec with the corresponding normal PDF both overall and grouped by household-years with or without harvest failure

holds, retaining only one third of the original sample. For this reason, these data are not leveraged for the main analysis, but only for further evaluations and robustness checks.

The GHSP covers 5,000 households in total, two thirds of which reside in a rural and one third in an urban environment. Some attrition of around 200 households per wave can be observed, which does not alter the representative nature of the data (National Bureau of Statistics, 2020). This is necessary to maintain external validity for the results. The representativeness is achieved by carefully selecting households according to the national and regional population structures. Households are interviewed twice for each wave, with everyone's interview dates being determined by the agricultural calendar. The first interview is conducted during the post-planting period, mainly covering input and labour questions. The second one is conducted post-harvest, mainly covering crops, harvesting activities and economic outcomes related to the harvest cycle. General information about the household and its members is retrieved in both instances. This setup of two interview dates enables consistency checks and a broader scope of questions.

The crucial question in this dataset is *"Has your household been affected by flooding that caused harvest failure in the past years?"*. The binary reply whether such an economic shock occured was recorded to the exact year. The location of households, which is matched to the weather variables, is in close proximity to the respective agricultural plots

(median distance of 0.8km). This ensures that weather shocks can be precisely linked to affected plots and therefore households.

Clustered by household, shock and year, a number of auxiliary variables concerning location, urban versus rural environments and geographical features are included. Furthermore, to test for potential resilience strategies, the education and communication sections of the GHSP are utilised. In particular, datapoints for literacy, educational attainment and internet access are included on the household level.

One potential source of endogeneity bias that should be noted concerns the difficulty to reach certain households when they have been flooded. This would lead to an underestimation of the number of affected households. However, as the National Bureau of Statistics (2020) points out, there was no significant hold-up due to such events.

3 Empirical Strategy

The main hypothesis evaluated in this paper states that the risk of harvest failure due to flooding is driven by local weather volatility. The empirical analysis aims to quantify the impact of varying weather conditions on agriculture, particularly in light of their likely more frequent occurrence in the future due to climate change. The question to be answered is whether such conditions account for the economic damage in the agricultural sector of developing countries, exemplary in Nigeria, that was observed over the past years.

The second hypothesis states that educational attainment constitutes a potential policy goal to increase resilience against the economic damages contingent on the risks of flooding. More educated households are presumably capable of choosing their protections against natural disasters more wisely by physically preserving their harvest using sheltering methods. Alternatively, such households are able to identify and choose to relocate to less risky territory or regions.

The third hypothesis states that the availability of communication and information technology acts as a resilience strategy. In particular, access to the internet not only functions as an early warning system, but also provides necessary information on how to protect the harvest.

The weather data used follow the approach of Deschênes and Greenstone (2012) and Guiteras (2009), which evaluates short-term events relative to a long-term average. This short-term year-to-year variation is assumed to be random and accordingly independent of unobserved factors in agricultural outcomes. The high geographic resolution of the underlying data facilitates a granular analysis of spatial weather variation, enabling the isolation of the meteorological impact as the sole effect by filtering out other regional or national shocks.

Harvest failures are identified using survey panel data covering individual households. The self-reporting of the severity of crop losses and self-assessment of economic outcomes has the advantage of facilitating a precise and individual analysis. Households can evaluate more reliably to what extent they were hit than what would be feasible with aggregated flooding data. The broad range of survey questions furthermore provides a basis for various control variables. Econometric identification is achieved using the spatial and temporal variation of weather conditions across 324 distinct locations in Nigeria over the years 2007 to 2016.

To model the relationship between weather variation and harvest failure, while taking into account the binary nature of the outcome variable, this paper uses the probit estimation method. While OLS provides similar results for the case at hand, which is indicated in Section 4.1, it is only reliable for values close to the average of the sample. The non-linear nature of the probability link function therefore requires a more sophisticated binary response model.

3.1 Weather Deviation

The goal of the econometric analysis is twofold. Firstly, the effect of weather variation on flooding-induced harvest failures is quantified. Multiple estimation strategies of choosing the appropriate variables are outlined and discussed. Secondly, it is investigated whether there is evidence for effective resilience strategies against such events that can point towards sensible policy recommendations.

The estimation equation for evaluating the main hypothesis is

$$Pr(harvestfailure)_{it} = \beta_0 + \beta_1 * SPEI_{it} + X_i + \epsilon \tag{1}$$

The subscripts indicate variation by household (i = household identification number) and year (t = 2007 to 2016). The outcome variable is the binary response to whether a given household i experienced harvest failure due to flooding in each year t. It is transformed into a probability measure using a probit estimation. Standard errors are clusterd on the regional level on which the representative household sampling procedure took place to make the results more robust.

As described in Section 2.1.2, weather variation is measured using the Standardized Precipitation Evapotranspiration Index (SPEI). To precisely analyse the effect of weather conditions within the Nigerian agricultural growing cycle, it is crucial to select an appropriate time frame for the Index. Nigeria has a tropical-warm climate with one main wet season peaking between July and September (World Bank, 2023).

The most obvious time frame is twelve months in order to cover a whole year and therefore the full growing cycle. The advantage of this measure is the inclusion of all seasonal variation during a given year that affects the harvest. Consequently, the relevant independent variable is SPEI-12m-Dec in this case (cf. Section 2.1.2).

A closer analysis of the yearly weather variation, however, reveals a core time frame of about six months during which agricultural production predominantly takes place (Figure A.1). This is largely due to the lack of virtually any precipitation during the dry season, which is especially dominant in the north of Nigeria. Accordingly, the agriculturally most important rainy period is between May and October (Figure A.2), which supports using the SPEI-6m-Oct for the analysis to cover exactly these rainy months. Especially during these months, when flooding is a potential threat, the crops are vulnerable to such disasters due to active cultivation.

Lastly, flash floods are a major concern and increasingly responsible for much of the meteorological damage to households in developing countries. In order to capture these very short-term shocks, the smallest possible time frame of three months is evaluated. The advantage of this brief period is the potential identification of extensive but isolated weather deviation events that might be averaged out in longer observation periods. As this time frame cannot cover the whole growing cycle of all main crops, it is reasonable to select a period when each of these crops is actively cultivated or harvested and flooding consequently has the highest possible impact in terms of harvest failure across various

crops and regions. According to Figure A.1, this applies best to the three months before September (SPEI-3m-Sep).

The basic SPEI variable that was discussed above measures any deviation from the usual weather. However, this paper is especially concerned with *extreme* weather conditions. It might therefore be sensible to only include conditions that exceed a certain threshold (cf. Bertoli et al., 2022). The standardised nature of SPEI makes it easy to only consider weather anomalies that differ from the mean by more than one and a half or two standard deviations. This would respectively consider the categories 'very wet' and 'extremely wet' described by WMO (2012), i.e. the top 6.7% and 2.3% of weather conditions on the flooding spectrum. $SPEI_{it}$ as implemented in estimation equation (1) can therefore be chosen according to the distinct application both on the dimension of different time frames and the dimension of relative intensity.

Furthermore, variation in the individual degree of vulnerability of the 5,000 surveyed households is likely. Some households might even face no threat of harvest failure due to flooding whatsoever, e.g. if their occupation is not in agriculture. It is therefore sensible to run the analysis only for households that have a general vulnerability to such harvest failures. In a first step, non-agricultural households, as defined by the GHSP, are excluded from the sample. This ensures the mere possibility to experience harvest failure and results in a subsample of 3,299 agricultural households, around 66% of the full sample.

An even stronger measure in this regard aims at households that are verifiably highly vulnerable to flooding. The best predictor of such immediate vulnerability is whether a household is ever hit by harvest failure due to flooding during the observed time frame. While the period of analysis remains between 2007 and 2016 due to the restricted availability of weather data, the constructed potential vulnerability measure can utilise data from the most recent fourth wave of the GHSP. The arising subsample covers 475 households, around 9% of the full sample, also including those that were only hit during the years 2016 to 2019. These latter households are a natural control group, as they did not experience a shock during the main period of analysis.

Additionally to the main variable of interest, a vector of control variables X_i is included in the regression equation (1). X_i controls for household-specific effects that stay constant over time. In particular, *Urban* is a dummy variable signaling whether

the household's location is in an urban or rural area; *Slope* indicates the incline of the ground where the household is located; and *HHdistpc* measures the distance to the nearest population center with at least 20,000 inhabitants. Additional time fixed effects are not necessary for this analysis as they are implicitly contained in the SPEI measure.

3.2 Resilience Strategies

Having identified the channel through which weather volatility can potentially harm households, this poses the question of how to counter such exposure. The second aim of this paper is therefore the development of potential policy recommendations on how to protect households from floods in order to make them more resilient against weather extremes and future climate change implications. Resilience is defined as the building up of human, economic or physical capital that serves the purpose of making households less vulnerable to exogenous shocks and reducing the risk of an adverse economic impact.

Both presented strategies roughly follow the econometric setup used for the analysis of weather variation in equation (1). The estimation uses the probit method as well as the established variable indicating harvest failure due to flooding as an outcome measure. This way, the impact of the proposed resilience strategies on the risk of economic damage can be assessed directly in relation to the impact of weather variation. Additionally, the results are comparable amongst different strategies.

3.2.1 Education

Education policy is generally seen as one of the most pivotal instruments for improving productivity, welfare and economic outcomes in developing countries (Patrinos and Psacharopoulos, 2010). However, it might also have further positive side effects. Mavhura et al. (2013) find that formal education is a necessary foundation for learning and applying resilience measures to cope with natural disasters. They identify literacy rates as well as the level of educational attainment as good explanatory proxy factors.

In order to replicate this analysis and apply it to the Nigerian setting, two household variables are constructed. As an indicator of literacy is available for every individual in a household, it is possible to derive the household's average literacy rate. The higher this rate, the more educated people live in the household. Consequently, this increases the household's potential to apply existing resilience measures.

An alternative way to measure the level of education is by using the highest educational degree attained by any member of the household. The advantage of taking the maximum value here is that individual household members that are still in school cannot downward-bias the variable. A higher degree of education is hypothesised to indicate a higher propensity to take up resilience measures against flooding damages.

$$Pr(harvestfailure)_{it} = \beta_0 + \beta_1 * education_{it} + X_i + \epsilon \tag{2}$$

While the two channels mentioned constitute a rather short-term advancement, education might also enable resilience in the longer term via two different channels concerning the choice of occupation and residence by the households. Firstly, given a higher education, household members might be able to find work in other sectors or businesses, exiting agriculture and making the household de facto completely resilient against harvest failure. Secondly, they might stay in the agricultural sector, but choose their specific living location more carefully, avoiding areas that are prone to hazards such as river flood plains.

On a final note, in the context of education, there is potential for reverse causality. While education can have the described positive channels, flooding can destroy school buildings or prevent pupils from attending classes, leading to poor education outcomes. However, an analysis of the available data shows that literacy rates are rather stable and independent of flood events. There is furthermore ample evidence in the existing literature that educational attainment has a significantly positive effect on individual resilience (Striessnig et al., 2013).

3.2.2 Communication

Communication and information technology are considered to be some of the most defining factors of today's economy. However, their marginal benefit is likely especially large in developing countries, where the propagation of new technologies is only in the process of catching up to the standards of industrialised nations. Still, the internet has quickly become the most important source of information for individuals in developing countries, which supports the goal of improving resilience against natural disasters by quickly spreading crucial information (Field et al., 2012).

According to Cervigni et al. (2013), the national government of Nigeria increasingly relies on the digital distribution of knowledge, for example through the National Agri-

cultural Research System or Agricultural Development Programs. The internet therefore not only functions as an early warning system in the case of disaster, but also facilitates individual research efforts towards the protection of harvest from floods.

$$Pr(harvestfailure)_{it} = \beta_0 + \beta_1 * internet_{it} + X_i + \epsilon \tag{3}$$

For this analysis, internet access is measured on the household level per year. As only around 40% of households in the representative GHSP sample had access to the internet in 2016, there is potentially large room for improvement. While there could be a confounding effect of education or location of residence, a preliminary analysis of the data only finds a weak relationship between these variables. Alternative forms of communication such as mobile phones or radios could also be used for identification. However, the preliminary analysis shows that they are too commonplace to provide meaningful insights.

4 Results and Discussion

This section brings the outlined empirical strategy to the data and provides an interpretation of the results. Probit coefficients are parameters of the latent (underlying) model and cannot be interpreted directly due to the underlying non-linear distribution function. The marginal effect needs to be calculated for each coefficient at appropriate values. In particular, the subsequent analysis uses the Average Marginal Effect (AME) to estimate the average change in outcome probability.

4.1 Weather Deviation

The evaluation of the impact of weather variation on harvest failures follows three steps. First, the basic probit model under the three identified time frames is presented. Second, the role of relative intensity is examined using weather measures that are *extreme* events, i.e. that are an applicable number of standard deviations away from the average. Third, the effect is explored for different subsamples of the data.

4.1.1 Basic SPEI model

Table 1 reports the estimation results for the first step. The model considers the full sample of households, agricultural and non-agricultural, to obtain a comprehensive picture

of the situation representative for the whole country. While some of these households, i.e. the non-agricultural ones, cannot experience harvest failure, this basic analysis serves as an informative baseline scenario on which the remainder of the results is built. This sample assumption is relaxed in the third part of this subsection in the analysis of relevant subsamples.

Each of the three chosen time frames is shown in two columns, divided into the OLS model results and the Average Marginal Effect AME of the probit model. All models feature the control variables layed out in Section 3.1. The number of observations, consisting of households times the number of years, differ slightly due to attrition in the GHSP and sporadically unavailable weather data.

Column (1) shows the OLS coefficients when harvest failure due to flooding is regressed on the SPEI-12m-Dec measure and the control variables. All coefficients are

Table 1: OLS and probit estimation results of the basic SPEI models for different time frames including household controls

	12 months		6 months		3 months	
	(1) OLS	(2) AME	(3) OLS	(4) AME	(5) OLS	(6) AME
SPEI-12m-Dec	0.00369***	0.00332***				
	(4.73)	(5.00)				
SPEI-6m-Oct			0.00271***	0.00238***		
			(3.68)	(3.66)		
SPEI-3m-Sep					0.000795	0.000723
					(1.38)	(1.24)
Controls						
Urban	-0.00745***	-0.0118***	-0.00775***	-0.0121***	-0.00751***	-0.0120***
	(-3.55)	(-3.43)	(-3.72)	(-3.52)	(-3.65)	(-3.55)
Slope (percent)	-0.000865**	-0.00115*	-0.000811**	-0.00106*	-0.000890**	-0.00113*
	(-3.08)	(-2.42)	(-2.89)	(-2.29)	(-3.10)	(-2.29)
HHdistpc	0.000235**	0.000155**	0.000221**	0.000146**	0.000235**	0.000164***
	(2.98)	(3.16)	(2.86)	(3.02)	(3.02)	(3.32)
Constant	0.00979***		0.0116***		0.0119***	
	(3.68)		(4.53)		(4.73)	
Observations	47935	47935	48128	48128	47889	47889

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

significant at the 0.1%-level. As argued in Section 3 and now confirmed quantitatively, the results for OLS have a similar magnitude for central values of the sample as the probit model's AME.

The quantitative interpretation of the probit model is derived using the Average Marginal Effect in column (2). The AME of SPEI-12m-Dec indicates that an infinitesimal positive deviation of the weather in a given year from its long-term average, i.e. relatively more precipitation, accounts for an on average 0.33% larger probability of harvest failure due to flooding. A more intuitive interpretation, for example when the SPEI changes by one unit, is not possible due to the non-linear nature of the underlying variable. This will be elaborated on below.

The control variable *Urban* has a negative effect, indicating that households in a city environment have a lower risk of harvest failure than those in rural areas, which is plausible as urban households are less likely to be active in the agricultural sector. *Slope* also has an expectedly negative effect. A steeper incline of the ground facilitates faster drainage of precipitation to lower-lying areas. Lastly, *HHdistpc* is positively associated with harvest failure as geographic remoteness likely entails worse infrastructure and less outside support in case of devastating weather events.

The AME of SPEI-6m-Oct is about one third lower than the AME of SPEI-12m-Dec. Weather variation in this shorter time frame can only account for an on average 0.24% increase in the probability of harvest failure given the discussed infinitesimal change. This points towards the proposition that flooding is promoted by adverse weather conditions being present over a whole year and growing cycle rather than by shorter-term events during the main agricultural season only. The even smaller and insignificant effect for the AME of SPEI-3m-Sep, which measures the impact of sudden extreme weather volatility, supports this argument. Flash floods are seemingly not as relevant for harvest failures as full seasonal variations. The SPEI-3m-Sep is therefore omitted in the subsequent analysis.

A robustness check for the other direction, evaluating the SPEI-24m-Dec, also returns lower and less robust marginal effects. This highlights the SPEI-12m-Dec and SPEI-6m-Oct as a good compromise between very long time frames that might average out relevant short-term weather events and very brief time frames that cannot provide a full picture of all substantial incidents.

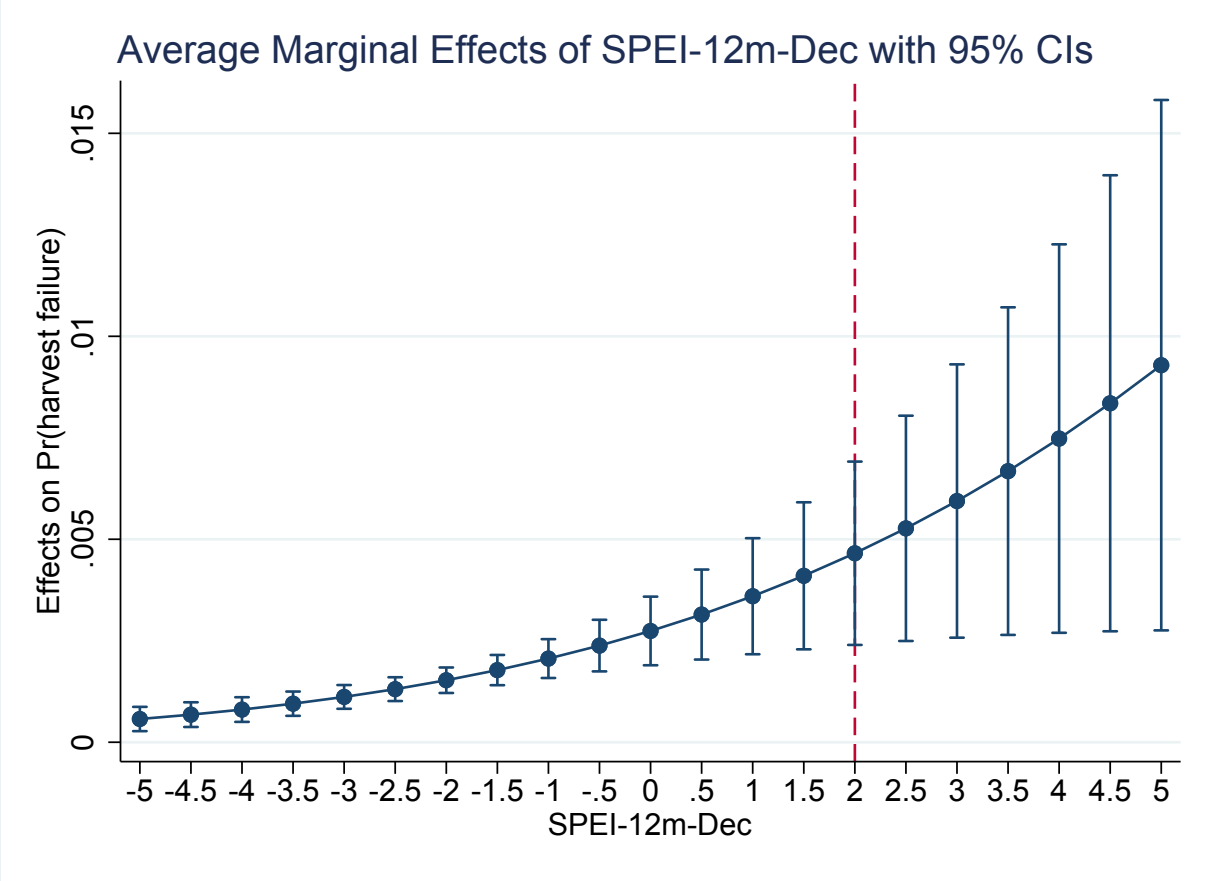

Figure 2: Average Marginal Effects at different values of SPEI-12m-Dec

An alternative representation of the effect of weather variation on the probability of harvest failure due to flooding is shown in Figure 2. It depicts a scenario analysis of the Average Marginal Effect for different values of SPEI-12m-Dec. The idea behind this graph is to imagine a household in a given year that experiences a weather deviation in the direction of flooding risk (positive values) from the long-term average e.g. by two standard deviations (as indicated by the reference line in Figure 2). At this point of evaluation, the weather positively affects the household's probability of harvest failure due to flooding by 0.47%. Furthermore, examining the trend across the AMEs, there is a clear positive association between more extreme weather that can lead to flooding and an increased risk of harvest failure which supports the main hypothesis.

4.1.2 Impact of Extreme Weather

Up until here, weather was considered as a continuous variable on the whole spectrum from ordinary conditions to more unusual events. In the following the focus will be on the latter in order to measure the impact of *extreme* weather conditions in particular. In

the literature there is no common definition of when to consider a weather situation as extreme. However, based on the design of the SPEI variable, it makes sense to choose conditions that are at least a certain number of standard deviations (SDs) away from the long-term average. For the purpose of this analysis weather conditions are defined as extreme if they deviate by at least two SDs from the mean.

The estimation considers the SPEI time frames of twelve and six months as they were identified above to be the most meaningful. The SPEI-12m-Dec-2SD is therefore a binary variable indicating household-years in which the weather was different by more than two SDs from the long-term average. The estimation results for 1.5 SDs are included in Table 2 as a robustness check.

Contrary to the continuous case, interpretation of the effect of a binary independent variable has a more intuitive meaning. The baseline of shock risk (not shown in table) is

Table 2: Probit estimation results of the extreme weather SPEI models for different time frames with household controls

	12 months		6 months	
	(1) AME	(2) AME	(3) AME	(4) AME
SPEI-12m-Dec-2SD	0.0151***			
	(6.94)			
SPEI-12m-Dec-1.5SD		0.0118***		
		(6.00)		
SPEI-6m-Oct-2SD			0.0154***	
			(6.51)	
SPEI-6m-Oct-1.5SD				0.0126***
				(6.13)
Controls				
Urban	-0.0118***	-0.0119***	-0.0118***	-0.0122***
	(-3.41)	(-3.45)	(-3.43)	(-3.54)
Slope (percent)	-0.00111*	-0.00110*	-0.00107*	-0.00103*
	(-2.36)	(-2.31)	(-2.24)	(-2.26)
HHdistpc	0.000150**	0.000150**	0.000145**	0.000141**
	(3.04)	(3.01)	(2.89)	(2.88)
Observations	47935	47935	48128	48128

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.1%, meaning that a shock occurred on average in 1.1% of household-years, i.e. around one shock for 1/10 of households in the observation period of 10 years. The AME of SPEI-12m-Dec-2SD then suggests that in a year with extreme weather (top 2.3%) the probability of harvest failure due to flooding is on average 1.5% points higher than in years with more ordinary conditions. This corresponds to more than a doubling of the risk of harvest failure by flooding due to extreme weather relative to the baseline of shock risk of 1.1%.

The AME of SPEI-6m-Oct-2SD is of similar magnitude, which is different to the continuous case in Table 1. This is a likely outcome if the continuous result of SPEI-12m-Dec was an overestimation driven by the months with agricultural inactivity early and late in the year. This finding holds on a lower level of an around 1.2% point increase of risk for the less extreme 1.5 SD-cases as well. The similar magnitudes that can be observed between the time frames support the robustness of the effect.

4.1.3 Subsample Evaluation

Diving deeper into the underlying causes, two relevant subsamples are examined. Firstly, households that are not active in agriculture cannot experience harvest failure and are therefore excluded from the sample. Secondly, households might live in areas where flooding is not very common. It is worthwhile to study the effect only on households that are located in flood plains or other areas with an existing level of flooding risk as they have increasingly been used for settlement in the past years. These households are included in the sample if they *ever* experienced harvest failure between the years 2007 to 2019.

Once again, the results in Table 3 are robust to the choice of time frame. The larger subsample of all 3,299 agricultural households experience a 2.3% points higher probability of harvest failure in the case of extreme weather. Such weather conditions more than double the risk of harvest failure compared to the baseline frequency of shocks for this group of 1.5%. As expected, the effect of *Urban* drops and becomes insignificant as agricultural households are predominantly located in rural areas.

The analysis of the smaller subsample of 475 households in evidently more risky areas should proceed with caution regarding the reduced sample size, which is about ten times smaller than the original sample. Households in this subsample are likely to be

clustered together in a number of regions across the country. A geographical analysis shows that these households are mostly located in the central-western and northeastern parts of Nigeria. They therefore also feature similar underlying conditions which becomes apparent in the insignificance of the control variables. Furthermore, there is a threat of endogeneity, as each household is treated by definition in at least one year.

However, the analysis can still provide important insights into the risk structures behind weather induced harvest failure, especially given the assumed randomness of weather events. According to Table 3, the impact of the occurence of extreme weather conditions in a given year on this risk is an increase by 17.2% (17.6%) points for the time frame of twelve (six) months. The corresponding baseline of shock frequencies for this group is 12.7%. Extreme weather conditions therefore have a substantial impact on the probability of harvest failure for at-risk households. This finding is especially important as the number of such households has been growing in recent years due to expansive housing developments in risky areas.

Table 3: Probit estimation results of the extreme weather SPEI models for specified subgroups and different time frames with household controls

	Agricultural HHs		High-Risk HHs	
	(1) AME	(2) AME	(3) AME	(4) AME
SPEI-12m-Dec-2SD	0.0226***		0.172***	
	(7.24)		(8.74)	
SPEI-6m-Oct-2SD		0.0228***		0.176***
		(6.72)		(8.07)
Controls				
Urban	-0.00642	-0.00669	-0.00773	-0.00411
	(-1.33)	(-1.39)	(-0.48)	(-0.26)
Slope (percent)	-0.00158*	-0.00146*	-0.00370*	-0.00231
	(-2.35)	(-2.16)	(-2.18)	(-1.48)
HHdistpc	0.000174**	0.000168*	-0.0000455	-0.0000306
	(2.73)	(2.57)	(-0.17)	(-0.11)
Observations	31945	31979	4174	4205

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To sum up, this section provides evidence on the conditions under which weather deviations have an impact on agricultural outcomes. The basic SPEI model identifies the most relevant time frames of twelve and six months to focus on in the analysis. There is a distinctly positive relationship between more extreme weather and increased risk of harvest failure. The categorisation into extreme versus ordinary weather conditions makes the results more robust and facilitates an intuitive interpretation of the data. The analysis of relevant subgroups finally reveals strong differences in meteorological risk structures across households in Nigeria. Overall, the magnitude of the impact of extreme weather conditions on the risk of harvest failure is very robust with a factor of around two to two and a half across all results and subsamples relative to the corresponding baseline scenarios.

4.2 Resilience Strategies

After having identified the relationship of weather and flooding-induced harvest failure, this section applies similar methods to examine whether educational attainment and internet access act as resilience strategies against such risk.

4.2.1 Education

As described in Section 3.2.1, a formal education is a necessary prerequisite for both the uptake and the application of available knowledge about flood prevention measures. Investment into education especially in rural areas might therefore enable more sophisticated self-protection by the population.

Educational attainment is assessed using average household literacy rates as well as a measure for the highest acquired degree per household. As can be seen in columns (1) and (4) of Table 4, for the basic model there is a significant and negative impact on the probability of harvest failure due to education, i.e. better literacy or a higher qualification.

However, as devised above, there is a large underlying imbalance between different groups and regions across the country. Restricting the sample to agricultural households in columns (2) and (5) immediately weakens the effect. This points towards a different, longer-term effect of education. Better educated households can diversify into other economic sectors and do not need to rely on agricultural production alone.

Table 4: Probit estimation results of the effect of educational attainment on flooding risk

	Average HH Literacy			Maximum Degree in HH		
	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
Literacy	-0.00916***	-0.00545*	0.000341			
	(-4.92)	(-2.33)	(0.14)			
Degree				-0.00116***	-0.000575	-0.000250
				(-3.52)	(-1.20)	(-0.57)
Agricultural HHs		✓	✓		✓	✓
Location Controls			✓			✓
Observations	47678	31807	31807	41559	26707	26707

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Introducing location controls on the basis of geographic regions in columns (3) and (6), the effect of education completely vanishes. This indicates that educated people might actually be more able to protect themselves from floods. However, they do that by choice of residence rather than by building up physical protections. A higher level of education enables them to select regions that are less prone to flooding-induced harvest failure. Overall, even though due to a different channel than the one stated in the original hypothesis, there is likely to be a significantly positive effect of education in dealing with the risk of harvest failure. The effect might only be seen in the medium to long run.

4.2.2 Communication

The Nigerian government increasingly relies on distribution of agricultural knowledge via the internet (cf. Section 3.2.2). However, according to the GHSP only around 40% of all households had access to the internet in 2016, compared to around 30% of rural ones. The question remains whether mere access to the internet and the potential subsequent broadening of the knowledge base already provides an advantage to households.

The probit estimation on the probability of harvest failure presented in Table 5 finds a diminishing effect of internet access on risk for the whole sample. However, as before there are likely confounding factors that bias the interpretation of this basic relationship. In particular, no significant effect is found for agricultural households, indicating that the effect in column (1) is likely due to higher internet access rates of non-agricultural

Table 5: Probit estimation results of the effect of communication on flooding risk

	Internet access		
	(1) AME	(2) AME	(3) AME
Internet	-0.00536*	-0.00294	-0.000408
	(-2.40)	(-0.89)	(-0.12)
Agricultural HHs		✓	✓
Location Controls			✓
Observations	44816	30154	30154

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

households in urban areas. Overall, there seems to be no strong evidence that internet access per se has a significant effect on mitigating the risk of harvest failure.

5 Implications and Concluding Remarks

The main purpose of this paper is to identify the role of weather volatility in flooding-induced harvest failure for developing countries such as Nigeria. Especially in light of the devastating natural hazards that have been observed in the past years, a clear picture of this relationship provides valuable input into modelling the impact of future events. As climate change intensifies over the coming decades, increasing the frequency of extreme weather events, these results offer the basis for a scenario analysis quantifying the economic damages involved. The proposed estimation using the SPEI measure as well as a probit model present a blueprint for future studies along these lines. The universal availability and flexibility of SPEI, covering both flooding as well as drought events, provide the opportunity for broad applicability across many countries. It is vital to obtain a clear picture of how extreme weather conditions will shape these countries in the next decades.

Using a probit estimation model, this paper assesses the risk of harvest failure due to varying weather conditions. Firstly, the time frames of twelve and six months are identified as most sensible for the analysis as they manage to represent the period most decisive to agricultural outcomes influenced by the weather. A time frame of three or twenty-four months is rejected as this period is too short or long, respectively, to provide valuable insights into the determinants of flooding events. Secondly, the definition of

extreme weather as divergence of at least two standard deviations from the long-term average provides an intuitive interpretation of the risk impact. Thirdly, the impact on agricultural households is expectably distinctly larger. The analysis of households in previously affected areas reveals a subgroup of high-risk households that are a natural focus for mitigating strategies and resilience policy. All results and subsamples have a magnitude of around two to two and a half with regard to the increase of risk of harvest failure above the corresponding baseline scenarios. This underlines the risks involved in the ongoing climatic trends under which developing countries will suffer in particular. Future research should quantify the economic and human losses that follow such an expansion in risk contingent on existing climate projections, such as climate scenarios reaching the 1.5°C or 2°C warming goals.

In order to identify potential resilience strategies, the effect of educational attainment and communication are assessed. Educational attainment, measured as average literacy or highest academic degree in a household, promotes resilience along two trajectories. Firstly, better educated individuals are enabled to shift their work effort into other economic sectors, decreasing their reliance on economic activity vulnerable to weather volatility. Secondly, higher education facilitates a more sophisticated choice of the household's location of residence. Communication, measured by access to the internet per household, does not seem to have an effect on the most affected households. This is likely due to the poor network development into rural regions.

The approach taken also provides further opportunities for future studies. A worthwhile avenue for research concerns the choice of variables measuring the extent of flood events instead of the SPEI variable. A geographical flood model can provide granular insights into the scope and intensity of different flooding events. In particular, the mitigating effect of man-made protections such as dams or drainage channels can be modelled precisely on this basis. However, there is also a clear advantage in the broad availability and simplicity of the SPEI measure. Especially the future impact of climate change in this setting can be incorporated using projections of the underlying weather data. A geographical flood model can therefore be seen only as complementary but never as a full substitute to this analysis.

To conclude, the field of extreme climate impacts in developing countries still provides ample opportunity for further research. This paper provides a framework for an analysis

that is easy to replicate in different environments. A more complete understanding of the underlying causality improves the ability to develop effective policy for resilience strategies.

References

Adger, W. Neil, Saleemul Huq, Katrina Brown, Declan Conway, and Mike Hulme (2003). "Adaptation to climate change in the developing world". *Progress in Development Studies* 3 (3) (July 2003), pp. 179–195. DOI: 10.1191/1464993403ps060oa.

Alexander, L and N Herold (2016). "ClimPACT2 Indices and Software (R Software Package)".

Auffhammer, Maximilian and Wolfram Schlenker (2014). "Empirical studies on agricultural impacts and adaptation". *Energy Economics* 46 (Nov. 2014), pp. 555–561. DOI: 10.1016/j.eneco.2014.09.010.

Azzarri, Carlo and Sara Signorelli (2020). "Climate and poverty in Africa South of the Sahara". *World Development* 125 (Jan. 2020), p. 104691. DOI: 10.1016/j.worlddev.2019.104691.

Bertoli, Simone, Frédéric Docquier, Hillel Rapoport, and Ilse Ruyssen (2022). "Weather shocks and migration intentions in Western Africa: insights from a multilevel analysis". *Journal of Economic Geography* 22 (2) (Nov. 2022), pp. 289–323. DOI: 10.1093/jeg/lbab043.

Blankespoor, Brian, Susmita Dasgupta, Benoit Laplante, and David Wheeler (2010). "The Economics of Adaptation to Extreme Weather Events in Developing Countries". *SSRN Electronic Journal* (January 2010). DOI: 10.2139/ssrn.1542720.

Bosello, Francesco, Lorenza Campagnolo, Raffaello Cervigni, and Fabio Eboli (2018). "Climate Change and Adaptation: The Case of Nigerian Agriculture". *Environmental and Resource Economics* 69 (4) (Jan. 2018), pp. 787–810. DOI: 10.1007/s10640-016-0105-4.

Cervigni, Raffaello, Riccardo Valentini, and Monia Santini (2013). *Toward Climate-Resilient Development in Nigeria*. The World Bank, June 2013. DOI: 10.1596/978-0-8213-9923-1.

Del Ninno, Carlo, Paul A. Dorosh, Lisa C. Smith, and Dilip K. Roy (2001). *The 1998 Floods in Bangladesh: Disaster Impacts, Household Coping Strategies, and Response*. 122. Washington, D.C.: International Food Policy Research Institute, pp. 1–114. DOI: 10.2499/0896291278rr122.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2012). "Temperature Shocks and Economic Growth: Evidence from the Last Half Century". *American Economic Journal: Macroeconomics* 4 (3) (July 2012), pp. 66–95. DOI: 10.1257/mac.4.3.66.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2014). "What Do We Learn from the Weather? The New Climate-Economy Literature". *Journal of Economic Literature* 52 (3) (Sept. 2014), pp. 740–798. DOI: 10.1257/jel.52.3.740.

Deschênes, Olivier and Michael Greenstone (2012). "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply". *American Economic Review* 102 (7) (Dec. 2012), pp. 3761–3773. DOI: 10.1257/aer.102.7.3761.

Field, Christopher B, Vicente Barros, Thomas F Stocker, and Qin Dahe (2012). *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. Ed. by Christopher B. Field, Vicente Barros, Thomas F. Stocker, and Qin Dahe. Cambridge: Cambridge University Press. DOI: 10.1017/CBO9781139177245.

Guiteras, Raymond (2009). "The impact of climate change on Indian agriculture". *Manuscript, Department of Economics, University of Maryland, College Park, Maryland*.

Hanisch, Wolfgang (2006). *Climate Chart Jos, Nigeria*. GeoKlima 2.1.

Hsiang, Solomon (2016). "Climate Econometrics". *Annual Review of Resource Economics* 8 (1) (Oct. 2016), pp. 43–75. DOI: 10.1146/annurev-resource-100815-095343.

Jacobsen, Michael, Michael Webster, and Kalanithy Vairavamoorthy (2012). *The Future of Water in African Cities*. The World Bank, Oct. 2012. DOI: 10.1596/978-0-8213-9721-3.

Loayza, Norman V., Eduardo Olaberría, Jamele Rigolini, and Luc Christiaensen (2012). "Natural Disasters and Growth: Going Beyond the Averages". *World Development* 40 (7), pp. 1317–1336. DOI: 10.1016/j.worlddev.2012.03.002.

Mavhura, Emmanuel, Siambabala Bernard Manyena, Andrew E Collins, and Desmond Manatsa (2013). "Indigenous knowledge, coping strategies and resilience to floods in Muzarabani, Zimbabwe". *International Journal of Disaster Risk Reduction* 5 (Sept. 2013), pp. 38–48. DOI: 10.1016/j.ijdrr.2013.07.001.

McKee, Thomas B, Nolan J Doesken, John Kleist, et al. (1993). "The relationship of drought frequency and duration to time scales". *Proceedings of the 8th Conference*

on Applied Climatology. Vol. 17. 22. American Meteorological Society Boston, MA, pp. 179–183.

Mendelsohn, Robert, Ariel Dinar, and Arne Dalfelt (2000). "Climate change impacts on African agriculture". *Preliminary analysis prepared for the World Bank, Washington, District of Columbia* 25.

Mistry, Malcolm Noshir (2019). *A High-Resolution (0.25 degree) Historical Global Gridded Dataset of Climate Extreme Indices (1970-2016) using GLDAS data*. data set. DOI: 10.1594/PANGAEA.898014.

Muttarak, Raya and Anna Dimitrova (2019). "Climate change and seasonal floods: potential long-term nutritional consequences for children in Kerala, India". *BMJ global health* 4 (2), e001215.

National Bureau of Statistics (2020). *Nigeria National Bureau of Statistics. General Household Survey Panels 2010-11/2012-13/2015-16/2018-19*. DOI: 10.48529/Y9E2-B753.

Noy, Ilan, Cuong Nhu Nguyen, and Pooja Patel (2019). "Floods and Spillovers: Households After the 2011 Great Flood in Thailand". *Economic Development and Cultural Change* (Feb. 2019), p. 703098. DOI: 10.1086/703098.

Patrinos, H.A. and George Psacharopoulos (2010). "Returns to Education in Developing Countries". *International Encyclopedia of Education*. Elsevier, pp. 305–312. DOI: 10.1016/B978-0-08-044894-7.01216-1.

Pielke, Roger A (2013). *Climate Vulnerability: Understanding and Addressing Threats to Essential Resources*. Elsevier, pp. 1–1331. DOI: 10.1016/C2009-1-62116-X.

Salvucci, Vincenzo and Ricardo Santos (2020). "Vulnerability to Natural Shocks: Assessing the Short-Term Impact on Consumption and Poverty of the 2015 Flood in Mozambique". *Ecological Economics* 176 (Oct. 2020). DOI: 10.1016/j.ecolecon.2020.106713.

Shiru, Mohammed Sanusi, Shamsuddin Shahid, Eun-Sung Chung, and Noraliani Alias (2019). "Changing characteristics of meteorological droughts in Nigeria during 1901–2010". *Atmospheric Research* 223 (July 2019), pp. 60–73. DOI: 10.1016/j.atmosres.2019.03.010.

Smith, Christopher J, Russell J Buzalko, Nathan Anderson, Joel Michalski, Jordan Warchol, Stephen Ducey, and Chad E Branecki (2018). "Evaluation of a Novel Handoff

Communication Strategy for Patients Admitted from the Emergency Department." *The Western Journal of Emergency Medicine* 19 (2) (Mar. 2018), pp. 372–379. DOI: 10.5811/westjem.2017.9.35121.

Striessnig, Erich, Wolfgang Lutz, and Anthony G. Patt (2013). "Effects of Educational Attainment on Climate Risk Vulnerability". *Ecology and Society* 18 (1), art16. DOI: 10.5751/ES-05252-180116.

Tiague, Berenger Djoumessi (2023). "Floods, Agricultural Production, and Household Welfare: Evidence from Tanzania". *Environmental and Resource Economics* (Mar. 2023). DOI: 10.1007/s10640-023-00769-3.

Urama, Nathaniel E, Eric C Eboh, and Anthony Onyekuru (2019). "Impact of extreme climate events on poverty in Nigeria: a case of the 2012 flood". *Climate and Development* 11 (1) (Jan. 2019), pp. 27–34. DOI: 10.1080/17565529.2017.1372267.

Vicente-Serrano, Sergio M, Santiago Beguería, and Juan I López-Moreno (2010). "A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index". *Journal of Climate* 23 (7) (Apr. 2010), pp. 1696–1718. DOI: 10.1175/2009JCLI2909.1.

WMO (2012). *Standardized Precipitation Index User Guide WMO-No. 1090.* Ed. by Mark Svoboda, Michael Hayes, and Deborah A Wood. Vol. 21. No. 1090 1090. World Meteorological Organization (WMO), pp. 1333–1348.

World Bank (2023). *World Bank Open Data.* Apr. 2023.

A Appendix

Table A.1: Summary statistics of relevant variables

	Mean	StDev	Min	Max
SPEI-3m-Sep	-.2960906	1.652053	-6.69348	5.90246
SPEI-6m-Oct	-.0156354	1.645714	-6.28203	8.12589
SPEI-12m-Dec	.4347661	1.497626	-7.83143	7.6596
Urban	.324	.4680047	0	1
Slope	3.133817	2.552579	0	30.59215
HHdistpc	19.7324	19.97041	.1	102.2
Literacy	.6621968	.3824755	0	1
Degree	5.158364	2.673462	1	12
Internet	.1563929	.3632314	0	1
Agricultural HH	.6598	.473781	0	1

Definition of variables

SPEI-3m-Sep	Standardized Precipitation Evapotranspiration Index for the three months before September of a given year
SPEI-6m-Oct	Standardized Precipitation Evapotranspiration Index for the six months before October of a given year
SPEI-12m-Dec	Standardized Precipitation Evapotranspiration Index for the twelve months before December of a given year
Urban	Dummy for urban (1) vs. rural (0) household location
Slope	Incline of the household grounds in percent
HHdistpc	Household's distance to the nearest population center ($\geq$20,000)
Literacy	Share of HH members that can read/write
Degree	Highest educational level of any HH member
Internet	Access to the internet (1) or not (0)
Agricultural HH	HH active in agricultural sector

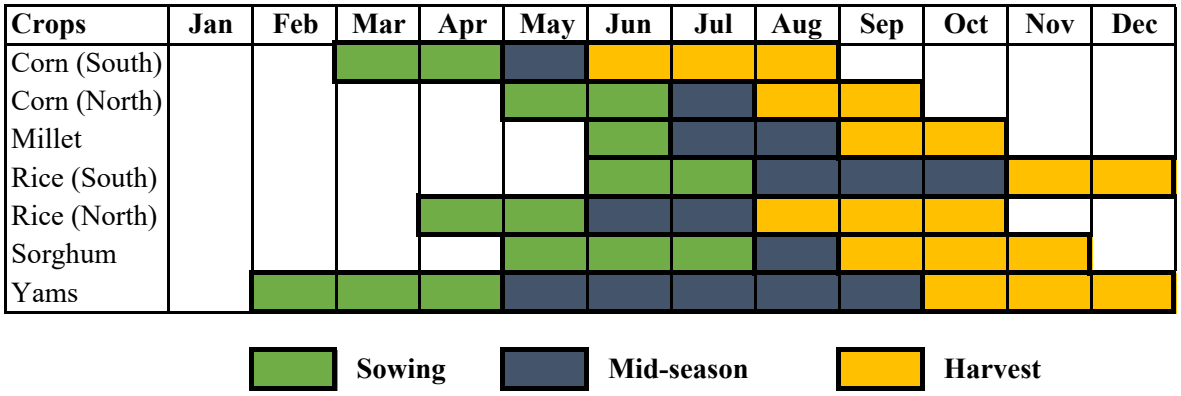

Figure A.1: Growing cycle for main crops in Nigeria adapted from Shiru et al. (2019)

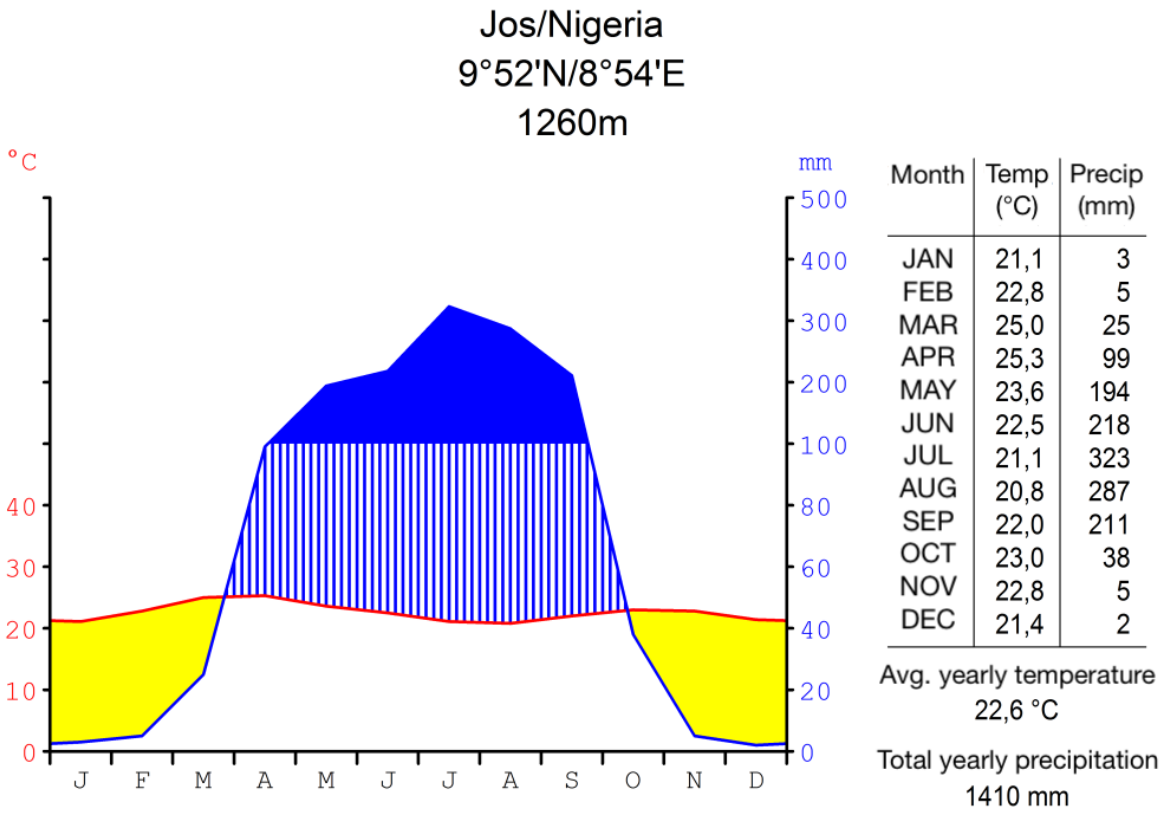

Figure A.2: Climate diagram for a typical central Nigerian city (here: Jos, NIG) from Hanisch (2006)