Impacts of repetitive droughts and the key role of experience : evidence from Nigeria

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Abstract

Western African Sahel faced severe droughts in the 1980s, affecting agricultural production and food security. In recent decades, farmers have faced uncertainty in the timing and amount of rainy seasons and are confronted with erratic rainfall with high interannual variations. Can the experience of past dry events reduce the vulnerability of households to short-term rainfall shocks? In this paper, I match three waves of panel household surveys focusing on agriculture in Nigeria (GHS, from 2010-2016) and high temporal resolution precipitation data set from the Climate Hazard Center (CHIRPS). I show evidence of the extreme importance of the long-dry period of the 1980s and identify more recent droughts in 2013/2015, which are in line with a change in the characteristics of the rainfall trends. Through a two-way-fixed effect strategy, I exploit the spatial variation of the exposition to the 2015 drought. First, I look at the short-term effects of being hit by a drought on agricultural production and food security indicators. I show that being hit by a drought decreases yields by 14%, and decreases the food diversity of households by around 1%. Second, I look at the impacts' heterogeneity according to the plot's experience, using the timing of the year of acquisition of the plot. I compare short-term droughts' effects on households that acquired their first plot before the 1980s dry period to those that acquired it after. Results suggest that acquiring the land before 1985 attenuates the harmful effects of a climate shock, as these particular households have only a 3% reduction in their yields due to the 2015 drought. This is especially the case when households were severely hit in the 1980s. This result might suggest that having a long-lasting experience under extreme dry events on cultivated land reduces vulnerability to rainfall variability.

Keywords: Nigeria, Droughts, Climate Change, Agricultural Production, Adaptation.
JEL codes: Q54; Q56; Q15; Q12 .

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1 Introduction

Reducing the sensitivity of agricultural production to climate shocks is a key factor in tackling food insecurity. In particular for Sub-Saharan countries, where most of the population is rural, involved in predominant rainfed agriculture, soils suffer from aridity and are vulnerable to droughts [Benson and Clay, 1998] and smallholder farmers face malnutrition and limited resources [Lobell et al., 2008]. Historical higher temperature and rainfall fluctuations have reduced economic output in Africa, and especially agricultural productivity [1] and farm income, increasing the gap with developed countries [Barrios et al., 2008; Dell et al., 2012; Nordhaus, 2006] [2].

If rainfall strongly declined during the prolonged dry period of the 1970s-1980s in the Sahel, climatologists have observed a partial recovery of seasonal precipitation in most recent decades [Nicholson, 2005], leading to the re-greening of the Sahel [Brandt et al., 2015; Fensholt et al., 2012]. Satellite-based analysis of vegetation greenness in semi-arid areas has found an increase in the vegetation index, the NDVI, used as a proxy for vegetation production [Fensholt et al., 2012]. However, the NDVI signal combines leaf biomass of woody species and herb biomass, and Brandt et al. [2015] have shown that the greening phenomenon was born by tree species, which are more resilient to droughts than herbs. On the contrary, the dynamics of biodiversity was found to decline over the study period. There is also a debate about the return of normal precipitations [Biasutti, 2019]. Since the 1990s, Sahelian farmers have reported changes in rainfall characteristics, noticing fluctuations in the timing, amount, and pattern of the rains (decreases during shorter rainy seasons) [Tambo, 2013]. Analyses of rainfall trends from gauges find that the recovery results from increases in daily rainfall intensity rather than in frequency, rains being concentrated in the late rainy season and away from the west coast [Giannini et al., 2013; Panthou et al., 2018]. Unlike temperature trends, predictive models for Sahel rainfall changes due to climate change and its impact on yields are also uncertain but point towards more variation in precipitations [Biasutti et al., 2008]. Schlenker and Lobell [2010] predict serious future damages of temperature increase for maize production in Sub-Saharan Africa. Sultan et al. [2013] have realized several projections to quantify the yield responses of varieties of mil and sorghum over Africa to a pair of temperature and

[1] case of Millet in Niger

[2] Under the assumption of climate-economy equilibrium, [Nordhaus, 2006] finds in a global cross-section analysis that 20 percent of the income differences in Africa relative to high-income regions can be explained by geographic variables, including temperature and precipitation, but also elevation, soil quality. Looking at annual changes in historical temperature, Dell et al. [2012] show that being 1°C warmer reduces per capita income by 1.4 %, but only in poor countries.

rainfall anomalies. They show that future responses and patterns will be very different from historical ones, as past mean yields were mainly vulnerable to rainfall anomalies, while higher temperatures will shape future ones.

Such uncertainty about seasonal precipitations is an important challenge for agriculture. Smallholder farmers in developing countries, who lack credit [Cole et al., 2013; Banerjee et al., 2015], and lack information about suitable measures and knowledge of climate change, might be able to mitigate negative impacts using adaptive strategies. However, farmers' perceptions of climate change and variability are hard to assess directly or even proxy. Besides, understanding the long-run effects of climate on agricultural production and other socio-economic outcomes requires distinguishing the historical multiple responses and to link inter-annual and longer-term patterns of precipitations. This project's first goal is to contribute to the literature by linking the recent rainfall variability to the longer-term evolution of the rains. Particular attention is devoted to the analysis of rainfall variability and its relation to changes in precipitation trends over the country. Refuting the theory of the recovery of rainfall over Nigeria, this analysis identifies important droughts over the more recent decades, from 2013-2015, which are linked to less frequent and more intense rains in the long-rain in the Gulf-Guinean part of the country since the dramatic dry year period of the 1980s.

I match socio-economic data from a three-round panel survey, the Nigerian General Household Survey Panel (GHS) to high-resolution historical precipitation data, the CHIRPS product. This paper's research question is to assess the effects of short-term droughts on agricultural outputs and food security. I use a two-way fixed effect strategy over a three years survey panel in 2010, 2012 and 2015. I exploit the spatial variation of droughts occurring before/during the last wave. Second, the main goal is to understand the heterogeneity of the impacts using retrospective questions. Ideally, I aim to test whether past exposure to the severe dry period of the 1980s explains the capacity to adapt to recent rainfall shocks and to reduce the negative impacts on yields and food security. For the moment, I only test a reduced form and run a heterogeneity analysis according to the timing of acquisition of the first plot of the household. I compare the impact of recent rainfall shortages for households that acquired their first plot before the 1980s dry year to those who acquired it later, the hypothesis being that having experience of your own plot under drastic dry conditions might increase your knowledge of climate change, good practices and how to adapt, and thus reduce the effect of recent droughts. The main research question is: can the experience of past dry events reduce the vulnerability of households to rainfall shocks?

The first main result of the paper shows that facing a dry year in the recent decade decreases yields by 14%, and implies a reduction in the diversity food score of households, losing 0.14 food group over 12 (1.2% reduction). The heterogeneity analysis shows that the results are mainly driven by households who acquired their land after the 1980s dry period, especially those that were severely hit by the 1980s droughts.
The heterogeneity analysis suggests that being hit by a drought decreases the yields on average by 19% for households that acquired their first land after 1985, in comparison to those who acquired it previously, for which the effect is attenuated by 16%, facing a 3% decrease. This result suggests that working on the same land that was hit by the intense droughts from 1980s reduces the vulnerability to the 2015 drought. As the year of land acquisition is an endogenous variable, this is only descriptive evidence, and these results can not be interpreted in a causal way. This is a suggestion of the role that plays experience, knowledge, and past exposure to intense dry years. Based on a reduced form, I can not directly conclude whether this means that the land acquisition before past extreme events results in better adaptive strategies and a better perception or knowledge. However, this result suggests that having a long-lasting experience of the cultivated land reduces vulnerability to rainfall shocks, and especially when having experience of the land under past extreme dry conditions.

The remainder of the paper is organized as follows. Section 2 presents the context in light of the literature. Section 3 describes the data, the context, as well and the statistical analysis of long-trends of climate change and how they can be linked to recent rainfall variability. Section 4 details the main empirical strategy. Section 5 introduces the results and Section 6 the heterogeneity analysis, while Section 7 proposes a list of robustness checks. Section 8 concludes.

2 Literature review

Assessing the historical and future effects of climate change and variability on agricultural production requires understanding how farmers adapt or, if not possible, account for it. This is the main limitation of agronomic studies, which construct crop models based on plant physiology to predict how climate change will directly affect yields [Adams, 1989; Adams et al., 1995; Antle and Stöckle, 2017; Asseng et al., 2015] [3]. These studies usually ignore adaptation strategies due to the lack of information on farmers' behaviors and practices and then overestimate the impact of climate change on yields.

The Ricardian method is based on Ricardo's approach that land values reflect land productivity and allow for adaptation (land is put to best use) [Kurukulasuriya et al., 2006; Seo et al., 2009; Seo, 2007; Mendelsohn and Dinar, 2003; Sanghi and Mendelsohn, 2008; Wood and Mendelsohn, 2014; Fleischer et al., 2008; Kurukulasuriya and Ajwad, 2006] . Net revenue or profit from farms are used as a proxy for land values and are regressed on temperature and precipitation, with environmental and socioeconomic controls such as soil quality, latitude for day length, population density for access to market, and opportunity costs of the land. Large-scale studies [Mendelsohn and Dinar, 2003; Schlenker et al., 2005; Kurukulasuriya et al., 2006; Seo et al., 2009; Seo, 2007] have applied the Ricardian model to large countries such as for the US [Schlenker et al., 2005; Mendelsohn and Dinar, 2003], India and Brazil Sanghi and Mendelsohn [2008], and at continental level, and compare values across climatic regions. In a cross-sectional analysis of the two latter countries, [Sanghi and Mendelsohn, 2008] find lower climate sensitivity of agriculture than agronomic models based on yields, because of adaptation mechanisms [4]. Continental cross-sectional Ricardian studies showed the heterogeneity of the sensitivity to climate change within Africa. Kurukulasuriya and Mendelsohn [2008] emphasize the importance of crop switching as an adaptation strategy for farmers. Looking at primary crop choices and production for 11 African countries in 2003, they look at the marginal effects of climate on conditional net revenue, taking into account the probability of crop switching. Results show that farmers adapt their crop choices endogenously to the climate they face, leading to smaller losses.

Smaller scale studies restrict to more homogeneous areas displaying important climate

[3] Asseng et al. [2015] even shows that crops models are less accurate at higher temperatures

[4] When comparing simulations based on their Ricardian analysis to findings from the agronomic literature, the authors find lower climate sensitivity of agriculture (net revenue reduction between 7-17 % in India for a warming of 3.5 with a 7 % precipitation increases, *vs* yields losses between 30-40 %)

variations [Fleischer et al., 2008; Kurukulasuriya and Ajwad, 2006; Wood and Mendelsohn, 2014; Ouedraogo, 2012; Molua and Lambi, 2007], Deressa et al. [2005]. In the Fouta Djallon area (Northern Guinea and Southern Senegal) Wood and Mendelsohn [2014] show that the effect of temperature increases and precipitation variations on net revenue depends on the season considered, and that production losses from the summer and rainy seasons can be balanced by benefits in the winter.

Ricardian approaches argue that the net revenue reductions are lower than predicted losses in yields because farmers' adaptation strategies and potential adjustments are taken into account. However, the Ricardian approach is a partial equilibrium analysis. As agricultural prices are assumed to remain constant, the comparability between negative effects on net revenue and yields does not hold if markets are not integrated, and Ricardian analysis might underestimate the negative effects of climate on crops. Ricardian methods might be biased due to omitted variables acting as confounders of climatic variables in a cross-section. One concern is the forgotten role of irrigation, implicitly relying on a cost fee adaptation, and cannot be used to estimate dynamic adjustments costs [Cline, 1996; Schlenker et al., 2005] [5]. As positive effects of irrigation water access are higher in hotter areas, cross-sectional estimates of the effect of temperature/rains on land values are biased Schlenker et al. [2005]. [6].

In contrast, panel studies [Blanc and Schlenker, 2017; Dell et al., 2012; Deschênes and Greenstone, 2007] look at exogenous year-to-year variations in temperature and precipitation and use location-fixed effects to absorb time-invariant factors. They rule out confounding variation, accounting for the fact that areas might differ in other variables correlated to climate. They estimate the effects of inter-annual variations in temperature and rainfall on yields or profits from deviations from location-specific means. Barrios et al. [2008] and Schlenker and Lobell [2010] use panel analyses to assess the response of yields to climate change for specific Sub-Saharan crops and suggest that well-fertilized modern seed varieties are more sensitive to climate variations.

However, effects and adaptive responses from short-term variations are likely to differ from the ones from climate change in the longer run Dell and Olken [2014]; Auffhammer et al. [2013]. Panel studies look at weather shocks, and because they only take into ac-

[5] Cline [1996] reproaches to Ricardian analysis to implicitly assume infinitely elastic supply of irrigation water at today's prices, potentially wrong for Sub-Saharan countries.

[6] Schlenker et al. [2005] empirically shows that land values vary for dry land versus irrigated American counties.

count coping strategies, they are not informative enough to predict the future evolution of agricultural output. It is still unknown whether short-run responses to weather will increase or decrease damages from long-run global warming. The sign of the bias introduced by estimations from panel data is still debatable. It is commonly assumed that short-run coefficients overestimate the negative effects of longer-run changes on agricultural outcomes because, in the short run, farmers might not have the time to find available adaptive strategies. Otherwise, Schlenker et al. [2005] gives the example of pumping groundwater for irrigation during punctual drought as a short-run adaptation to weather anomalies, which is not tenable in the longer run because of limited resource. This is an example where short-run analysis might underestimate long-run impacts of climate on yields under adaptation. Trying to give an answer to this debate for US trends, Burke and Emerick [2016] compare estimates of the impacts of temperature and precipitation of long difference versus panel strategies. They find negative responses of productivity to decadal changes but cannot distinguish it from responses to annual variation in extreme heat in the same period.

Thus, it is hard to distinguish the different impacts of short-run from long-run climatic factors under adaptation behaviors. Besides, if farmers can choose strategies that will increase yields, such as changing planting dates or crop variety, risk-averse ones might decide to shift to activities less dependent on rainfall and temperature, such as migration, tree planting, or diversification of business activities. If that is the case, studies will misinterpret the impact of climate on agricultural productivity because it does not distinguish between different adaptive responses. One way to investigate this further is to rely on a two steps analysis, taking into account the link between perception of climate change, weather, and adaptation strategies [Maddison, 2007; Tambo, 2013; Silvestri et al., 2012; Komowski et al., 2015]. In a case study in the region of Djougou in Benin, Komowski et al. [2015] find that the most used strategies are tree plantation, shift of planting dates, and use of new crop choices (new crops or mix-crops). Farmers do not directly identify climate change and variability as the main reason for changes in practices and seem to respond to favor short-run food security. In the Nigerian Savannah, the majority of respondents have noticed both a decrease in rainfall and changes in the timing of the rains [Tambo, 2013]. The most common adaptation is the use of drought tolerant and early maturing varieties, but also changes in dates, irrigation, afforestation, and off-farm income diversification. Limitations of this two steps literature are that self-reported perceptions might be biased and that perceptions are not enough to generate adaptive behaviors (credit constraints for poverty-trapped households). Adaptation might happen under collective behaviors rather than based on individual perceptions, and adaptation can reduce vulnerability to climate change without being made under this purpose.

Despite debate about the recovery of rainfall and the re-greening of Sahel since the 1990s, evidence points towards more erratic precipitations [Biasutti, 2019] and decline of biodiversity [Brandt et al., 2015]. Farmers face uncertainty in the timing, amount and pattern of precipitations. Understanding the long-run effects of climate on agricultural production requires distinguishing the multiple historical responses. If Ricardian methods look at long-run impacts and take into account farmers' adaptation by using land values (often proxied by net revenue), they are biased due to omitted variables acting as confounders of climatic variables in a cross-section. Using exogenous inter-annual changes in rains and temperature, panel data rule out confounding variations. However, they take into account coping strategies in responses to short-run shocks, that might differ from adaptation to long-run global warming. The sign of the bias introduced by short-run estimates is not direct. It is not clear whether estimation from panel data relying on year-to-year variations over or underestimates future impacts of longer-run climate change. This is especially the case for Sub-Saharan countries, highly dependent on agricultural activity and with smallholder farmers that might be credit-constrained, lacking information, or risk-averse. As there is a lack of studies differentiating between the effects of different types of adaptive behaviors, this research will contribute by comparing responses and damages linked to inter-annual and longer-run fluctuations. An important part of the paper is to link recent climate variability to long-term patterns and to assess whether exposure to past dry conditions might affect recent responses to rainfall shortages.

3 Data and Context

In this paper, I match socio-economic data from the Nigerian General Household Survey-Panel (GHS), which is a four waves panel survey with a strong focus on agriculture, to the CHIRPS product for rainfall.

3.1 Socio-economic data

The socioeconomic variables are built from the GHS, a panel survey conducted by the Nigerian Bureau of Statistics (NBS [2012]), and the World-Bank as part of the Living Standards Measurement Survey - Integrated Surveys on Agriculture (LSMS-ISA). The survey is a stratified two-stage sample design. Within each of the six Nigerian geopolitical zones, the Enumeration Areas (EAs, also mentioned as villages in this paper) were firstly selected with a probability proportional to the size, and then a random sampling procedure was used to select surveyed households within each EAs. The four waves of the LSMS-ISA are a subsample of the GHS-Panel Sample, which is initially made of 5000 households from 500 EAs, each contributing 10 households. The survey is nationally representative, as well as representative of the Nigerian geopolitical zones. The GHS has been conducted through four waves in 2010/2011, 2012/2013, 2015/2016 and 2018/2019. In each wave, households are visited twice over a 12-month period in order to collect detailed information on agricultural activities. Both post-planting, from September to November, [7] and post-harvest, from February to April, data were collected with Agriculture, household, and community questionnaires.

The GHS-Panel has been conducted over four waves, however, there has been a partial refresh of the sample for the last wave During the fourth wave, 3600 households have been refreshed, added to a subsample of the original panel from 2010. The long panel, including the four waves, includes only 1447 households from 157 EAs. For this reason, this paper focuses only on the three waves, 2010/2011, 2012/2013 and 2015/2016 in order to build a 5 years panel, which is described in Table 9 in Section A.1 in Appendix. The final sample used from the three waves includes 4162 households from 463 EAs, households that have stayed within their 2010 village. Please note that 189 households migrated and were tracked in the second and/or third waves but were not included in the final analysis. Table 10 displays attrition rates for the second and third waves, and shows the levels of attrition overall Nigeria at the household level (2.7% for the second wave *vs* 13% for the third wave). Table 10 identifies higher levels of attrition in the North East and the South West of the country for the 2015/2016 wave.

The coordinates of the EAs have been modified to keep the data anonymous, and the displacement procedure relies on a random offset of cluster center coordinates (the average of household GPS within each EAs) within specific ranges (0-2km for urban areas, while 0-5km offset for rural areas). As the distance between each EAs is higher, there is no mismatch between villages, and I am able to match EAs with their respective climate characteristics as the clusters of climate data is around 5km.

[7]For the three last waves, the timing of the post-planting survey was the same, from September to November. In the first round, the post-planting occurred in August-October 2010 instead

The GHS survey collects rich information on household on-farm and off-farm livelihoods, total agricultural production, agricultural practices, food security outcomes, and welfare variables. The panel dimension makes it possible to control for omitted variables and to adjust for time and spatial-specific confounders. I will exploit a balanced panel in order to capture the heterogeneity in household outcomes and choices when facing rainfall variability.

3.1.1 Mains Variables

The main variables of interest are measured at the household level for each GHS wave. This analysis focus on agricultural production and food security variables. Work-in-progress is made in order to capture the impact of droughts on livelihood strategies - including off and on-farm activities, income diversification [Fowowe, 2020], short-term migration [Ghebru et al., 2019]- as well as other agricultural choices - such as technology adoption [Fadare et al., 2014], farm diversification [Ayenew et al., 2018], land fragmentation [Veljanoska, 2018]. Another variable of interest in this paper, which is used in the heterogeneity analysis, is the year of acquisition of the plot by the household. This section displays some context and descriptive statistics for the main variables.

Agricultural Production

The main variables computed to account for agricultural production are yields. Crop yields are the total crop production per land area planted [8] and rely on self-reported information, both on crop production, and cultivated area. Total crop production is computed for each crop, on each plot of each household per survey rounds. The quantities are computed in kilograms (kg), measured using the conversion factors given by the World Bank, as self-reported crop production are displayed in non standard measurement units [9]. The planted area for each crop is given in hectares (ha) [10] and is self-reported by the household (same for the harvested area).

Self-reported crop yields suffer from measurement errors and are subject to non-classical measurement errors (over-estimated on smaller plots) [Yacoubou Djima and

[8] Robustness checks will be done to compare yields per land area planted *vs* per land area harvested

[9] Households report harvested quantities in kg/gram/litre for standardized measures, but also in number of bags, baskets, basins, bundles, wheel barrows.

[10] The land area is measured using conversion factors as well, as the planted area is displayed in the LSMS-ISA in heaps, ridges, stands, plots acres, hectares and sqmeters

Kilic, 2021; Carletto et al., 2015]. The source of bias is twofold, as both the numerator (total crop production) and the denominator (cultivated land area) face complications [Yacoubou Djima and Kilic, 2021]. Self-reported crop productions suffer from potential recall bias [Wollburg et al., 2021], a high probability of rounding the numbers [Wollburg et al., 2021], and the noise introduced by the use of non-standard measurement units and conversion factors. Accordingly, self-reported land areas suffer from the use of conversion factors and rounding numbers [Carletto et al., 2015], and display discrepancies from GPS-based measures [Yacoubou Djima and Kilic, 2021]. Literature tends to conclude that farmers tend to over-report land areas, all the more at, the lower end of the plot area distribution. Overall, self-reported yields tend to be over-estimated for smaller plots when compared to objective measures, which suggests non-classical measurement errors linked to these data [Yacoubou Djima and Kilic, 2021]. Table 12 from Section A.1 in the Appendix displays descriptive statistics of the main variables of interest and shows the discrepancies between GPS measures and Self-reported measures of land areas. In this paper, I try to correct the self-reported yields by treating outliers according to different techniques. [11]. Another solution will be to look at the correlation of yields (at aggregated levels) with satellite image products, and to correct yields in places with the lowest rates of correlation. Work-in-progress ongoing, using the NDVI and the Global Dataset of Historical yields for major crops, the GDHY (Iizumi and Sakai [2020]; Wing et al. [2021]).

Work-in-progress is made in order to capture variations in agricultural production using another measure than self-reported yields, such as agricultural income (which is, unfortunately, a noisy measure as well). This is also the reason why I also address the effects of rainfall shocks on food security outcomes.

Food Security

Food insecurity is mainly driven by four dimensions, including food availability, food access, utilization, and stability [Bertelli, 2019]. In this paper, I will focus on the two first dimensions, which are food availability and food access. Food availability is captured using a food insufficiency measure, which is a dummy indicating whether, in the past 12 months, the household have been faced with a situation when it did not have enough food to feed the household [12]. Food access is measured using two indicators. Firstly, I use

[11] For the main analysis, the outliers are imputed at the median. For now, outliers are simply defined as the 10% and 90% percentiles of the distribution, work-in-progress is made to change the identification of the outliers, such as data points whose z-score is below the third standard deviation. Robustness checks are made, yields are winsorized and trimmed at 10% and 5%.

[12] this indicator can be also used as a continuous variable, which indicated the number of months of

the food security scale score, also named the Food Insecurity Experience Scale (FIES), which captures the level of food insecurity based on 8 questions on the experience of the last 7 days. These experience questions are listed in Table 11, and the variable displays the number of days when the household faced the particular situation (ranges from 0, never occurred to 7, occurred every day). The FIES is built by summing up all the responses. We follow the strategy from Bertelli [2019], and in the main analysis, I reverse the score so that the higher the FIES, the more food secure is the household, and we standardize the indicator. Finally, I build the Household Dietary Diversity Score HDDS which captures food diversity and is measured as the number of the food groups that the households have consumed during the seven days preceding the survey. The HDDS has been computed by Swindale and Bilinsky [2006], and gathers 12 different food groups : (1) cereals, (2) root and tubers, (3) vegetables, (4) fruits, (5) meat/poultry and offal, (6) eggs, (7) fish/seafood, (8) pulses/legumes/nuts, (9) milk and milk products, (10) oil/fats, (11) sugar/honey, (12) miscellaneous. The main difference between the HDDS from Swindale and Bilinsky [2006] is that it is computed based on the household consumption from the last 7 days, *vs* the last day from Swindale and Bilinsky [2006]. Descriptive statistics of the indicators are displayed in Table 12 from Section A.1 in Appendix.

Year of Land Acquisition

Another variable of interest used in the heterogeneity analysis is the year of acquisition of the land. This is a single variable fixed over waves for each household. For households cultivating several plots, I define the year of land acquisition as the year of acquisition of their first plot. Figure 9b plots the distribution of this variable. If discrepancies existed for the year of acquisition of a particular plot across the three waves, I favored the year that was given by the manager of the plot. If discrepancies still persisted, I took the minimum amongst the year given by GHS. More than the timing of acquisitions, the survey gives insights of how the plot was acquired by the household. Overall, 5.7% acquired it via *"outright purchase"*, 7.5% because *"rented for cash or in-kind goods from"* an outside person. 8.6% respond having acquired the land *"free of charge"*, while 78% report acquiring it because it was *"distributed by community or family, or family inheritance"*. Only the last wave disentangles between *"distributed by community or family"* and *"Family inheritance"*, and shows that the majority of households (70.5% *vs* 7.5) inherited the plot. Inheritance might play an important role in the mechanisms of results from Section 6, and work in progress is done in order to better understand the social and cultural norms

critical situation

of land inheritance in Nigeria.

3.2 Climate data

I use the CHIRPS product by the Climate Hazard Center (CHC), which combines a satellite-based rainfall product (CHIRP [13]) with station observations data. It gives a good spatial (0.05 lat/long), and temporal (daily, decadal and monthly) resolution for historical (1981-2019) mean, maximum and minimum precipitations. It has been validated over Africa and assessed as the best satellite-based product Dinku et al. [2018]. For temperature, I use the CHIRTS product, also from the CHC, which also combines satellite and station-based estimates of maximal temperature (T_{max}), with the same spatial and temporal resolution as CHIRPS Funk et al. [2019].

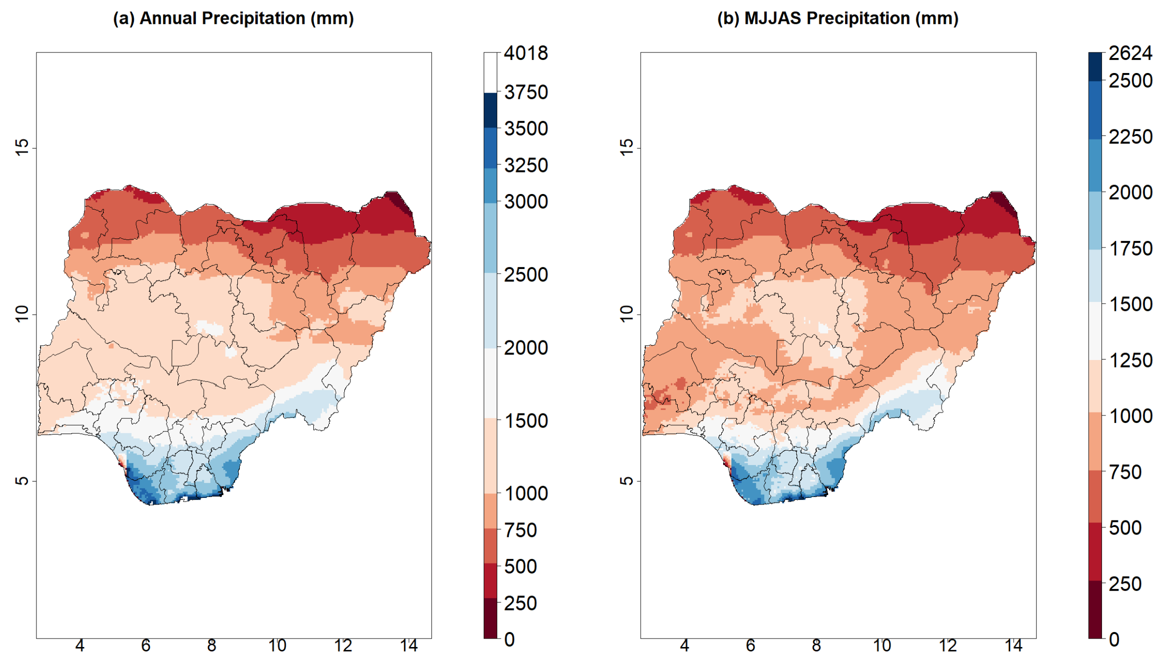
3.2.1 Context and climatology of Nigeria

Nigeria is a context highly dependent on agriculture and rain-fed activities, as 70% of households are engaged in crop farming activities, 47% own or raise livestock, which makes it highly vulnerable to climate events. Nigeria has an impressive population (the most populated African country, around 200 millions), but lacks of adaptive capacity due to low financial and technological tools, weak institutions and low knowledge of climate change. Nigeria includes an important part of Western African farmers that have faced climate change and food security issues and had to adapt to rainfall changes over time. Amongst the adaptive strategy described in the literature, portfolio diversification, changing dates of planting, planting trees, and use of irrigation have been identified in the southern Nigeria rainforest zone Onyeneke and Madukwe [2010]; Sofoluwe et al. [2011]. Crop diversification, but also the change of crop varieties to drought/early mature resistant varieties, and farm relocation are used as adaptive strategies in the northern part of the country Dabi et al. [2008]. Based on a field survey within the Nigerian savanna, Tambo [2013] shows that most of the farmers have noticed changes in rainfall patterns and that those who lack information on climate change are facing limitations in adapting. This shows the key role of the perceptions and experiences of climate change in the adaptive capacity of Nigerian farmers.

Nigeria is a diverse setting, with high heterogeneity of livelihood zones and climatology, from tropical rainforest and tropical monsoon in the south to tropical savanna and Sahel climate in the North. Overall, it has a tropical climate with two seasons, the wet

[13] Climate Hazards Group Infrared Precipitation

Figure 1: Rainfall long-term average



Notes : The Figures represent the spatial distribution of (a) long-term annul average, based on the 1981-2019 long-term period, and (b) the long-term average of the long rainy season MJAS of cumulative precipitation. Units of long-term averages are in mm.
Sources : authors' elaboration on CHIRPS

season being from May to September (MJJAS) (cf Figure 10). Annual precipitation are amongst the highest in Western Africa - especially in the Gulf of Guinea - with a long-term average (1981-2019) of annual rainfall being 1491mm, and of cumulative rains over the MJJAS wet season of 1101 mm. The country displays important differences in terms of climatology, which are shown in Figure 1, which maps the long-term rainfall average of annual precipitation (1 (a)) and of cumulative rains over the long-rainy season, MJJAS (1 (b)). The means are computed from the long-term period from 1981-2019. Nigeria is dominated by four climate types, changing in the meridional direction, from south to north. Monsoons from the Atlantic Ocean influence the south tropical monsoon climate (AM), which is the most humid region of the country, experiencing abundant rainfall (up to 3750mm long-term annual mean). The geography of the southern part of Nigeria is dominated by the Niger Delta, an important river area composed of deltas and humid mangrove swamps. The tropical savanna climate covers the major part of the country, and annual rainfall varies from 1000mm (lowlands) to 1500mm (southwestern). The zone is made of the Guinean forest-savanna (plains and tall grass/trees), then the Sudan savannah is arider (short grass/trees). The northern part of Nigeria lies within the Sahel and experiences a semi-arid climate (BSh), and has dramatic low rainfall, with annual means varying from 500mm to lower than 250mm. The Sahel savanna is mostly composed of grass and sand and is the aridest area o the country.

Across the country, seasonal rainfall patterns also vary sharply in the meridional direction. When averaging rainfall at the country level, the main rainy season, which corresponds to the primary agricultural season, extends from May to September (MJJAS), with a peak in August, as we can see in Figure 10. However, the south of Nigeria has two rainy seasons (cf Figure 11). The first rainy season starts from March to July (peak in June), which is followed by a short dry season (2/3 weeks) in August. The second wet season lasts from September to October. In the northern part of the country, the unique wet season is shorter, lasting from June to September. For the purpose of this paper, we define the main rainy season over the country, the MJJAS period, from May to September. Work-in-progress is made to refine the main rainy seasons according to the agro-ecological zones.

Going further, defining the main rainy season according to the geography, work-in-progress is ongoing to define the main agricultural season according to the main crop (following Wichern et al. [2019], we can obtain crop specific parameters on rainfall using the R package dismo and the Ecocrop database from the FAO). Indeed, the main cultivated crops differ between the main zones, as shown in Figure 13, mainly maize cassava and yam in the south and maize, guinea corn, and beans in the north.

3.2.2 Long-term changes in rainfall patterns and characteristics

The Sahelian Droughts

Nigerian rainfall characteristics from the north, which is part of the Sahel, differ from the characteristics of the rainfall along the coast of the Gulf of Guinea, in the southern part of the country. However, the very dry decades of the 1970-1980 hit both of the regions and had devastating impacts on food and livestock supply. Farmers and pastoralists of the zone had to find adaptive strategies, such as changing the timing of the planting, weeding, and harvesting using different types of crops and varieties, diversifying the livelihoods Mortimore and Adams [2001].

Western Africa Sahel faced severe droughts in the 1970s and in the 1980s. The 1980s decade included some of the most extreme droughts years on record Aiguo et al. [2004]; Nicholson [2005, 2018], which were mostly enforced by sea surface temperature anomalies Biasutti [2019]. The dry events of the 1980s called the 'Sahelian droughts,' are said to be *among the most undisputed and largest recent climate changes recognized by the climate research community* Aiguo et al. [2004]. If these droughts are more associated with the Sahel because they were more pronounced there, they were also dramatic in the Gulf Guinea area. Figure 2 displays the departure of the rains for each pixel from the long-term mean (1981-2019) for each year of the period over Nigeria. It gives the spatial distribution of precipitation extremes for both deficits and intensive rains and displays as well the comparability of the magnitudes of the different events. In line with climatologic literature, Figure 2 clearly identifies the dry period of the 1980s and shows that both the Sahelian and Gulf Guinean parts were severely impacted mostly in the early 80s, 1982, and 1983 being intense dry years with national coverage. We observe the persistence of the dry period up to 1987, mostly in the Sahelian part of the region. Figure 2 also shows the high magnitudes of the 1980s dry events in comparison to the rest of the time period.

Debate on the recovery of the rains in the recent decades - Sahel region

Since the 1980s heavy rains over the Sahel and Guinea Gulf, the climatologic literature observes rainfall trends going upward, referring to the most recent period from 1990 to be a period of rainfall recovery for the Sahel Aiguo et al. [2004]; Nicholson [2005] and the Guinea Gulf Sanogo et al. [2015]. However, the rainfall recovery is debated in the literature, both for the Sahelian Biasutti2019 and Gulf Guinean region Bichet and Diedhiou [2018].

More evidence is found in the literature concerning the Sahel, in particular, thanks to long-term observations such as the International African Monsoon Multidisciplinary Analysis (AMMA - CATCH) program Panthou et al. [2018]. First, evidence from field-surveys show that farmers have noticed recent changes in climate, such as changes in the characteristics of the rain season and more erratic rains Tambo [2013]. Second, statistical studies of rainfall data, both from station gauges and satellite observations, corroborate farmers' perceptions and refute the theory of the return to normal conditions. Giannini et al. [2013] analyze rainfall gauges in Burkina Faso and Senegal and find that the recovery of the rains is mainly born by daily rainfall intensity. Salack et al. [2014] look at interannual rains and intra-seasonal droughts episodes using stations in Senegal and Niger and show that if cumulative rains seem to have reached pre-1970s normal conditions, seasonal rainfall amounts are susceptible to an extreme that implies delayed start and cessation of cropping seasons. Accordingly, Panthou et al. [2014] observe an increased probability of extreme daily rainfall looking at gauges from Benin, Burkina-Faso, and Niger.

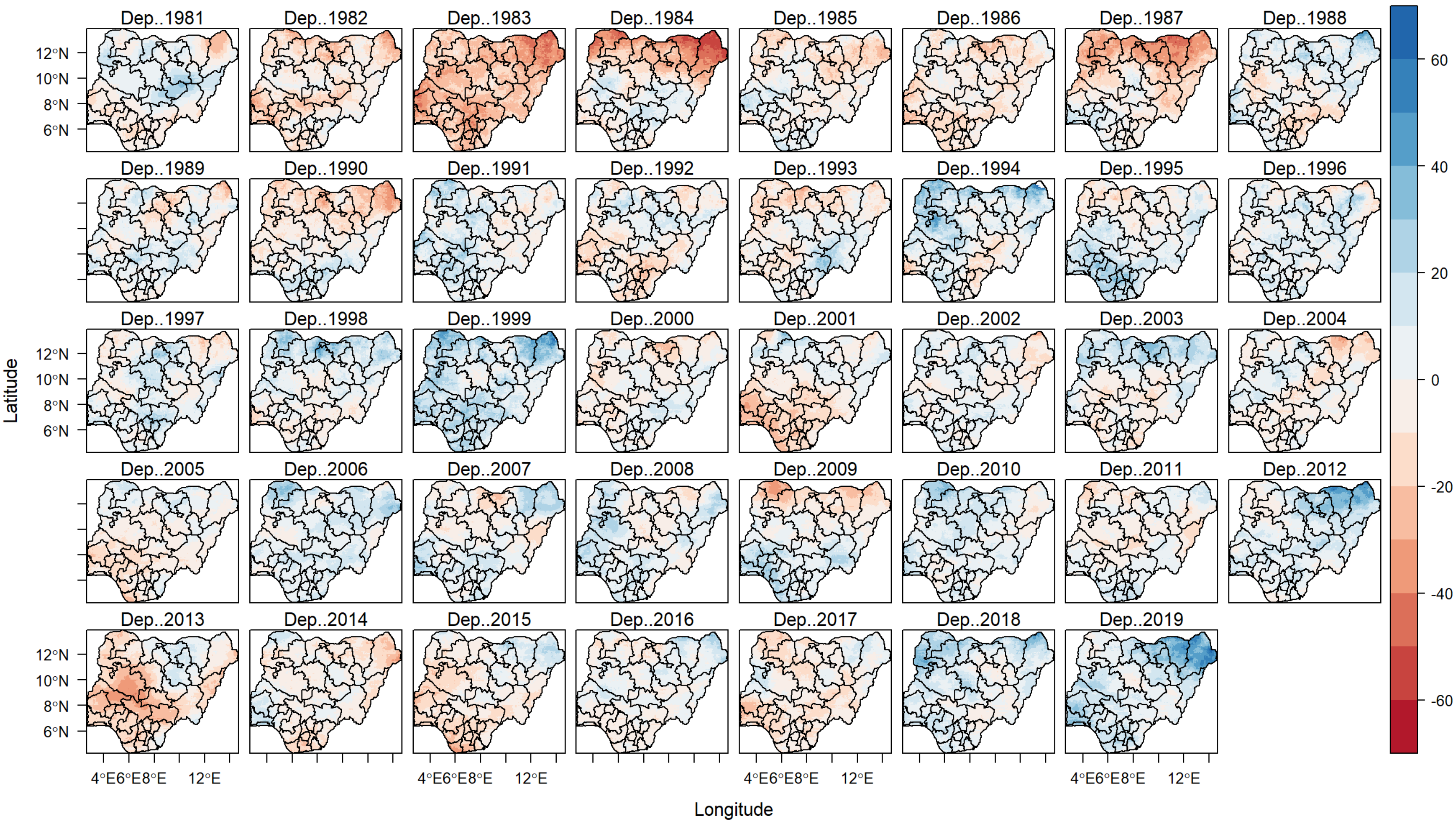
Figures 14, 16 and 17 from Section A.2 display the long-term trends of climatic indicators based on the CHIRPS product over the 1981-2019 period. Figure 14 shows the trends of yearly precipitations (Figure 14 (a)), and of wet season MJJAS cumulative precipitations (Figure 14 (b)) over the long-term period of 1981-2019. Both annual and MJJAS precipitations display a significant increasing trend in the Sahelian part of the country, with up to 11mm increase in the North East. This result is in line with the recovery of the cumulative rains after the 1980s dry decade in the Sahel, a phenomenon that I observe less in the south of Nigeria. Still, in the North, I observe significant changes in the characteristics of the rains. I observe significantly increasing trends in the MJJAS numbers of wet days (Figure 16 (a)), in the number of extreme rains as well (16 (c)), and in the intensity of daily rains (Figure 17 (a)). Trends in patterns and characteristics of the rains entirely depend on the long-term period chosen to describe the evolution. When taking the 1981-2019 long-term period, the severe droughts from the 1980s account for the evolution and mainly explain the partial recovery of cumulative rains. Figures 15 reproduce the exact same figures as Figures 14, but rely on the 30-year period from 1989 to 2019, instead of 1981-2019, excluding the extreme droughts from the 1980 decade. If these figures show that the cumulative rains seem to be increasing on average in the Sahelian region, the trends are no longer significant, suggesting interannual variability occurring in the more recent decades instead of steady trends.

Debate on the recovery of the rains in the recent decades - Gulf -Guinea region and Central Nigeria

Despite the importance of the dry 1980s period in the Gulf of Guinea region, less analysis is made in comparison to the Sahel. However, there is also debate in the literature about the recent decades being a period of partial recovery of the rains of the region Sanogo et al. [2015]; Bichet and Diedhiou [2018]. Using the CHIRPS product over the 1981-2014 overall, the Gullf-Guinea region, Bichet and Diedhiou [2018] find absence of significant trends of rains during the wet season but find trends towards less frequent but more intense rainfall. The results from our study are in line with these results. In Figures 14, 16 and 17, I display trends of rainfall indicators using the CHIRPS data over the 1981-2019 long-term period. Figure 14 shows no significant trend evolution of the annual and wet season rains in the southern and central parts of Nigeria. However, Figure 16 displays a significant decrease in the number of wet days over the main rainy season (Figure 16 (a)), in the south and central regions. This is associated with a significant increase in the trends of the daily intensity of rains (Figure 17 (a)), up to 0.22 mm/day, and a significant decrease in the length of the wet spells (Figure 17 (b)) Consecutive Wet Days Index CWD.

These evolution in the characteristics of the rains are in line with the literature on the climate evolution of rains in the region of Gulf-Guinea, and refutes the fact that recent decades represent a recovery period for Nigeria. We show that the absence of significant decreasing or increasing trends of cumulative rains in the Southern part of Nigeria hides a change in the characteristics of the rains. Rains over the wet season are becoming less frequent, more intense, and more concentrated, which is expected to increase the likelihood of extreme events such as droughts Bichet and Diedhiou [2018].

Figure 2: Rainfall percent departures of the annual rains from the 1981-2019 mean



Notes : The Figure plots the percent departure from the long-term mean of the main rainy season (1981-2019) for each pixels.
Sources : author's elaboration on CHIRPS data.

3.2.3 Main shock of interest

As explained previously, Nigeria faced a severe dry period over the 1980 decade (especially over the early years). Long-term trends evolution suggest less frequent but more intense rains in the south/central region in recent decades, which can cause extreme events such as droughts. If the long-term trends evolution of the Sahelian rains seem to increase significantly, it is entirely driven by the intensity of the dry years over the 1980s. The evolution of the 30 years period from 1981 to 2019 shows no significant trends, and evidence from the literature points to more erratic rains, which increases the probability of droughts as well. Section 3.2.2 shows the key role of the long-term period chosen when looking at rain patterns, which will play a key role in the definition of our main shock of interest.

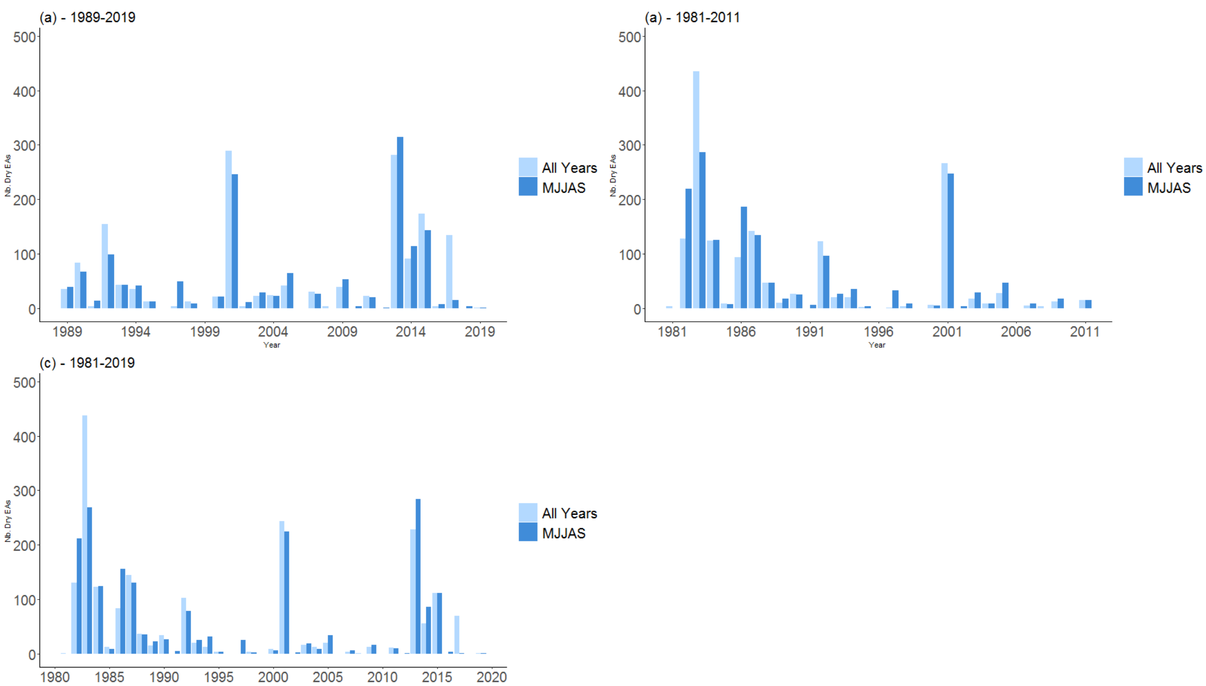
The first part of this paper intends to look at the effects of short-term rainfall variation over agricultural outputs, the GHS panel survey covering the 2010-2016 period. The main dependent variable for the main analysis is defined as follows. I construct a dummy for each year, based on the long-term mean (that will be defined) of each GHS EAs (also called villages in the paper), which equals 1 when the year/MJJAS is dry, 0 otherwise. I define a year/MJJAS season as dry if the cumulative rains over the year/MJJAS are lower than the 15th percentile of the cumulative rains for the EAs over the chosen long-term period. The climatic indicator I will use for the main analysis is whether the year of the survey is dry or if the agricultural season MJJAS is dry the year of the survey. The choice of the threshold is discussed in Section 7.3.1.

Each GHS survey has two rounds. For instance, for the second wave, the post-planting occurs from August to September 2012, while the post-harvest occurs from February to April 2013. The critical timing of the rains for this cropping season is the wet rainy season in 2012, which is defined form May to September, which is why I focus on the rains occurring in 2012. Figure 12 plots this timeline between the cropping seasons and the post-planting and post-harvest GHS rounds.

Figure 19 plots for each year the total number of EAs for which the dummy dry $D_{i,t}$ equals 1. The three figures plot the dry variable for three long-term periods, each of thirty years at least in order to catpure climate change Auffhammer et al. [2013]. Figure 19 (a) plots over the 1989-2019 period, in order to emphasize recent droughts. Figure 19 (b) plots over the 1981-2011 to capture the dry decade of 1980, while Figure 19 (c) plots over the 1981-2019 period, which makes it possible the comparison between recent extreme events and the 1980s dry events. Figure 19 (b) identifies the droughts from 1980s, and underlines the importance of 1982, 1983 and 1984 as dry year (we see that 1983 has a national coverage, as all EAs are dry). Figure 19 (a) shows the 2001 dry year (El Nino phenomenom), and the increase in the frequency of dry events since 2010, in particular for the 2013, 2014 and 2015 years. Over the thirty year period, normal conditions would imply a dry year occuring every decade. Having more than one dry year over the timing of the GHS-panel is the shock that I exploit in order to look at the effect of rainfall variability on socio-economic outcomes. Finally, Figure 19 (c) compares the intensity of the three main dry periods over 1981-2019 (which are 1982-1984, 2001 and 2013-2015).

The main shock used in this analysis will be based on the thirty long-term mean from 1989-2019. I intentionally do not take into account the 1980s dry year in the construction of the independent variable, as they would have influenced the treated group from our

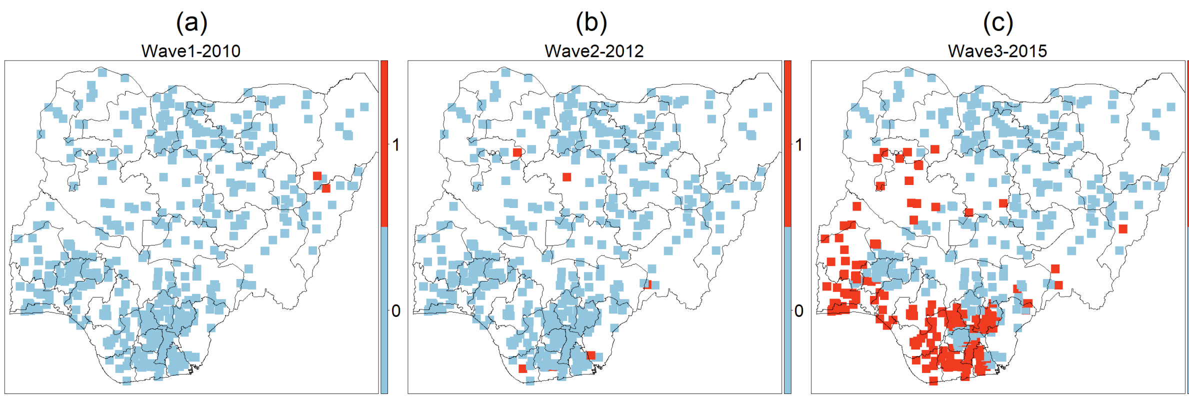
Figure 3: Number of dry EAs according to the long-term average



Notes : The Figures plot the number of GHS villages (over 483 EAs) for which the year is dry, when the dry dummy is built according to different long-term mean. Figure (a) plots the number of dry EAs per year, over the 1989-2019 long-term mean, Figure (b) according to the 1981-2011 long-term mean and Figure (c) according to the 1981-2019 long-term mean. Figure (a) points the importance of the dry period from 2013-2016, Figure (b) of the dry perdion over 1981-1989, while Figure (c) makes it possible the comparison between the two dry spells. The Figure is made for the EAs from the GHS panel.
Sources : authors' elaboration on CHIRPS and GHS data.

Difference-in-Difference strategy (EAs particularly shocked in the 1980s would have been mechanically counted as control, as the main dry years would have been concentrated in the 1980s). As the second goal of this paper is to understand whether the past experience of the 1980s changes the impacts of short-term rainfall variability on agricultural outcomes, I must avoid the independent variable to be *de facto* correlated to the exposition to the 1980s droughts. I must avoid accounting as treated EAs as those that were the least affected in the 1980s decade.

Figure 4: Spatial distribution of the number of dry rainy seasons -Binary treatment- current years



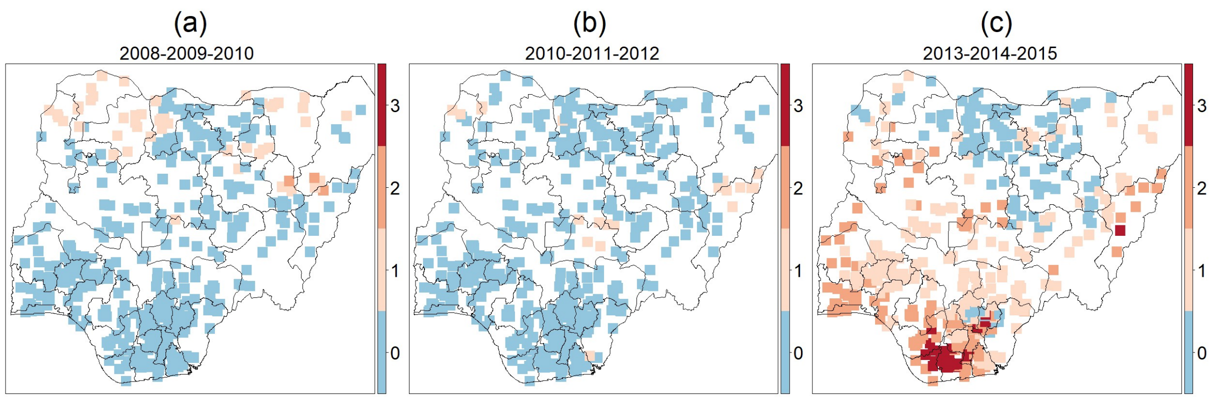
Notes : The Figures plot the dry rainy seasons for each GHS village from the panel, per GHS waves. Figure (a) plots the 2010 dry rainy seasons, Figure (b) in 2012, while Figure (c) in 2015. Dry years are defined according to the 1989-2019 long-term average.
Sources : authors' elaboration on CHIRPS and GHS data.

Figures 4, 5, as well as 18 and 19 in Appendix display the spatial distributions of the shocks observed in Figure 19. Figure 4 plots the spatial variation of the main independent variable and indicates for each survey year which villages are hit by a drought occurring over MJJAS. It shows the treated and controls EAs that will play a key role in the two-way fixed effects analysis. The dry years are mainly concentrated in the last wave (2015-2016), and have spatial variation. The Southern and western parts of the country were mainly affected in 2015. Figure 4 shows that the 2015 drought is spatially clustered, which is discussed in Section 7.2.1. Figure 5 plots the number of dry years during the GHS survey year and the two years before for each wave, based on the 1989-2019 long-term mean.

It shows that some areas where hit by cumulative droughts over the 2013-2015 period, which might have critical effects on agricultural production. The Southern part of the country is mainly affected, with several villages impacted in the three years, while the Central and North Eastern part of the country shocks vary between two and one dry years.

Figure 18 from A.3 maps the spatial distribution of the 19 (b) and shows the spatial distribution of the 1980s dry period. Figure 19 shows the spatial distribution of Figure 19 (c), and underlines the relative importance of the shocks in the 1980s to the ones occurring over 2011-2019.

Figure 5: Spatial distribution of the number of dry rainy seasons - current years



Notes : The Figures plot the number of dry rainy season for each GHS village from the panel, per GHS waves. Figure (a) plots the number of dry rainy season from 2008 to 2010 (including), Figure (b) from 2010 to 2012, while Figure (c) from 2013 to 2015, the maximum being three dry rainy seasons. Dry years are defined according to the 1989-2019 long-term average.
Sources : authors' elaboration on CHIRPS and GHS data.

4 Empirical strategy

4.1 Identification Strategy

The main identification strategy relies on a two-way fixed effects (TWFE) with a binary treatment. I estimate the effect of being hit by a drought the year of the survey on socio-economic outcomes including yields and food security indicators. The TWFE regression is made over the three first waves of the GHS, in 2010, 2012 and 2015, with both household and year fixed effects, on a balanced panel of households. The treatment is defined at the EA level, as defined in Section 3.2.3 : it is the dummy being under a dry year, defined according to the 1989-2019 long-term mean period. GHS villages are mainly treated in wave 3, as shown in Figure 5. The group of switchers are EAs that have experienced a change in their treatment status over the three waves. More formally, the empirical strategy can be formally written as follows :

$$Y_{h,i,t} = \alpha_0 + \alpha_1 \times D_{i,t} + \alpha_2 X_{h,t} + \gamma_h + \gamma_t + \epsilon_{i,t} \tag{1}$$

Where $X_{h,t}$ account for socio-economic characteristics of the households, including the age, gender and level of education [14] of the household head, as well as the number of adults (aged over 15), which can be used as a proxy for labor endowment. γ_h and γ_t are household and time fixed effects adjusting for spatial and period specific confounders. $D_{i,t}$ is the dmmy indicating a drought during the year of the survey round, which is displayed for each EAs in Figure 5. Errors $\epsilon_{i,t}$ are culstered at the EA level. Finally, $Y_{h,i,t}$ represent a socio-economic outcomes. For agricultural production, $Y_{h,i,t} = log(yields_{h,i,t})$ where $yields_{h,i,t}$ are the yields of the household at wave t, defined as $yields_{h,i,t} = \frac{Q_{h,t}}{A_{h,t}}$, with $Q_{h,t}$ equals to the self-reported total crop production of the household at wave t (in kg) and $A_{h,t}$ the self-reported total planted land holding (h). For food security indicators, $Y_{h,i,t}$=$FIED_{h,t}$ or $HDDS_{h,t}$, as defined in Section 3.1.1.

The second aim of this paper is to understand whether experience plays a role in the capacity of farmers to face rainfall shocks. I run a heterogeneity analysis in order to assess whether the year of land acquisition can explain the results from regression 1. The year of land acquisition (defined and described in Section 3.1.1) is a dummy, which equals 0 if the household cultivates at least one plot that he has acquired before 1985, and 1 if after. The Year of land acquisition is a variable that proxies the experience of the household on his plot. The threshold of 1985 is used in order to account for the fact that the household has faced the main dry years of the 1980s (1982/1983/1984) working the same land that he works in recent years. The choice of the threshold year is discussed in Section 6. More formally, the role of the year of land acquisition on the impacts of rainfall variability is estimated following the equation :

$$Y_{h,i,t} = \alpha_0 + \alpha_1 \times D_{i,t} + \alpha_2 \times D_{i,t} \times L_h + \alpha_3 X_{h,t} + \gamma_h + \gamma_t + \epsilon_{i,t} \tag{2}$$

Where L_h is the dummy of land acquisition.

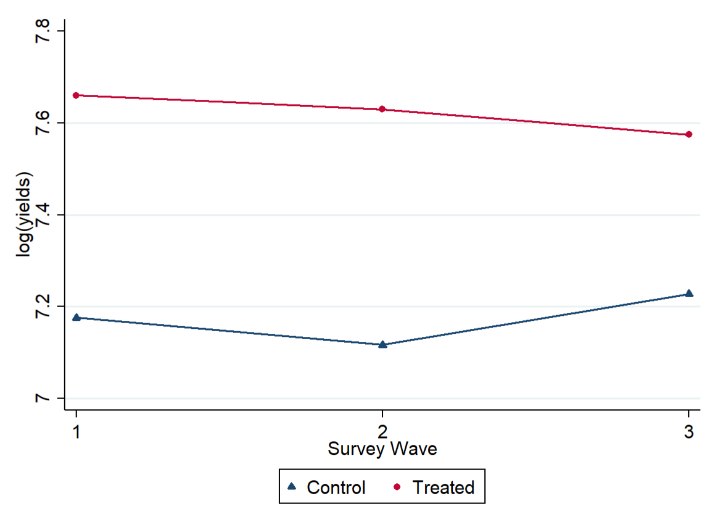
[14]The level of education of the household head is defined as the following : 0 if the head has no diplomas, 1 if he/she completed primary school 2 if he/she completed secondary school

4.2 Common trend assumption

The key assumption of a difference-in-difference (DiD) strategy is that the dependent variable would follow the same trends in the absence of droughts both in treated and control villages. In this section, I test for the common trend assumption using pre-treatment data. As Figure 4 shows, the drought mainly occurred during the last wave in 2015. For this test, I implemented a simple DiD design where I select villages that were not hit by any drought over wave 1 and wave 2. Treated villages were hit by the 2015 drought, while control villages were not. With this design, the evolution of yields over wave 1 and wave 2 are pre-treatment observation data that I use to test for the common trend assumption.

Figure 6 plots the linear trends of the logarithm of yields across the three survey rounds and distinguishes between treated and control villages. Figure 6 shows that yields follow similar trends over waves 1 and 2, suggesting that the treated and control villages follow a similar pattern of agricultural production. This test is only descriptive as it does not take into account any controls or fixed effects.

Figure 6: Linear trends of agricultural production across treatments



Notes : The Figure plots the linar trends of the log(yields) across survey rounds, averaged over treated and control groups, defined as being hit by the drought in 2015.
Sources : authors' elaboration on CHIRPS and GHS data.

5 Results

5.1 Agricutural Productivity

Table 1: Effects of short-term droughts on yields

	Annual drought		MJJAS drought	
	All crops	Main crops	All crops	Main crops
Yield (log)	(1)	(2)	(3)	(4)
Drought	-0.140**	-0.128**	-0.148**	-0.111*
	[0.0588]	[0.0598]	[0.0624]	[0.0625]
Nb. Adults	-0.0185	-0.00523	-0.0179	-0.00449
	[0.0148]	[0.0153]	[0.0148]	[0.0153]
Gender head	-0.00713	0.0252	-0.00520	0.0258
	[0.106]	[0.111]	[0.107]	[0.111]
Age head	-0.00271	-0.00441**	-0.00261	-0.00430**
	[0.00216]	[0.00219]	[0.00215]	[0.00216]
Education head	-0.0180	-0.0298	-0.0196	-0.0314
	[0.0431]	[0.0437]	[0.0424]	[0.0433]
Observations	5274	5183	5274	5183
R2	0.523	0.537	0.523	0.537
log(yields) Mean	7.305	7.344	7.305	7.344
Yields Mean	2369	2491	2369	2491
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1, ^{**} p < 0.05, ^{***} p < 0.01$.

Table 1 displays results from estimation 1, showing the effect of droughts on agricultural outputs [15]. Columns (1) and (3) give the results on the yields for all types of crops, while columns (2) and (4) for the main crops cultivated in Nigeria [16]. Columns (1) and (2) display the effects of a drought defined on an annual basis, while columns (3) and (4) during the main rainy season MJJAS. All estimations are made on a balanced panel of crops, meaning that each household intervenes three times in the regression.

The results show that being hit by drought during the main rainy season decreases

[15] I have to account for the fact that I am estimating a semi-log functional form, the yields being measured in terms of the log of the yields, while the independent variable is a dummy).

[16] The list of the main crops is : cassava, maize, sorghum, cowpeas, yam, millet, groundnut, rice, cocoyam and oil palm tree.

yields by around 14%, which is significant at 5%. On average, this corresponds to a decrease in yields by 333 kg/ha. This magnitude is in line with results from the literature, Veljanoska [2018] finding, for instance, that one rain deviation more reduces yields by 6.6%.

5.2 Food Security

Table 2 displays the results for the household security indicators. Columns (1) and (2) give the results of an annual drought, while columns (3) and (4) of a drought occurring during the agricultural season MMJAS. The gender of the household head is determinant in terms of food insecurity. I observe no statistically significant result regarding the FIES indicator. Regarding the food diversity score, I observe that being hit by a drought during MJJAS implies that the household loses around 0.14 food group over 12, which corresponds to a 1.2% decrease. This result suggests that droughts decrease the food diversity of households, which is only significant at the 10% level.

Table 2: Effects of short-term droughts on food security

	Annual drought		MJJAS drought	
	FIES	HDDS	FIES	HDDS
	(1)	(2)	(3)	(4)
Drought	-0.318	-0.0149	-0.264	-0.140*
	[0.268]	[0.0834]	[0.243]	[0.0806]
Nb. Adults	-0.0526	-0.0180	-0.0521	-0.0209
	[0.0645]	[0.0201]	[0.0643]	[0.0200]
Gender head	-1.622***	-0.240**	-1.620***	-0.236**
	[0.464]	[0.110]	[0.464]	[0.110]
Age head	0.0155	0.000662	0.0158	0.000693
	[0.0115]	[0.00320]	[0.0115]	[0.00320]
Education head	0.231	0.0737	0.230	0.0739
	[0.149]	[0.0486]	[0.149]	[0.0486]
Observations	11721	12123	11721	12123
R2	0.570	0.631	0.570	0.632
Outcome mean	-3.210	8.218	-3.210	8.218
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

6 Heterogeneity analysis

The main research question of this paper is to understand the role of experience and of exposure to the 1980s droughts on the impacts of short-term droughts. We proceed to a heterogeneity analysis, looking at the heterogeneity of the results from Section 5 according to the year of acquisition of the first plot purchased by the household and whether this plot was acquired before or after the main droughts of 1980s. As the year of land acquisition and the exposure to past droughts are highly endogenous variables, this section is mainly descriptive and intends to give some suggestive insights into the role that plays exposure to past climate events on households' vulnerability. Results can not lead to any causal interpretation.

6.1 Year of land acquisition

Table 3 gives the results for the yields of the main crops, while Table 4 for the HDDS. All estimations are made of a balanced panel for each dependent variable. From now on, I will only look at the effects of droughts occurring during the rainy MJJAS season, as it captures critical shocks of the cropping season. I control for the number of adults in the household and for the age, gender, and especially the educational level of the household head.

Columns (1) and (2) give the results of regression 2, when the short-term drought is interacted with the dummy of the year of land acquisition. Columns (2) control for the effect of the shock interacted with the household head's age, which is another measure of experience. Table 3 column (1) shows that short-term drought decreases yields by 19% for households that acquired their first land after 1985, in comparison to those who acquired it previously. The interaction term suggests that having acquired the land before 1985 attenuates the negative effect of being hit by a drought on yields. For households that acquired the land before, being hit by a drought decreases yields by 3%: the decrease is attenuated by 16 p.p in comparison to the decrease faced by households who acquired the land after.This result suggests that working on the same land that was hit by the intense droughts from 1980s reduces the vulnerability to the 2015 drought. This is a suggestion of the role that plays experience, knowledge and past exposure to intense dry year.

As the year of land acquisition is an endogenous variable, the interaction term does not directly capture exposure to the 1980's drought. Column (2) shows that the result does not longer hold when controlling for the dummy drought interacted with the age of the household head. Thus, columns (3) and (4) rely on another dummy, called *Dummy exposure*, which equals 1 if the household has acquired its land before 1985 and has been exposed to severe droughts over 1982/1983/1984, 0 otherwise [17].

I consider that a household has been exposed to severe droughts in the 1980s if it has been hit by at least two droughts. In order to limit endogeneity issues, I construct for the 1980s the dry dummy year in comparison to the long-term period from 1981 to 2011. In this sense, I avoid the fact that being hit by droughts in the 1980s decreases *de facto* the likelihood of being hit by a drought in more recent years (as the dummy is defined based on the 1989-2019 mean). However, endogeneity between recent and 1980s droughts still remains, as being severely hit in the past might still increase the probability of being hit by intense droughts in recent years, through environmental degradation, for instance. Again, this result is only descriptive and can not be interpreted in a causal way.

Column (3) suggests that the negative effects of recent drought on yields is mainly driven by individuals for which the dummy *exposure* is null. The interaction term suggests that individuals exposed to the 1980s droughts have an attenuation of the yield decrease by 38 p.p, compared to the yield decrease of households that were not exposed. This suggests an over-reaction of these households, for which being hit by a drought increases yields by 20% (-0.156+0.38). This might be explained by the fact that households implement adaptation strategies, whose benefits outweigh the negative effects of droughts. Again, this is only a suggestive insight, not a causal, and the magnitude effects are relatively large. Column (4) controls for the interaction of the recent shock and the age of the household.

Table 4 displays the same analysis for the HHDS, and shows little effect on food security.

[17] I do not run a triple interaction, mean that I do not directly interact the year of land acquisition and exposure to the 1980s drought because of endogeneity issues

Table 3: Effects of short-term droughts on yields - Heterogeneity according to year of land acquisition

	Main crops			
Yield (log)	(1)	(2)	(3)	(4)
Drought (MJJAS)	-0.198**	-0.222	-0.156**	-0.250
	[0.0863]	[0.192]	[0.0657]	[0.194]
Drought × Acquired Land Before 1985	0.164*	0.160		
	[0.0991]	[0.105]		
Drought × Dummy exposure			0.380***	0.377***
			[0.111]	[0.111]
Drought × Age		0.000472		0.00174
		[0.00325]		[0.00309]
Nb. Adults	-0.00289	-0.00281	-0.00240	-0.00199
	[0.0154]	[0.0153]	[0.0153]	[0.0152]
Gender head	0.0160	0.0160	0.0313	0.0304
	[0.112]	[0.112]	[0.112]	[0.112]
Age head	-0.00408*	-0.00414*	-0.00441**	-0.00460**
	[0.00215]	[0.00216]	[0.00215]	[0.00217]
Education head	-0.0271	-0.0273	-0.0294	-0.0296
	[0.0429]	[0.0428]	[0.0432]	[0.0432]
Observations	5183	5183	5183	5183
R2	0.538	0.538	0.538	0.538
log(yields) Mean	7.344	7.344	7.344	7.344
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 4: Effects of short-term droughts on HDDS - Heterogeneity according to year of land acquisition

	HDDS			
	(1)	(2)	(3)	(4)
Drought (MJJAS)	-0.144	-0.241*	-0.122	-0.230
	[0.107]	[0.144]	[0.100]	[0.147]
Drought × Acquired Land Before 1985	0.122	0.106		
	[0.120]	[0.123]		
Drought × Dummy exposure			0.304	0.298
			[0.231]	[0.230]
Drought × Age		0.00221		0.00231
		[0.00220]		[0.00217]
Nb. Adults	-0.0408*	-0.0397*	-0.0401*	-0.0389*
	[0.0232]	[0.0231]	[0.0233]	[0.0233]
Gender head	-0.133	-0.130	-0.130	-0.126
	[0.133]	[0.133]	[0.132]	[0.132]
Age head	-0.000516	-0.000895	-0.000602	-0.000980
	[0.00383]	[0.00388]	[0.00383]	[0.00388]
Education head	0.0821	0.0817	0.0802	0.0801
	[0.0567]	[0.0566]	[0.0567]	[0.0566]
Observations	8793	8793	8793	8793
R2	0.613	0.613	0.613	0.613
Outcome Mean	8.006	8.006	8.006	8.006
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

6.2 Exposure to the 1980s droughts

As the likelihood of being hit by droughts in the 1980s is endogenous to the likelihood of being hit in more recent years, the interaction with the *Dummy exposure* raises endogeneity issues. To deal with this issue, I investigate in this section the role of the year of land acquisition for villages that were severely hit in 1980 on one side and for villages that were less hit in the 1980s on the other side.

Table 5 gives the results for the yields of the main crops. Column (4) to (6) focuses on the sample of villages that were hit by two droughts in the early 1980s, while Column (1) to (3) focuses on the other less exposed villages. Columns (1) and (4) give the effects of being hit by a short-term drought on yields. It shows that for villages that were not highly affected in the 1980s, being hit by a dry rainy season decreases yields by 15.6%. This effect does not hold for villages hit in the 1980s, which suggests that the negative effects on yields are mainly driven by households who were not exposed to the 1980s droughts.

Columns (2) and (5) look at the interaction with the dummy of the year of land acquisition. Column (4) shows that for the comparison across households less hit in the 1980s, the decrease is only significant for households who acquired their land later. However, the year of land acquisition does not seem to play a key role as the interaction term is not significant. Column (5) shows that, for villages that were highly affected by the 1980s droughts, there is no longer a significant decrease in agricultural production. On top of that, the year of land acquisition seems to play a significant role, as, for households who acquired their land before 1985, the recent drought increases yields by 35%, in comparison to those who acquired it later. This is in line with the results found in Table 3, with large magnitude effects, raising endogeneity issues. Columns (6) and (7) control for another measure of experience, the interaction of the shock with the age of the household age.

Table 6 displays the same analysis for the HDDS indicator. Column (1) shows that being hit by a short-term drought decreases the food diversity by 0.3 food group, which corresponds to a 2.5% decrease. As column (4) displays no significant effects, it shows that the negative effects of short-term drought on food diversity is mainly driven by households who were less affected in the 1980s.

Results from the heterogeneity analysis are based on a reduced form. It is not possible to conclude whether this means that the acquisition of the land before past extreme events results in better adaptive strategies and a better knowledge of perception. However,

Table 5: Effects of short-term droughts on yields - Heterogeneity according to exposure to the 1980s droughts

	Main crops					
	Not hit by 1980s droughts			Hit by 1980s droughts		
Yield (log)	(1)	(2)	(3)	(4)	(5)	(6)
Drought (MJJAS)	-0.156**	-0.227**	-0.458*	0.0241	-0.130	0.202
	[0.0787]	[0.0987]	[0.239]	[0.122]	[0.188]	[0.282]
Drought × Acquired Land Before 1985		0.126	0.0935		0.351*	0.433**
		[0.107]	[0.113]		[0.200]	[0.212]
Drought × Age			0.00447			-0.00737
			[0.00402]			[0.00553]
Nb. Adults	0.00153	0.00284	0.00404	-0.0136	-0.00996	-0.0101
	[0.0207]	[0.0208]	[0.0207]	[0.0224]	[0.0224]	[0.0226]
Gender head	0.0410	0.0327	0.0324	-0.0527	-0.0517	-0.0505
	[0.125]	[0.126]	[0.127]	[0.262]	[0.267]	[0.266]
Age head	-0.00760***	-0.00736***	-0.00808***	0.000302	0.000351	0.000805
	[0.00262]	[0.00260]	[0.00262]	[0.00349]	[0.00346]	[0.00344]
Education head	-0.0411	-0.0370	-0.0394	-0.0193	-0.0137	-0.0127
	[0.0561]	[0.0556]	[0.0553]	[0.0693]	[0.0678]	[0.0668]
Observations	3185	3185	3185	1998	1998	1998
R2	0.515	0.515	0.516	0.523	0.525	0.525
log(yields) Mean	7.500	7.500	7.500	7.094	7.094	7.094
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 6: Effects of short-term droughts variability on HDDS - Heterogeneity according to exposure to the 1980s droughts

	HDDS					
	Not hit by 1980s droughts			Hit by 1980s droughts		
	(1)	(2)	(3)	(4)	(5)	(6)
Drought (MJJAS)	-0.281***	-0.215	-0.305*	0.0117	-0.120	-0.173
	[0.108]	[0.137]	[0.172]	[0.128]	[0.200]	[0.279]
Drought × Acquired Land Before 1985		0.0554	0.0384		0.358	0.351
		[0.133]	[0.138]		[0.257]	[0.259]
Drought × Age			0.00226			0.00119
			[0.00270]			[0.00403]
Nb. Adults	-0.0402	-0.0464*	-0.0449	0.00616	-0.0299	-0.0297
	[0.0247]	[0.0280]	[0.0279]	[0.0334]	[0.0406]	[0.0406]
Gender head	-0.231*	-0.151	-0.146	-0.255	-0.0938	-0.0941
	[0.133]	[0.155]	[0.155]	[0.195]	[0.257]	[0.257]
Age head	-0.00206	-0.00245	-0.00292	0.00387	0.00195	0.00183
	[0.00409]	[0.00486]	[0.00496]	[0.00505]	[0.00620]	[0.00623]
Education head	0.0151	0.0451	0.0448	0.141**	0.124	0.124
	[0.0658]	[0.0761]	[0.0760]	[0.0708]	[0.0844]	[0.0845]
Observations	7230	5400	5400	4893	3393	3393
R2	0.643	0.617	0.617	0.590	0.574	0.574
Outcome Mean	8.492	8.281	8.281	7.815	7.568	7.568
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

I show that having a long-lasting experience of the cultivated land reduces vulnerability to rainfall shocks, especially when having experience of the land under past extreme dry conditions. This is only a piece of descriptive evidence.

6.3 Endogeneity and discussion

The year of land acquisition is a highly endogenous variable. It might be endogenous to climate shocks, both those occurring in recent years and those that occurred in the 1980s, as farmers make their choice according to the accumulation of droughts. Besides, it is, of course, correlated to other measures of experience such as the age of the household head or the educational level. Even if the heterogeneity analysis is not a causal exercise, it might still be interesting to investigate to which variables the year of land acquisition is correlated.

Table 7: Table of correlation -land of year acquisition

	Acquisition before 1985	Year of land acquisition
	(1)	(2)
Drought 2015 (MJJAS)	0.0247	-1.740
	[0.0347]	[1.448]
Drought 1980 (MJJAS)	-0.0357	1.446
	[0.0299]	[1.211]
Nb. Adults	0.00656	0.0383
	[0.00501]	[0.201]
Gender head	0.0317	-1.863
	[0.0256]	[1.142]
Age head	0.0106***	-0.429***
	[0.000739]	[0.0318]
Education head	-0.0402**	1.624***
	[0.0164]	[0.567]
Observations	2931	2931
Outcome mean	0.525	1982.9
Region FE	Yes	Yes

Notes: Standard errors clustered at the village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table 7 runs two simple OLS regressions with region-fixed effects. Column (1) looks at the correlation of the dummy variable, which indicates whether a household acquired the land before 1985, while column (2) looks at the continuous variable, which is the year of land acquisition. As both variables are fixed over time, I only look at the third wave, 2015/2016, and at the correlation with the drought occurring in 2015, which is the most important. Table 7 shows that both variables do not seem to be correlated with the climate shock in 2015 nor in 1980. The timing of the land acquisition is, as expected, mainly correlated with the age of the household head and his educational level. The earlier the land has been acquired, the older and less educated the household head is.

There is no way to rule out entirely the possibility that these heterogeneity effects might be driven by endogenous self-selection occurring after the 1980s droughts. One main omitted variable in this paper is wealth, which might be highly correlated to the year of land acquisition. The previous analysis can not rule out that the observed heterogeneity is driven by differences in the wealth of the households rather than experience. The way the land was acquired might play a key role as well as if the land was acquired through inheritance, the person in charge of the plot would have had experience on the plot. Eventually, as the heterogeneity is mainly driven by agricultural production, it would be insightful to verify if adaptation occurred and through which method. Thus, work-in-progress is ongoing to include a variety of asset wealth indicators, the effect of inheritance, and identify adaptation strategies such as planting trees, changing planting dates, and crop diversification of innovation adoption.

7 Robustness and Sensitivity analysis

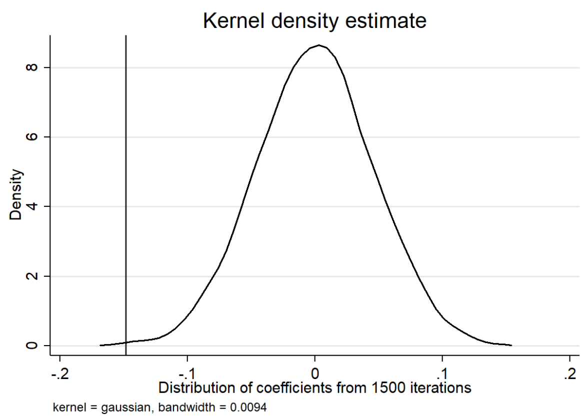
7.1 Placebo tests

This section runs inference tests to check whether the effect of short-term droughts on agricultural production is unlikely to be observed by chance. I test the main result from Table 1 column (3), which indicates that being hit by a drought decreases yields by 14.8%. I draw 1500 permutations and compute the precise p-value based on the distribution of the 1500 counterfactual treatment-effects, under the sharp null hypothesis of no effect [18].

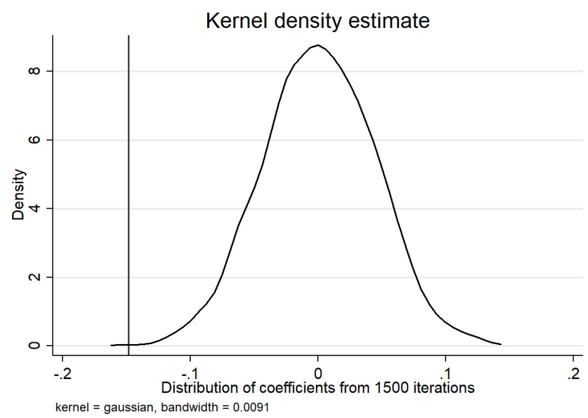
Figure 7a runs spatial counterfactuals as villages are assigned rainfall shocks from a randomly selected villages. This maintains the distribution of the independent variable and removes spatial patterns. This inference test accounts also for spurious correlation linked to spatially dependent trends [Lind, 2019]. Figure 7b randomly changes the timing

[18] The test is done using the *ritest* STATA command.

Figure 7: Effects of short-term droughts on yields - Temporal randomization inference tests



(a) Random sublocation



(b) Random timing

Notes: The two figures represent the distribution of the treatment effects of being hit by a drought when conducting 1,500 permutations. Figure (a) randomly changes the villages allocation to droughts while Figure (b) randomly changes the timing of a drought for each village. The vertical line indicates the location of the estimate under the implemented treatment assignment (Table 1 Column (3)), and displays the new estimated p-value.
Sources: Authors' elaboration on CHIRPS and GHS data.

of the rainfall shocks for each village.

Both simulations show that the model is not misspecified at the 1% level. The distribution of treatment effects drawn from permutations is shifted around zero and has the shape of a standard normal distribution. The vertical lines indicate the location of the main result from Table 1 -0.148^{***}.

7.2 Correlations

7.2.1 Spatial correlation

This section accounts for the spatial correlation within 100km using Conley [1999] standard errors, focusing on the results obtained for agricultural production. Table 8 shows that the results from Table 1 are robust (Column (1)), as well as those from Table 3 (Columns (2) and (3)) and those from Table 5 (Columns (4) to (7)).

Table 8: Effects of short-term droughts on yields - Spatial correction (100km)

	Main crops						
	All Observations			Not hit in 1980s		Hit in 1980s	
Yield (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Drought (MJJAS)	-0.111*	-0.198**	-0.156**	-0.156**	-0.227**	0.0241	-0.130
	[0.0652]	[0.0996]	[0.0686]	[0.0781]	[0.106]	[0.129]	[0.204]
Drought × Acquired before 1985		0.164			0.126		0.351*
		[0.122]			[0.137]		[0.204]
Drought × Dummy exposure			0.380***				
			[0.105]				
Observations	5192	5192	5192	3194	3194	1998	1998
R2	0.00273	0.00384	0.00491	0.00582	0.00658	0.000433	0.00374
log(yields) Mean	7.344	7.344	7.344	7.501	7.501	7.094	7.094
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Balanced Panel	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Conley [1999] standard errors correcting for spatial correlation at 100km , $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Each estimation controls for the number of adults in the household, the gender, age and educational level of the household head.

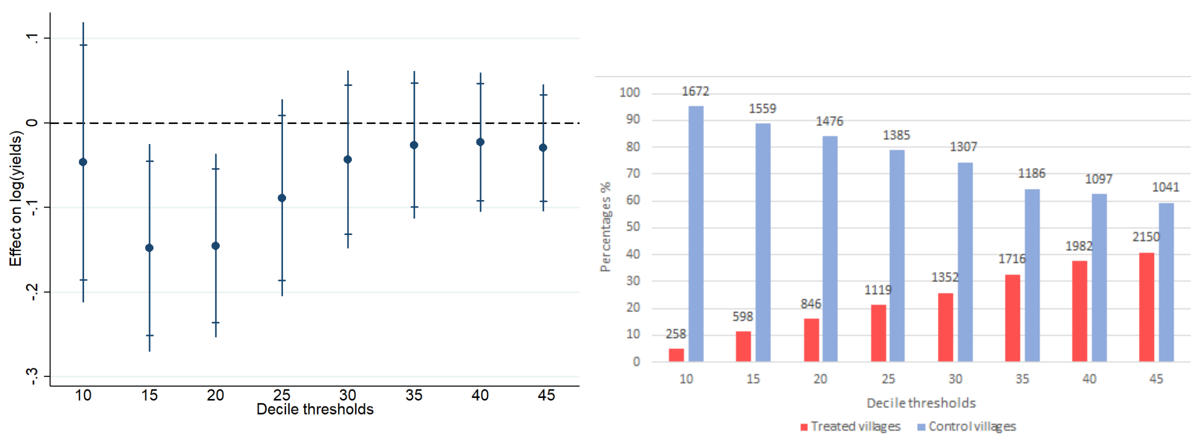
7.3 Changing thresholds

7.3.1 Rainfall threshold

In this section, I discuss the choice of the threshold to define a dry year. In the main analysis, a year is defined as dry if the cumulative rains over MJJAS are under the 15th percentile of the rainfall distribution of each village over the 1989-2019 long-term mean. Figure 8b gives the number and percentages of treated and control villages changing for different thresholds defining the treatment, which is mainly being hit by the 2015 drought. For instance, I could not choose the 10th threshold as very few villages were treated (4%). I choose the 15th decile as the best trade-off between being hit by a severe drought and having enough treated observations.

Figure 8a plots different estimations of the effect of short-term droughts on yields from Table 1 column (3), changing the thresholds of treatment. The coefficient under the 15th is the main estimation from Table 1. As expected, there is no effect of the 10th decile, mainly due to a limitation in the number of treated observations. The negative effect remains significant up to the 20th threshold and is then attenuated when the severity of the dry shock decreases.

Figure 8: Effect of droughts on yields - changing drought threshold



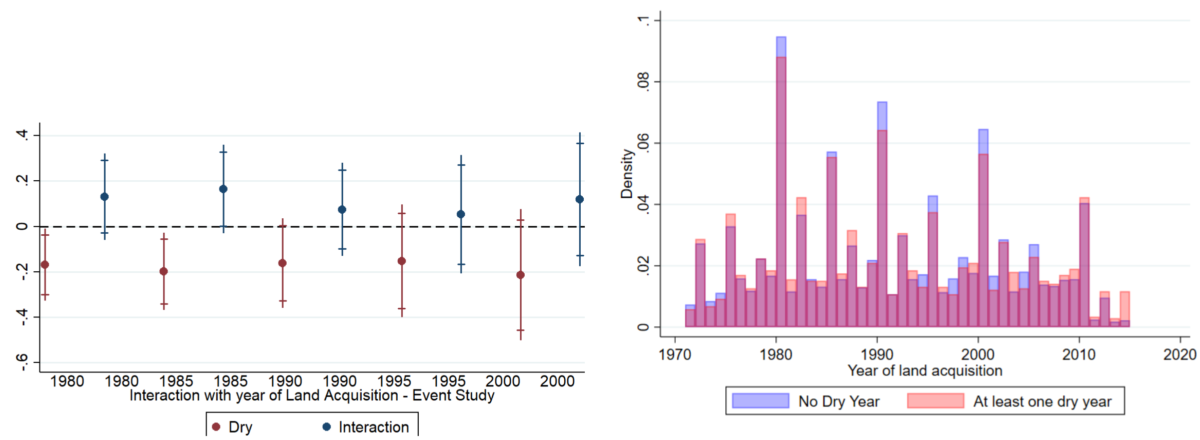
(a) (b)

*Notes :*Figure (a) plots the effect of being hit by a drought on yields changing the threshold for being treated. Figure (b) gives, for each threshold, the percentage of treated and control villages, as well as the number of villages in each group.
Sources : author's elaboration on GHS and CHIRPS data.

7.3.2 Timing of land acquisition

The threshold used to define the dummy of year acquisition of the land, 1985, is chosen in order to capture both experiences of the land under dry conditions and to compare households that have acquired their land after the intense Sahelian droughts or before. In this Section, I discuss the choice of this threshold to convince the reader that it is the past experience of the early 1980s that plays a key role.

Figure 9: Rainfall variability effects according to the year of land acquisition



(a) (b)

*Notes :*Figure (a) plots the results of the estimation 2 on the log of yields for different threshold for the dummy of year acquisition. 5% and 10% significance are given. Figure (c) plots the distribution of the distance.
Sources : author's elaboration on GHS and CHIRPS data.

Figure 9a plots the results of the estimation 2 on the log of yields for different thresholds for the dummy of year acquisition. In red is plot α_1, the estimator for households that acquired their first land after the indicated year, and in blue is plot the α_2, meaning the interaction term. For instance, the two first dots on the left give the two estimators from the same regression, where the dummy drought in recent years is interacted with a dummy, which equals 0 if the household has acquired the land after 1980, 1 if after. The five pairs of dots correspond to five distinct regressions. Figure 9a shows that the difference of impacts between before/after hous

8 Conclusion

This paper looks at whether the experience of past dry events can reduce the vulnerability of households to current rainfall variability. First, I analyze the statistical trends of rainfall over the 1981-2019 period in Nigeria, using the satellite and stations based rainfall product CHIRPS. If I show evidence of the long and severe dry period of the 1980s both in the Sahelian and Gulf Guinean regions, I find different patterns. This paper displays statistics that refute the recovery of rains in the Sahel and observe in the south that, if the cumulative rains show no significant patterns, rains are becoming significantly less frequent and more intense, which increases the probability of extreme events in the more recent decades. In line with this result, I give evidence of a period of high occurrence of droughts over the 2013-2015 period.

This paper matches a three-wave panel survey from 2010-2016 from the GHS, with a strong focus on agricultural outcomes, to the CHIRPS product. I use a two-way fixed effect strategy and exploit the variation in the occurrence of droughts, mainly over the last wave. First, I look at the short-term effects of droughts on agricultural production and food security indicators. I show that being hit by a drought decreases yields by 14%, and decreases the food diversity of households by around 1%. Second, I try to assess the role of experience in the capacity to find adaptive strategies and cope with rainfall variation. I look at the heterogeneity of the impacts according to the experience of the plot, using the timing of the year of acquisition of the first plot of the household. I compare the impacts of rainfall shocks of households that acquired their first plot before the 1980s dry period to those that acquired it after. Results show that one additional dry year decreases the yields on average by 19% for households that acquired their first land after 1985, in comparison to those who acquired it previously. This result suggests that having a long-lasting experience under extreme dry events on cultivated land reduces vulnerability to rainfall variability. This is only a piece of descriptive evidence, which can not lead to causal interpretation.

Important further work will be to understand in more detail the rules of land acquisition in Nigeria and check the role of acquisition through inheritance. Refining the definition of the rainy season according to the geographical context and the main crop is also the next step in the paper. A main limitation is the reduced form analysis. A key question is to assess the differences in terms of agricultural practices between households that experienced the 1980s with their land and the others. Work is still needed in order to understand what are the good agricultural practices facing rainfall variability. Additional data, based on satellite images, can also be used to look at correlations with our measure of yields.

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A Appendix

A.1 Descriptive Statistics

Table 9 give the composition of the Original Sample (columns (1) and (2)), and the final panel sample for the three first GHS rounds, including households that have moved and been tracked by the LSMS-ISA teams (column (5)), per Nigerian geopolitical zones. Table 10 gives insights of the attrition rates per waves and geopolitical zones of Nigeria.

Table 11 displays the different questions used in the survey to build the FIES (or scale score) food security variable. Table 12 displays the descriptive statistics of the main variables of interest of the paper. Each variables is driven from a panel sample. Households Characteristics outcomes statistics are given for the whole panel sample, Agricultural production and practices are given for the panel sample for which each household cultivated at least one plot for each wave (or answered), while Food security outcomes panel samples for which we were able to build the indicator for each waves per households. The number observation (column (6)) display the number of households from the sample, the real number of observations being three times this number (as for three waves). The descriptive statistics show discrepancies between GPS-based and self-reported plot areas, as mentionned in the literature Yacoubou Djima and Kilic [2021], both in terms of total land holding per household and average plot area per household. Please note that the GPS measures are asked for the entire land holdings of the households, while Self-Reported (SR) measures only for plots cultivated by the household at the time of the survey. The descriptive statistics show that SR measure of plot areas overestimate the land areas in comparison to GPS measures, which seem to be mainly explained by outliers and lower/higher end of the plot distribution. Indeed, while means highly differ, median seem to be more comparable. As Self-Reported total crop production can be also mismeasured, we observe that the median highly differ from the mean. Self-Reported Yields are thus twofold noisy, and the variables displayed in Table 12 have been treated for outliers (winsorized by the median at 10%).

Table 9: Descriptive Statistics of the 6 years panel per geopolitical Zones

Zones	Original Sample 2010-2011		Panel Sample Original Location		Panel Sample Moved/Tracked	Total	% Original Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	EAs	HHs	EAs	HHs	HHs	HHs	%
North Central							
Urban	22	217	22	200	1	201	7.37
Rural	57	577	57	548	11	559	3.12
Total	78	794	78	748	12	760	4.28
North East							
Urban	14	138	9	79	6	85	38.41
Rural	63	659	52	521	6	527	20.03
Total	77	797	61	600	12	612	23.21
North West							
Urban	17	170	16	150	2	152	10.59
Rural	69	728	69	704	10	714	1.92
Total	85	898	84	854	12	866	3.56
South East							
Urban	21	204	21	172	4	176	13.73
Rural	57	590	57	542	10	552	6.44
Total	76	794	76	714	14	728	8.31
South South							
Urban	23	229	23	186	15	201	12.23
Rural	55	540	55	460	32	492	8.89
Total	78	769	78	646	47	693	9.88
South West							
Urban	63	612	62	417	71	488	20.26
Rural	26	253	26	183	21	204	19.37
Total	87	865	86	600	92	692	20
Nigeria							
Urban	160	1570	153	1204	99	1303	17.01
Rural	327	3347	316	2958	90	3048	8.93
Total	481	4917	463	4162	189	4351	11.51

Table 10: Attrition rates for wave 2 and 3 per geopolitical zones

Zones	**Original Sample**	**Location**	**Moved**	**Total**	**Attrition (%)**	**Location**	**Moved**	**Total**	**Attrition(%)**
	Wave1	Wave2	Wave2	Wave2	Wave2	Wave3	Wave3	Wave3	Wave3
North Central									
Urban	217	206	5	211	2.76	201	0	201	7.37
Rural	577	576	7	583	-1.04	550	4	554	3.99
Total	794	782	12	794	0	751	4	755	4.91
North East									
Urban	138	123	2	125	9.42	96	0	96	30.43
Rural	659	643	5	648	1.67	523	5	528	19.88
Total	797	766	7	773	3.01	619	5	624	21.71
North West									
Urban	170	157	0	157	7.65	158	2	160	5.88
Rural	728	714	8	722	0.82	705	0	705	3.16
Total	898	871	8	879	2.12	863	2	865	3.67
South East									
Urban	204	194	8	202	0.98	172	1	173	15.2
Rural	590	572	4	576	2.37	545	2	547	7.29
Total	794	766	12	778	2.02	717	3	720	9.32
South South									
Urban	229	206	18	224	2.18	190	6	196	14.41
Rural	540	510	22	532	1.48	461	7	468	13.33
Total	769	716	40	756	1.69	651	13	664	13.65
South West									
Urban	612	504	67	571	6.7	431	13	444	27.45
Rural	253	219	18	237	6.32	188	8	196	22.53
Total	865	723	85	808	6.59	619	21	640	26.01
Nigeria									
Urban	1570	1390	100	1490	5.1	1248	22	1270	19.11
Rural	3347	3234	64	3298	1.46	2972	26	2998	10.43
Total	4917	4624	164	4788	2.62	4220	48	4268	13.2

Table 11: FIES descriptive statistics - List of survey questions

FIES - GHS Questions
In the past seven days, how many days you or someone in your household had to :
(1) Rely on less preferred food?
(2) Limit the variety of food eaten?
(3) Limit the portion size at meal-times?
(4) Reduce number of meals eaten in a day?
(5) Restrict consumption by adults in order for small children to eat?
(6) Borrow food, or rely on help from a friend or relative?
(7) Have no food of any kind?
(8) Go at sleep hungry because there is not enough food?
(9) Go a whole day and night without eating?

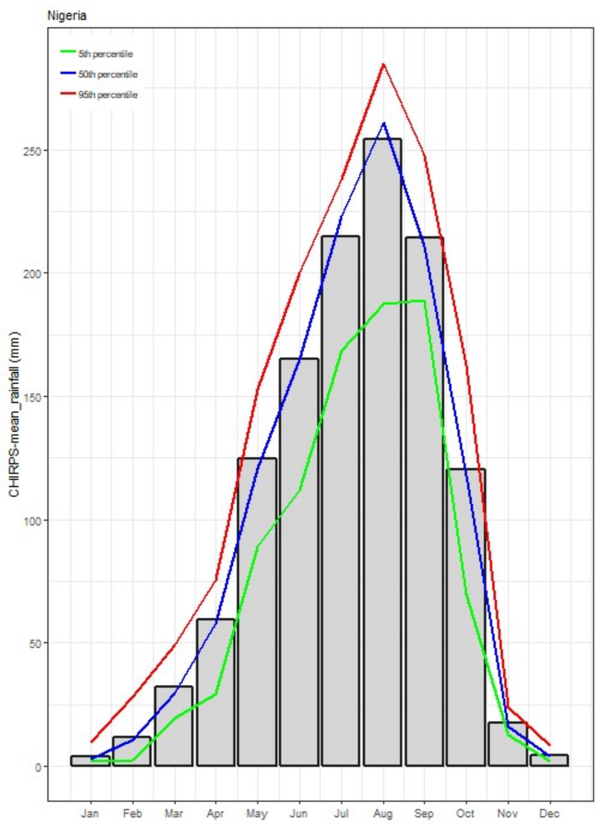
Table 12: Descriptive Statistics of main variables

	Mean (1)	SD (2)	Med (3)	Min (4)	Max (5)	Obs. (6)
Household Characteristics						
Household size						
Number of adults	3.38	1.89	3	1	26	4041
Head is female	0.16	0.37	0	0	1	4041
Age of head	51.7	14.7	50	22	87	4041
Agricultural Production						
GPS measured total land holding (ha)	1	1.52	0.53	0	26.5	1758
SR total cultivated land holding (ha)	8.4	219	0.98	0	10^4	1758
GPS measured plot area (ha) - average per hh	0.56	0.83	0.35	10^{-4}	26.5	1758
SR cultivated plot area (ha)- average per hh	4.44	103	0.58	0	4800	1758
SR total crop production (kg)	4435	25591	1751	0	10^6	1758
SR Yields (kg/ha)	2369	2617	1436	202	14880	1758
SR Yields main crops (kg/ha)	2491	2788	1435	210	15104	1758
SR Yields maize (kg/ha)	1670	1805	1000	148	11752	777
Agricultural Practices						
Number of cultivated plots per hh	2.08	1.18	2	1	11	1758
Number of cultivated crops per plots - average per hh	2.37	1.16	2	1	12	1758
Food Security						
FIES	-3.21	6.21	0.51	-57	0.7	3907
Food insufficiency	0.20	0.40	0	0	1	4055
HDDS	8.22	2.06	8	1	12	4041

Notes: Descriptive statistics are displayed for the panel sample including the three first waves of the GHS. The mean and other mathematics are given for the three waves, the number of observations are the number of households (the real number of observation being three times the one given). Household characteristics outcomes are given for the whole sample. Agricultural production and practices are displayed for the panel of households that cultivated at least one plot in each waves (the one used in the main regression analysis), while the Food security outcomes for the panel sample for which we were able to build the indicator for each wave. Please note that SR Yields have been treated to correct the outliers, winsorized by the median.

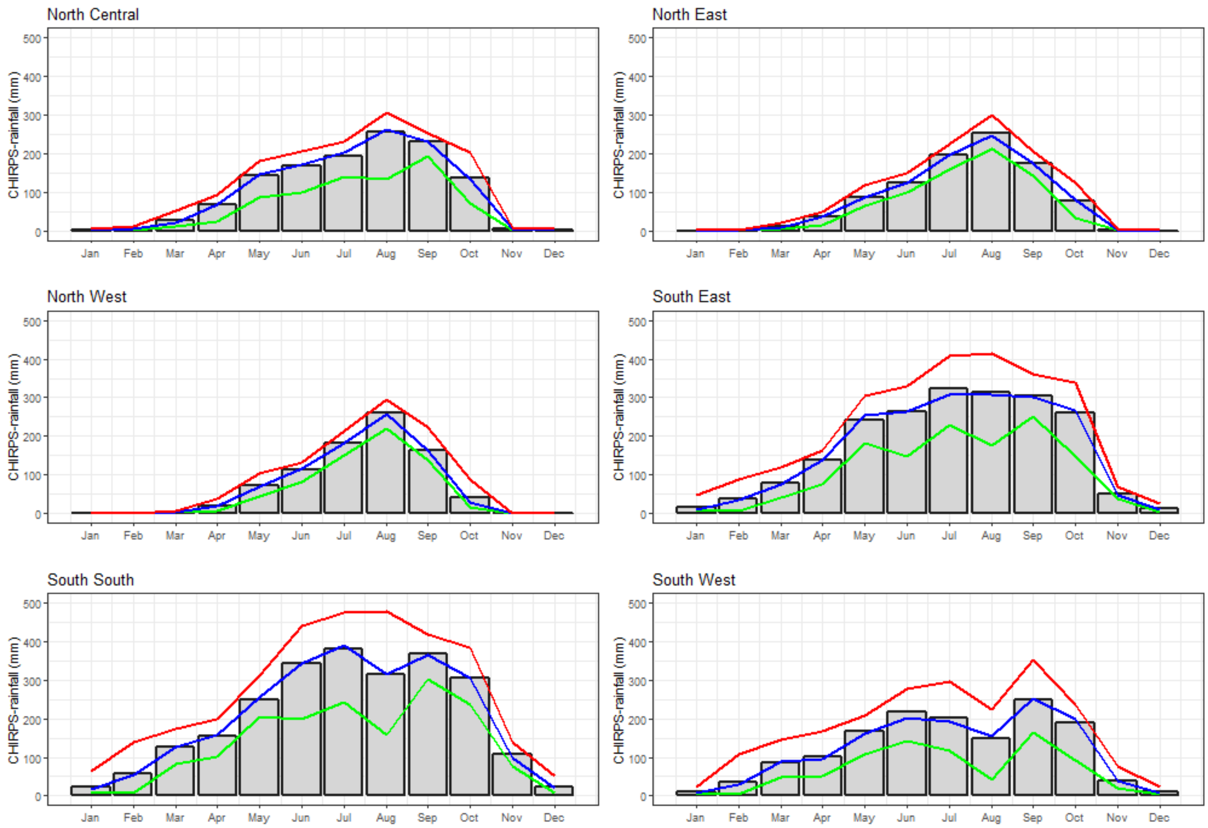
A.1.1 Figures

Figure 10: Monthly precipitation of long-term average



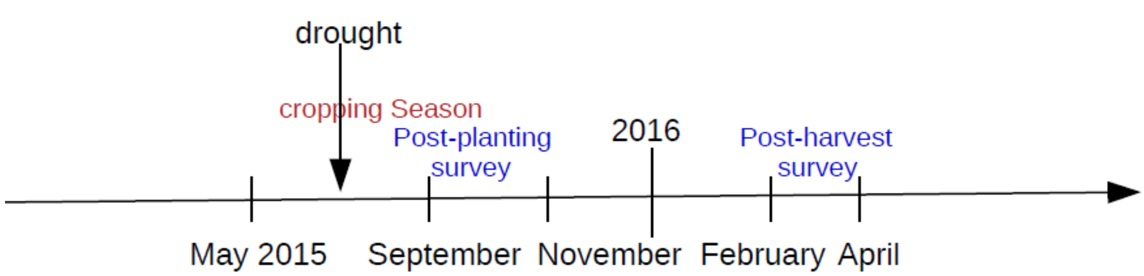
Notes : The Figure represent the long-term average (1981-2019) of the monthly precipitation over Nigeria. Red lines draw the 95th percentile of the long-term rainfall distribution, while the blue line the 50th percentile and the green line the 5th percentile.
Sources : authors' elaboration on CHIRPS

Figure 11: Monthly precipitation of long-term average per geopolitical zones



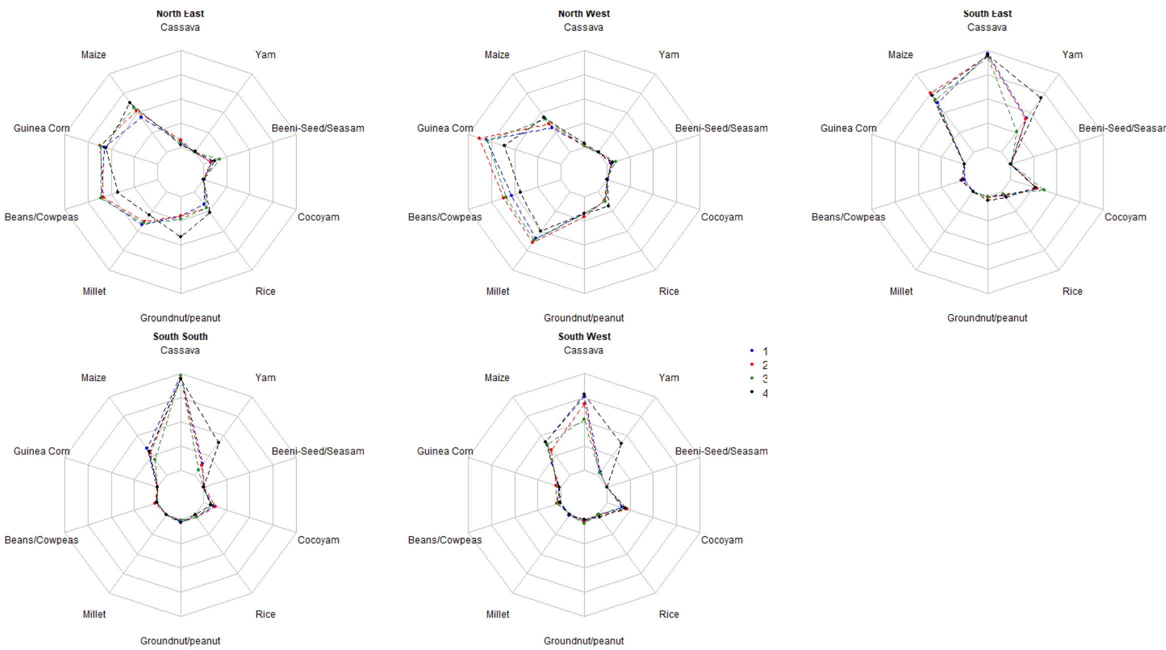
Notes : The Figure represent the long-term average (1981-2019) of the monthly precipitation over the six geopolitical zones of Nigeria. Red lines draw the 95th percentile of the long-term rainfall distribution, while the blue line the 50th percentile and the green line the 5th percentile.
Sources : authors' elaboration on CHIRPS

Figure 12: Timeline of cropping season and survey rounds



Notes : The Figure gives the timeline of the cropping season and the post-planting and post-harvest survey rounds.
Sources : authors' elaboration on GHS data

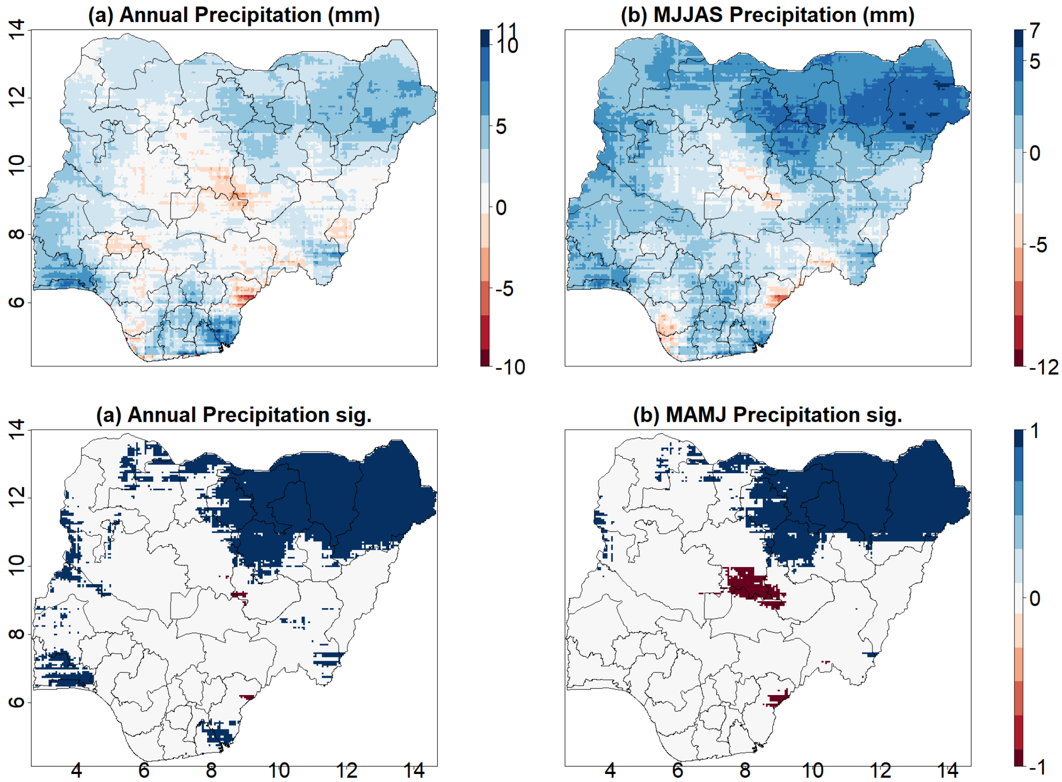
Figure 13: Main cultivated crops per geopolitical zones per GHS waves



Notes : The Figure plots the distribution of main cultivated crops per geopolitical zones of Nigeria, for each GHS waves (wave 1 in blue, wave 2 in red, wave 3 in green and wave 4 in dark).
Sources : authors' elaboration on GHS data

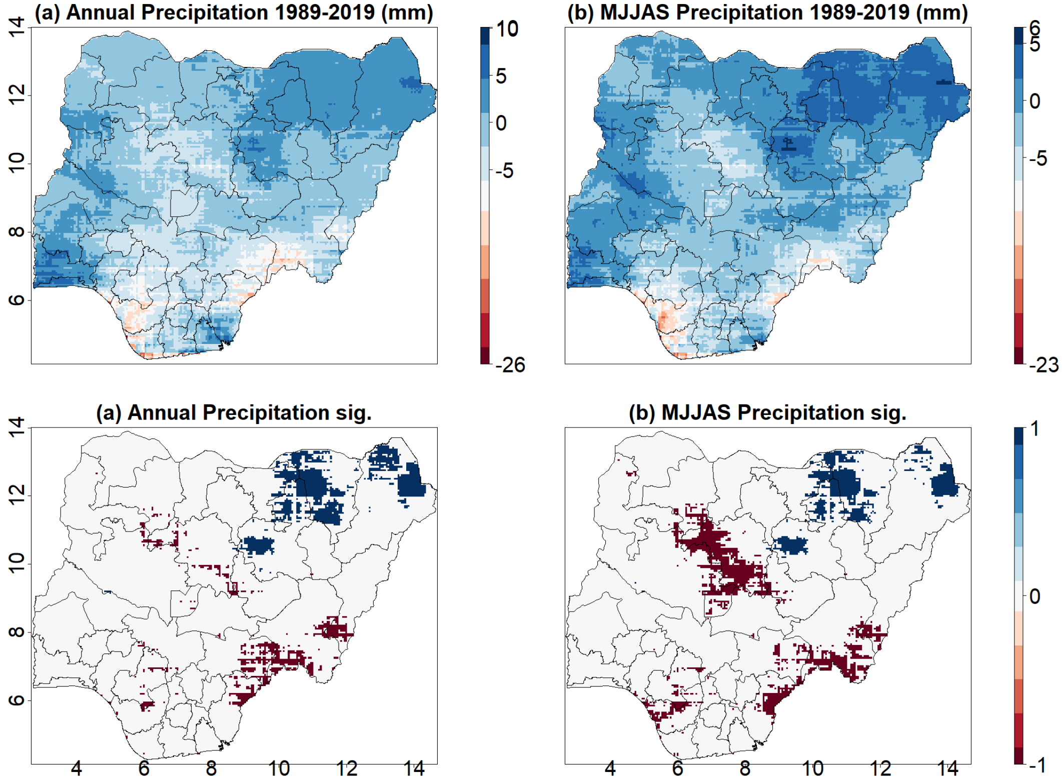
A.2 Long-term changes in rainfall patterns and characteristics

Figure 14: Long-term trends of climate indicators - 1981-2019 long-term period



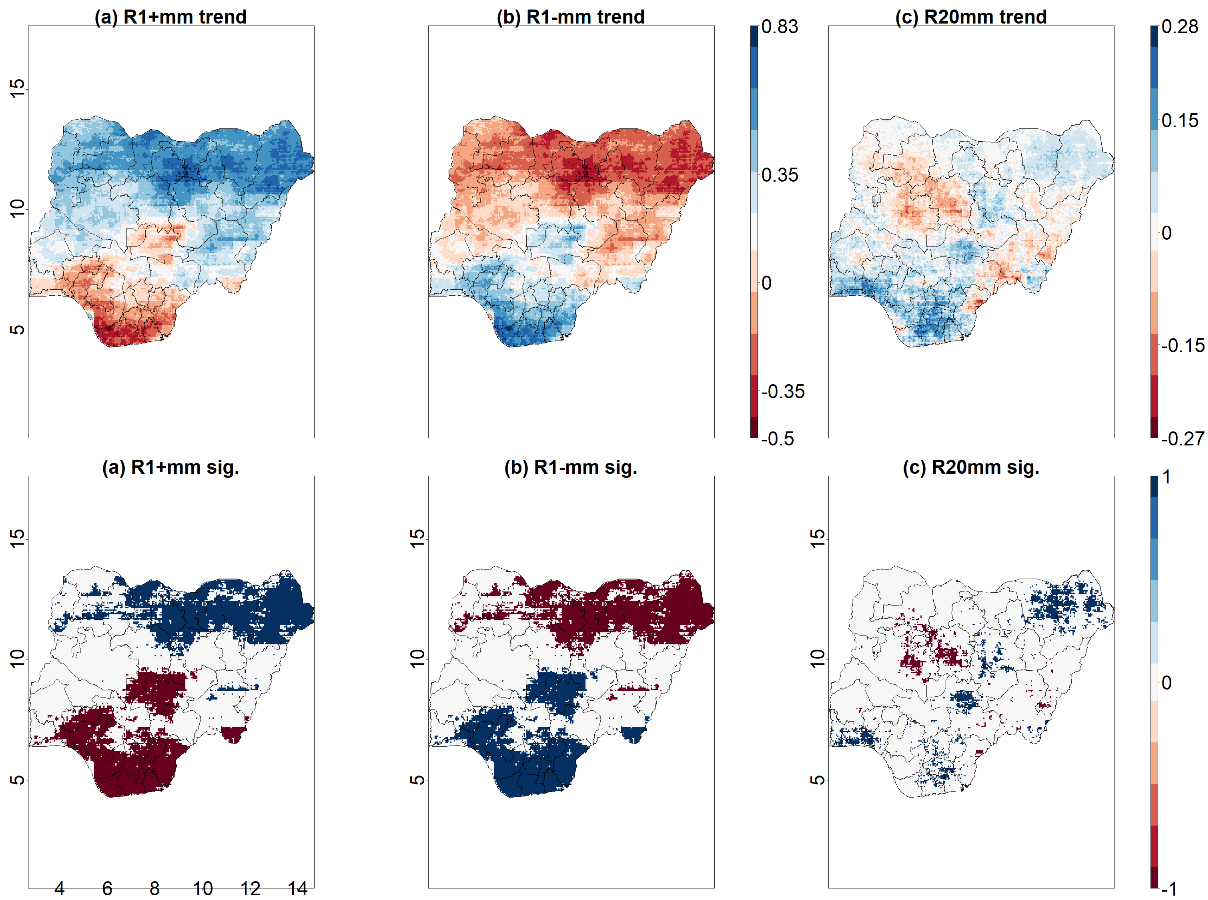
Notes : The Figure plots the annual (a) and long-rainy season trends (b) of precipitation amounts (mm) during the **long-term period 1981-2019**, based on CHIRPS data. Bottom panels show the significance of the trends at $p < 0.05$. Blue (+1) displays a significant increasing trends, while red (-1) a significant decreasing one and 0 non significant changes.
Sources : author's elaboration on CHIRPS data.

Figure 15: Long-term trends of climate indicators - 1989-2019 long-term period



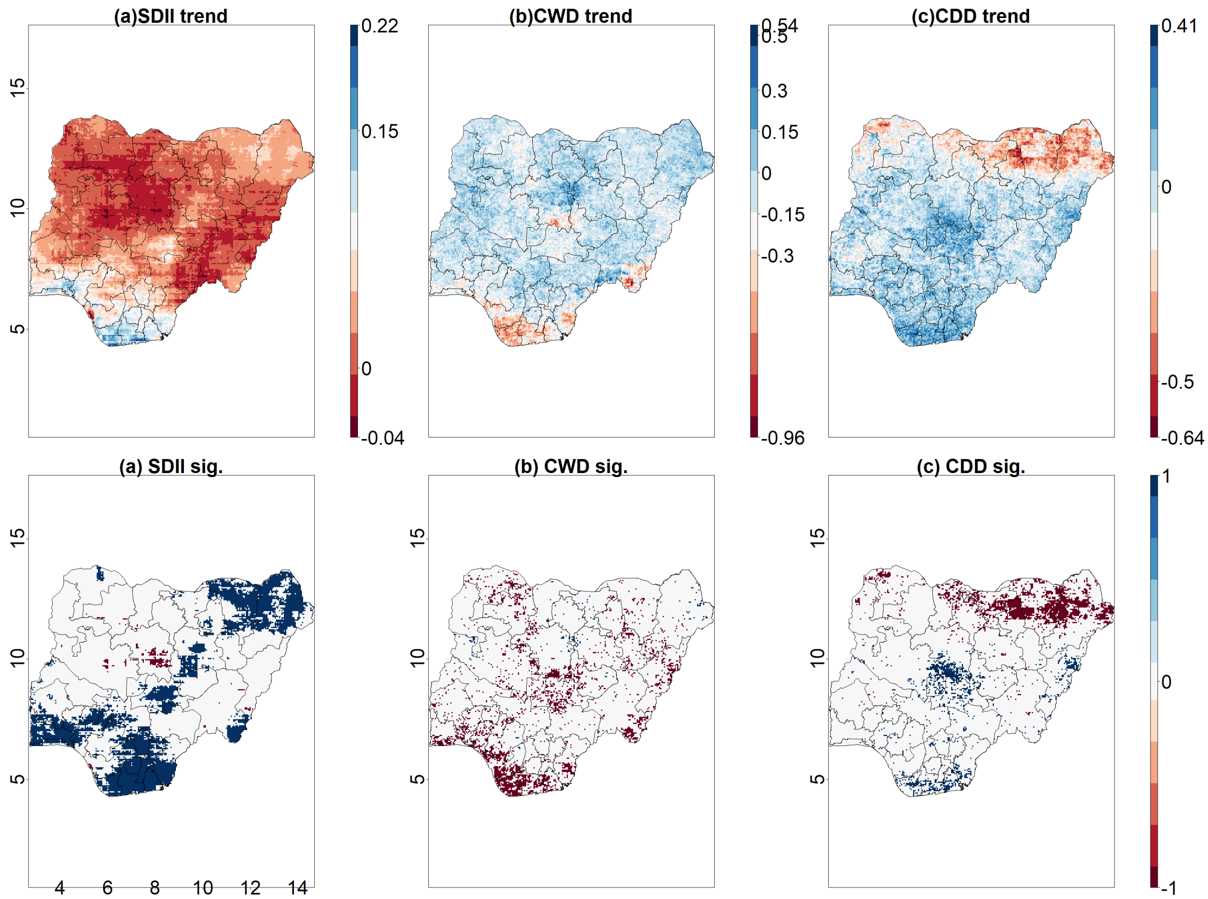
Notes : The Figure plots the annual (a) and long-rainy season trends (b) of precipitation amounts (mm) during the **long-term period 1989-2019**, based on CHIRPS data. Bottom panels show the significance of the trends at $p < 0.05$. Blue (+1) displays a significant increasing trends, while red (-1) a significant decreasing one and 0 non significant changes.
Sources : author's elaboration on CHIRPS data.

Figure 16: Long-term trends of climate indicators (2) -1981-2019 long-term period



Notes : The Figure plots (a)R1+mm(b)R1+mm and (c) R20mm trends over the long-rainy season (days), during the **long-term period 1981-2019**, based on CHIRPS data. Bottom panels show the significance of the trends at $p < 0.05$. Blue (+1) displays a significant increasing trends, while red (-1) a significant decreasing one and 0 non significant changes. R1+mm indicator is the number of wet days (i.e the rains are strictly positive), R1-mm is the number of dry days (i.e when the rains equal zero), and R20mm the number of heavy rains (i.e when rains aver over 20mm). By construction, R1+mm and R1-mm account for the total period and are symmetric.
Sources : author's elaboration on CHIRPS data.

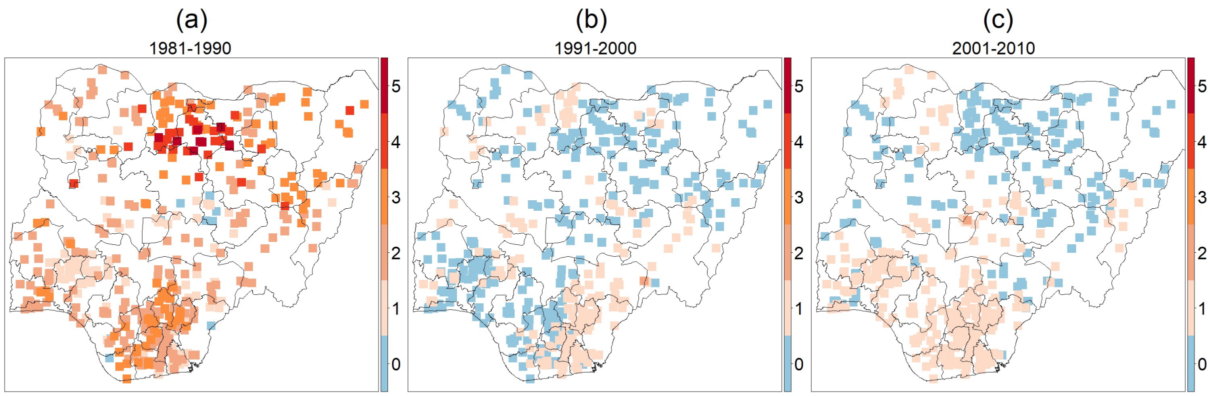
Figure 17: Long-term trends of climate indicators (3) - 1981-2019 long-term period



Notes : The Figure plots (a)SDII ($mm.day^{-1}$)(b)CWD and (c) CDD(days) trends over the long-rainy season (days), during the **long-term period 1981-2019**, based on CHIRPS data. Bottom panels show the significance of the trends at $p < 0.05$. Blue (+1) displays a significant increasing trends, while red (-1) a significant decreasing one and 0 non significant changes. SDII is the Simple Daily Intesity Index, CWD the Consecutive Wet day Index and CDD the Consecutive Dry Day Index.
Sources : author's elaboration on CHIRPS data.

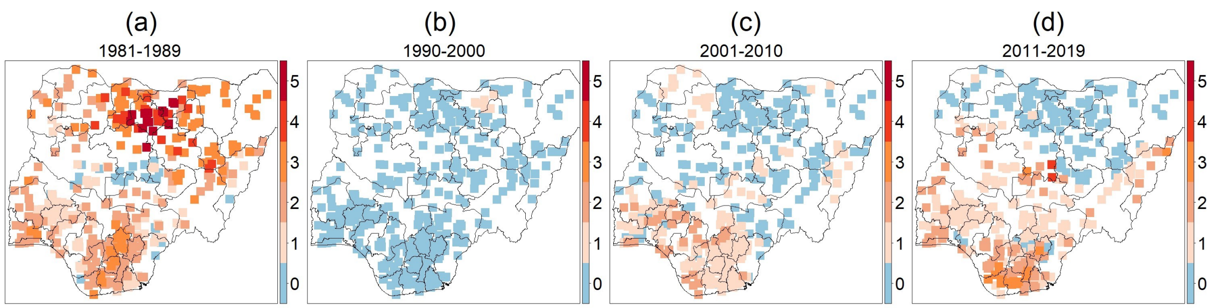
A.3 Main Shock of interest

Figure 18: Spatial distribution of the number of dry rainy seasons - past years



Notes : The Figures plot the number of dry rainy season for each GHS village from the panel, during the three decades over the thirty years period 1981-2010. Figure (a) plots the number of dry rainy season from 1981 to 1990 (including), Figure (b) from 1991 to 2000, while Figure (c) from 2001 to 2010. Dry years are defined according to the 1981-2010 long-term average. Please note that the number of dry rainy season reach 5 for some GHS village, as the dummy is constructed using the 10th percentile of the normal distribution of the rains (but this is scarce).
Sources : authors' elaboration on CHIRPS and GHS data.

Figure 19: Spatial distribution of the number of dry rainy seasons - past years



Notes : The Figures plot the number of dry rainy season for each GHS village from the panel, comparing 4 time periods over the full long-term period from 1981 to 2019. This Figure makes it possible to compare the intensity of dry spells, comparing the dry period of the 80s to the 2001 drought and the more recent years, used as contemporaneous short shocks in the first stage analysis. Figure (a) plots the number of dry rainy season from 1981 to 1989 (including), Figure (b) from 1990 to 2000, Figure (c) from 2001 to 2010, and Figure (d) from 2011 to 2019. Dry years are defined according to the 1981-2019 long-term average. Please note that the length of the 4 length periods vary in order to have the same number of years between Figure (a) and Figure (d), which are the main shocks that we intend to compare in this Figure.
Sources : authors' elaboration on CHIRPS and GHS data.