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IFPRI Discussion Paper 02185

May 2023

Climate Change, Income Sources, Crop Mix, and Input Use Decisions

Evidence from Nigeria

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Abstract

This paper combines panel data from nationally representative household-level surveys in Nigeria with long-term satellite-based spatial data on temperature and precipitation using geo-referenced information related to households. It aims to quantify the impacts of climate change on agricultural productivity, income shares, crop mix, and input use decisions. We measure climate change in harmful degree days, growing degree days, and changes in precipitation using long-term (30 year) changes in temperature and precipitation anomalies during the crop calendars. We find that, controlling for other factors, a 15 percent (one standard deviation) increase in change in harmful degree days leads to a decrease in agricultural productivity of 5.22 percent on average. Similarly, precipitation change has resulted in a significant and negative impact on agricultural productivity. Our results further show that the change in harmful degree days decreases the income share from crops and nonfarm self-employment, while it increases the income share from livestock and wage employment. Examining possible transmission channels for this effect, we find that farmers change their crop mix and input use to respond to climate changes, for instance reducing fertilizer use and seed purchases as a response to increases in extreme heat. Based on our findings, we suggest policy interventions that incentivize adoption of climate-resilient agriculture, such as small-scale irrigation and livelihood diversification. We also propose targeted pro-poor interventions, such as low-cost financing options for improving smallholders' access to climate-proof agricultural inputs and technologies, and policy measures to reduce the inequality of access to livelihood capital such as land and other productive assets.

Key Words: Climate change, Income sources, Crop mix, Input use.

Acknowledgments

This work was undertaken as part of the Nigeria Strategy Support Program, which has been managed by the International Food Policy Research Institute (IFPRI) and has been financially made possible by support of the United States Agency for International Development (USAID) through the Feed the Future Nigeria Agriculture Policy Activity; CGIAR Research Initiative on National Policies and Strategies (NPS); and Fragility, Conflict, and Migration (FCM). CGIAR launched NPS with national and international partners to build policy coherence, respond to crises, and integrate policy tools at national and subnational levels in six countries in Africa, Asia, and Latin America. Other CGIAR centers participating in the Fragility, Conflict, and Migration initiative include ABC, IITA, ILRI, and IWMI. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: https://www.cgiar.org/funders/.

1. Introduction

Climate variability and extreme weather events, including unpredictable and irregular rainfall, drought, and rising temperatures, threaten the food production, livelihoods, and food security of farm households in sub-Saharan Africa (SSA) (Di Falco et al., 2011; Di Falco and Veronesi, 2013). Such climatic shocks are expected to increase in frequency and intensity, and their impacts are projected to increase over time (IPCC, 2012). Smallholder farm households with fewer livelihood assets, limited coping strategies, and adaptation deficits are most vulnerable to climatic shocks (Calzadilla et al., 2013; Fankhauser and McDermott, 2014; Asfaw et al., 2018). The interactions between climatic and non-climatic factors, such as lack of access to productive assets and markets, reduce the resilience capacity of poor households and exacerbate their food insecurity. Within this context, an understanding of the effects of alternative adaptation strategies for coping with extreme climate events is crucial for developing interventions to mitigate the adverse impacts of climate shocks.

The rainfed agriculture that smallholders rely on is inherently exposed to risks of climate variability and change. These risks have significant economic implications because agriculture accounts for over 65 percent of the labor force in SSA countries and approximately three-fourths of total household income (Gollin et al., 2002; World Bank, 2007). Thus, various adaptation strategies are needed to mitigate the effects of climate change on agricultural productivity and household food insecurity. Engaging in activities that are less susceptible to the disruptions of climate change is one way for rural households to manage uncertainties surrounding agricultural production (Newsham and Thomas, 2009).

Smallholders may adopt livelihood diversifications as effective adaptation strategies to mitigate the effects of climate variability and climate change. Past studies document a range of livelihood diversification strategies, including diversification of crop portfolios (Barrett and Carter, 2013; Asfaw et al., 2018); livestock diversification (FAO, 2016); diversification of income sources (Minot et al., 2006; FAO, 2016); adjustment in agricultural input usage (Jagnani et al., 20201; Aragón et al., 2021); and labor diversification (FAO, 2016; Asfaw et al., 2018).

However, the nature and extent of these livelihood diversifications as ex ante climate risk mitigation strategies (Smit and Wandel, 2006) or ex post risk coping strategies (Murdoch, 1995; FAO, 2016) depend on households' risk-bearing capacity. This capacity reflects a household's asset endowments, human capital, and the climate risk perceptions of the household (Dercon and Christiaensen, 2011).

Regarding the choice of a specific diversification strategy, empirical evidence in SSA suggests that poverty is correlated with greater crop diversification, but with less income and labor diversification (Barrett et al., 2001; Babatunde and Qaim, 2009). For poor farmers who have the lowest capacity to effectively manage risk, crop diversification may be a response to the constraints imposed by climate risk (Howden et al., 2007). In this sense, a lack of alternative economic opportunities pushes them into crop diversification. In contrast, wealthier and more educated households are likely to be pulled into adopting income and labor diversification strategies because these households have greater access to productive assets (Ellis, 2000; Barrett et al., 2001). In the context of developing countries, however, climate variability and climate change can be seen in general as push factors to diversification, as risk-averse farmers implement ex ante risk management strategies to reduce their vulnerability to extreme climatic events (Barrett et al., 2001). In addition to endowments and poverty levels, heterogeneities in spatial conditions, such as market access, missing or imperfect credit, and insurance markets, can also play a significant role in farmers' diversification decisions (Jalan and Ravallion, 2002). Regardless of the different drivers of diversification (pull or push factors), empirical evidence suggests that more diversified households have better livelihood outcomes (Babatunde and Qaim, 2009).

This paper aims to quantify the impacts of climate change on agricultural productivity, income diversification, crop mix, and input use decisions. We measure agricultural productivity by the real net crop income per unit of land per hectare, and income diversification by the income share of the main income sources of the farm household. In addition to examining the overall impact of climate change on agricultural productivity and income sources, this research also aims to shed light on some of the specific pathways that mediate agricultural productivity and household income diversification, focusing on farmers' crop mix and input use decisions.

To address these questions, we use panel data from nationally representative household-level surveys for Nigeria that contain rich socioeconomic and demographic information. We combine these data with long-term satellite-based spatial data on temperature and precipitation using geo-referenced information related to households and farm plots. Satellite-based long-term precipitation data are less likely to suffer from the classic measurement errors of gauge measurements (Brückner and Ciccone, 2011; Amare et al., 2021a).

Our study contributes to the climate adaptive agriculture and livelihood strategies transformation literature in several important ways. First, using long-term temporal variabilities in precipitation and temperature indicators to measure climate change, we explore the impact of climate change on several outcome variables such as households' income sources, agricultural productivity, crop mix and input use decisions. Second, we explore the nonlinear effects of changes in precipitation and temperature on agricultural productivity and other outcome variables. To the best of our knowledge, we have not come across past studies in agricultural economics literature that explicitly model the nonlinear effects of these climatic factors, although it has been described in agricultural sciences (see, for example Schlenker and Roberts, 2006, 2009; Kawasaki and Uchida, 2016; Lesk et al., 2016). Third, this study examines the long-term combined effects of precipitation and temperature on outcome variables of our interest. We also examine the differential impacts of climate change on relatively poor and nonpoor groups of households. The findings of this paper thus provide key decision-support evidence to better understand the impacts of climate change on agricultural productivity and livelihoods of smallholder farm households and identify different adaptation strategies aimed at reducing climatic risks and enhancing adoption of climate-resilient practices to ensure agricultural sustainability, livelihoods, and food security.

We find that climate change, measured through harmful degree days, growing degree days, and changes in precipitation, exerts significant impacts on agricultural productivity, crop mix, and input uses. The change in harmful degree days has a negative effect on agricultural productivity. Controlling for other factors, a 15 percent (one standard deviation) increase in change in harmful degree days leads to a 5.22 percent decrease in agricultural productivity on average. The change in harmful degree days also decreases the income share of crops and non-farm self-employment, while it increases the income share of livestock and wage employment. Similarly, our estimates confirm that precipitation change has a significant and negative impact on agricultural productivity. Examining possible transmission channels, we find that farmers adopt changes in crop mixes and input use as adaptation strategies to respond to climate changes. We show that increases in extreme heat days increase area planted, decrease fertilizer use, and decrease seed purchases. For instance, we find that a one standard deviation increase in harmful degree days leads to a 1.17 percent increase in area planted.

The remainder of the paper is organized as follows: Sections 2 and 3 present the conceptual framework and hypotheses and the Nigerian context respectively. The data and measurement of variables, empirical model, and identification strategies are presented in sections 4 and 5. The empirical results are presented in section 6, and section 7 concludes with the main findings and policy implications.

2. Conceptual Framework and Hypotheses

This section presents the conceptual basis and the hypotheses that underpin our empirical analyses. Climate change poses serious challenges for farming households, affecting their food production, planning capacity, and livelihood outcomes like food security and household income (Barrios et al., 2008; Arslan et al., 2017; Hochman et al., 2017; Nguyen et al., 2020). For example, a study based on crop modeling in Nigeria finds that a 5–25 percent loss of yield in sorghum in the northern Sahelian zone is likely related to temperature increases (Hassan et al., 2013). Crop mix and input use decisions are important considerations in response to climatic factors among smallholders in SSA (Bert et al., 2006; Mertz et al., 2009; Yang et al., 2016; Roberts et al., 2017). Hassan et al. (2013) project an increase in the production of cassava, sweet potatoes, yams, and other root and tuber crops in Nigeria in response to climate risk implying that farmers may shift their land from climate-sensitive crops to crops that are resilient to climate variability. Similarly, farmers may adapt to drought by abandoning farming, reducing or expanding the land area cultivated, and/or changing crop types or mixes to mitigate climate risks to agricultural production (Yang et al., 2016).Thus, climate-related information on the magnitude, timing, and distribution of precipitation and temperature changes can have a significant effect on the farmers' crop mix decisions and their adoption of sustainable agricultural practices (Bezabih and Di Falco, 2012; Teklewold et al., 2013). Climate-related information can prompt farmers to reduce the effects of climate shocks by allocating their farmland into more than one cropping season, particularly for crops with a shorter growing period, and improve their farm income earnings (Howden et al., 2007; Barrett and Carter, 2013). Climate changes also affect farmers' decisions about input use, including decisions related to fertilizer, pesticides, hired labor, and seeds (Jagnani et al., 2021). The nature and extent of such decisions are usually motivated by the objectives of the farming household and the environmental constraints, including those outside the farmers' control (Wallace and Moss, 2002).

Climate variability and change may also affect a household's off-farm income source diversification, including through participation in wage employment on other farms or in other sectors, starting one's own business, or migrating to towns and cities (FAO, 2016; Asfaw et al., 2018). Ersado (2003) shows that households in Zimbabwe pursued income diversification to reduce their vulnerability to weather shocks; Newsham and Thomas (2009) demonstrate that climate change pushed farmers into income diversification in Namibia.

In a nutshell, a farm household's livelihood diversification can take different forms — diversification of crops, income sources, or use of labor on wage employment and the farm. Farmers diversify their crops to protect themselves against total crop failure or the effects of reduced crop yields. They respond to climate change by adopting multiple cropping systems — growing two or more crops on the same field either at the same time or one after the other (Waha et al., 2013). This strategy reduces the threat of climate change to various facets of household food security. The conceptual framework that underpins the relationship between livelihood diversification and vulnerability implies that vulnerability should decline as diversification increases (Ersado, 2003; Babatunde and Qaim, 2009; FAO, 2016; Nguyen et al., 2020). Against this backdrop, we propose three hypotheses to guide our empirical investigation.

Hypothesis 1. Several studies in SSA show that smallholders prioritize the cultivation of staple crops in the face of unpredictable weather shocks, for example, growing subsistence maize in Zambia (FAO, 2016), root crops such as cassava and yams in Nigeria (Hassan et al., 2013), and less risky crop portfolios in Ethiopia (Bezabih and Di Falco, 2012). We argue that, in the context of imperfect or missing credit, insurance, and labor markets, food security will be the primary objective of farm households (Wheeler and von Braun, 2013). Farmers may mitigate the risks of food insecurity caused by climate change by changing crop mixes, that is, allocating farmland to crops that are less susceptible to climate shocks (Bezabih and Di Falco, 2012).

Hypothesis 2. Existing evidence confirms that poor farmers are more vulnerable to the impacts of climate change and extreme weather events (World Bank, 2013). We hypothesize that adverse climate change pushes vulnerable farm households to diversify off-farm activities and thus to decrease their income share from crop and livestock but increase their income share from off-farm sources.

Hypothesis 3. Investments in agricultural productivity have been shown to reduce poverty and foster economic growth (Gollin et al., 2002; Irz and Tiffin, 2006). However, uptake of modern agricultural technologies is low in many SSA countries (Amare et al., 2018; Sheahan and Barrett, 2017; Binswanger-Mkhize and Savastano, 2017). Climate changes may limit uptake of new farm technology (Barrett and Carter, 2013; Dercon and Christiaensen, 2011, Amare et al., 2022). Following findings on input use decisions among Kenyan farmers (Jagnani et al., 2021; Amare et al., 2022), we hypothesize that climatic factors led farmers to shift from purchasing productivity-enhancing inputs such as fertilizer to loss-reducing inputs such as pesticides to protect their crops from pests, crop diseases, and weeds.

3. The Nigerian Context

Nigeria provides an interesting case study in SSA to examine the effects of climate change on agriculture and rural livelihoods. With over 207 million people, Nigeria is the most populous country in Africa. Like most SSA countries, agriculture is a major source of employment and economic development, accounting for about 23 percent of GDP and a 70 percent share of the labor force (World Bank, 2018). Unfortunately, about 40 percent of Nigeria's population lives below the international poverty line of $1.90 per day (World Bank, 2018). Food insecurity and a shortage of energy and nutrient-rich foods remain the country's major challenges (FMARD, 2016; NPC and IFC, 2019). Agricultural productivity remains low due to factors such as inadequate use of yield-enhancing agricultural inputs and technologies. Yields of staple cereals and root crops in Nigeria are less than half the world average, for example the average yield gaps for Nigeria's three major staple crops — rice, maize, and cassava — are more than 75 percent; 84 percent; and 25 percent respectively (World Bank, 2018). Adverse climatic changes exacerbate the challenges in the agriculture sector, which is already performing well below its potential.

According to the Nigerian Meteorological Agency's assessment of the 60-year period from 1941 to 2000, annual rainfall decreased by 2–8 mm across most parts of the country, and the length of the growing season decreased due to a later onset and earlier cessation of rainfall (NIMET, 2008). The assessment further shows a long-term temperature increase in most parts of the country and significant increases (a rise of average temperature by 1.4° to1.9°C) in the extreme northeast, extreme northwest, and extreme southwest of the country. Simulations of future climate conditions based on various scenarios show a warmer and drier climate (BNRCC, 2011). Recent climate projections for the country indicate a temperature increase of between 1° and 4°C for all ecological zones in the coming decades (Cervigni, et al., 2013; Hassan et al., 2013). According to the BNRCC report[1], in the absence of adaptation measures, climate change could reduce GDP by 6 and 30 percent by 2050.

Nigerian agriculture is highly vulnerable to changes in climate factors, especially in terms of production losses, income losses, and household food insecurity. Because of Nigeria's dependence on rainfed agriculture, anomalies in precipitation such as long dry spells and a late onset and short duration of the growing season have significant impacts on agricultural production. Crop modeling studies comparing crop yields in 2050 with climate change and the yields with the 2000 climate predict yield losses of 5 to 25 percent in areas planted with sorghum in the northern Sahelian zone of Nigeria (Hassan et al., 2013). On the other hand, there may be future increases in the production of millet, cassava, sweet potatoes, yams, and other root and tuber crops (Hassan et al., 2013). Results from a World Bank study (Cervigni et al., 2013) also predict a high probability of lower yields for all crops in 2050 in all agroecological zones of Nigeria except the outlook for yams, cassava and millet is uncertain. The study highlights the vulnerability of rice in northern parts of the country, where yields are predicted to decline by about 20–30 percent in the longer term (2050).

In 2011, as a policy response to the effects of climate change, the country produced the National Adaptation Strategy and Plan of Action on Climate Change for Nigeria (NASPA-CCN) (BNRCC, 2011). The document identified agriculture as a key sector in which to develop adaptation strategies and implement climate-resilient practices. In 2014, Nigeria produced a sector-specific policy document to foster adaptation strategies in the agriculture sector specifically — the National Agricultural Resilience Framework (NARF) (FMARD, 2015).[2] The NARF is Nigeria's first sector-specific climate adaptation and risk mitigation program. It includes a plan of action for innovative agricultural production strategies and risk management mechanisms that promote resilience in the agriculture sector. These adaptation strategies are intended to reduce the impacts of climate change, or even turn some aspects into advantages. For instance, higher temperatures might permit higher yields for some crops in some areas. Thus, it is important to understand the type of adaptation strategies adopted by farmers and how these vary spatially and temporally in order to promote context-specific strategies that ensure production sustainability and enhance livelihood outcomes.

[1] Building Nigeria's Response to Climate Change (BNRCC) project (http://csdevnet.org/wp-content/uploads/NATIONAL-ADAPTATION-STRATEGY-AND-PLAN-OF-ACTION.pdf)
[2] National Agricultural Resilience Framework (https://boris.unibe.ch/62564/1/Nigeria%27s%20Changing%20Cliamte.pdf)

4. Data Sources and Variable Measurement

4.1. Data sources

This study uses three wave panel datasets from the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) from Nigeria. These nationally representative datasets include detailed information on demographic and household characteristics, assets, agricultural production, nonfarm income and other sources of income, allocation of family labor, hiring of labor, and access to services. The agriculture module, among others, contains information on agricultural and livestock production, farm technology, use of modern inputs, and productivity of crops. The LSMS–ISA includes geo-referenced information related to household and plot data that allows us to link satellite-based datasets to households. Thus, we combine the survey panel data with long-term satellite-based spatial data on temperature and precipitation.

Since our objective is to explore how climate change affects agricultural productivity, crop mix, and input use decisions in Nigeria, we restrict the data to farm households that planted crops and for which data on temperature and rainfall is available at the household level. This procedure results in a balanced panel of 2129 farm households for three waves of panel data and a total of 6387 samples in all three waves. Our key variables of interest are climate changes, growing degree days (GDD) and harmful degree days (HDD): precipitation fluctuations, agricultural productivity, crop mix, income share and input use.

The temperature data are extracted from NASA MERRA-2 (Modern-Era Retrospective Analysis for Research and Application) (Wan et al., 2015). We use daily average temperatures in degrees Celsius over a 30-year period (1986 to 2015) at a spatial resolution of 0.05° x 0.05° (~ 5 km x 5 km). Similarly, we extract monthly precipitation data over a 30-year period at a spatial resolution of 0.05° x 0.05° (~ 5 km x 5 km) from the Climate Hazards Group InfraRed Precipitation Station (CHIRPS) archives provided by the Climate Hazard Group (Funk et al., 2015; Novella and Thiaw, 2013). We use satellite-based long-term precipitation data instead of gauge measurements (Brückner and Ciccone, 2011; Amare et al., 2021a). Satellite-based precipitation data are less likely to suffer from measurement errors as well as errors that may arise because of the sparseness and limited number of operating gauge stations in SSA countries. We restricted the data to farm households that planted croplands and for which data on temperature and precipitation at the household level are available.

4.2. Variable measurement

Climate changes: We use growing season to define the relevant period for the construction of our temperature and precipitation variables. Because Nigeria has a diverse agroecological landscape which a mix of tropical and drier rainfed regions (Benson et al., 2021; Amare et al., 2021b) The length of the growing season generally decreases from southern to northern Nigeria. We then capture this regional difference. The crop calendar for northern Nigeria typically extends from early May through late October, while for southern Nigeria it lasts from early March through October.

Growing degree days (GDD) and harmful degree days (HDD): We use daily average temperatures to calculate the number of days each household is exposed. We follow the standard convention of agronomic literature that converts daily mean temperatures into growing degree days (GDD) to estimate the effect of temperature on agricultural productivity, income share, and input use (Lobell et al., 2011; Lobell et al., 2013; Deryng et al., 2014; Hendricks and Peterson, 2014; Jessoe et al., 2018; Jagnani et al., 2021; Aragón et al., 2021). Growing degree days (GDD) are calculated using the cumulative exposure to temperatures between a lower bound (the standard base temperature of 8°C) up to an upper threshold of 32°C (Schlenker and Roberts, 2009). All temperatures above 32◦C also contribute 24-degree days (Schlenker and Roberts, 2006; Schlenker and Roberts, 2009). Degree days are then summed over the entire growing season. We convert daily temperatures into growing degree days (GDD) using the following formula:

$$GDD = \begin{cases} 0 & if \quad T \leq 8C \\ T-8 & if \quad 8C < T \leq 32C \\ 24 & if \quad T > 32C \end{cases} \tag{1}$$

In analyses of the effect of climate changes, we focus on the deviation of temperature from the norm (e.g., Macinni and Yang, 2009; Björkman-Nyqvist, 2013; Rocha and Soares, 2015). Specifically, we subtract the average growing season GDD for the last 30 years for growing season from the GDD for each of the waves of data collected in the previous year. Thereby, we derive the GDD deviation for each wave during the respective crop cycles for each survey household as:

$$\Delta \mathrm{GDD}_{it} = \ln\left(\mathrm{GDD}_{it}\right) - \ln(\overline{\mathrm{GDD}}_{i}) \tag{2}$$

Because agricultural production declines physiologically due to heat stress above 32°C (Jessoe et al., 2018; Jagnani et al., 2021; Aragón et al., 2021), we defined degree days above 32°C (GDD>32) as harmful degree days (HDD). In essence, HDDs are anomalies relative to the mean of HDDs over the 30-year period:

$$\Delta \mathrm{HDD}_{it} = \ln(\mathrm{HDD}_{it}) - \ln(\overline{\mathrm{HDD}}_i) \tag{3}$$

Precipitation fluctuations: We construct the change in precipitation variable as the deviation of a given year's precipitation during the growing season from the historical averages (over the 1986–2015 period) during the growing season for the same locality. The change in precipitation variable is defined as deviation of log rainfall from the norm using:

$$\Delta \mathrm{R}_{it} = \ln(\mathrm{R}_{it}) - \ln(\overline{\mathrm{R}}_i) \tag{4}$$

where R_{it} indicates the precipitation during the growing season in the previous year at the location of household i for year t. $\overline{\mathrm{R}_i}$ is the historical average precipitation (over the 1987–2016 period) during the growing season at the location of household i. Weather deviations are interpreted as the percentage deviation from the mean. For example, a value of 0.10 indicates precipitation was approximately 10 percent higher than normal.

Agricultural productivity: We measure agricultural (land) productivity as the real net crop income per hectare. Net crop income is calculated as gross crop income minus variable crop production costs. Net real crop income is adjusted to 2010 purchasing power parity (PPP) using the regional consumer price index.

Crop mix: We measure a farmer's crop mix using the share of area planted in major crops to total land area cultivated. To do so, we divide the total farmland area of a household into five crop categories: (1) cereal crops (maize, sorghum, millet, and rice); (2) pulses and legumes (bean, cowpeas, and chickpeas); (3) roots and tubers (cassava and yam); (4) tree crops (cocoa, oil palm, and banana); and (5) other uses, such as fishponds or own businesses.

***Income share*:** We break down household income into five different sources: (1) crop income; (2) income from livestock; (3) nonfarm self-employment; (4) wages; (5) and other sources, which include transfer income, pensions, and rents or income from properties. Total real income computed from these sources is adjusted to 2010 purchasing power parity (PPP) using the regional consumer price index. We measure the income share from each source by dividing that income by the total real income.

Input use: We measure input use including fertilizer, purchased seeds, and pesticides used in production. We define indicator variables for fertilizer use, purchased seeds, and pesticide use, which take the value of 1 if the farmer used these inputs and 0 otherwise.

A description of the variables and summary statistics used in subsequent regression analyses are presented in Table 1 and Table 2. Table 1 reports the deviation from the long-term mean of climate change variables (fluctuations in temperature and precipitation). The deviation from the long-term mean for GDD and for HDD is 0.07and 0.02, respectively. All sampled households received 4% less precipitation than normal during the survey years. Table 2 reports the mean values for agricultural productivity and input use; income share; crop mix income; demographic characteristics; wealth indicators including land, livestock, and the value of total assets. The average agricultural productivity, measured in term of net crop income per hectare (ha), is USD 3,425 per ha in Nigeria.

Figure 1 portrays the spatial variabilities of the GDDs and HDDs across Nigeria. The maps in panels (a) and (b) show the spatial distribution of GDDs and HDDs respectively; panels (c) and (d) present the distributions of differences in GDDs and HDDs over time. All four maps show the north–south differences in GDDs and HDDs in the country. Over the period of three decades (1985–2016), northern Nigeria generally experienced significant climatic fluctuations — from GDDs as low as 11ºC in states including Taraba and Adamawa to extremely high in states including Borono, Yobe, Sokoto, and Katsina. This implies the unpredictability of climatic factors in northern Nigeria, with a consequent negative effect on crop growth. Though Nigeria's northern region appears to experience warmer temperatures that favor fast crop development in some years, the extreme heats measured as HDDs above certain threshold that hinder plant growth were also recorded in the northern states. On the other hand, the southern region, with a growing season from March through October, had more stable GDDs over the three decades and no extreme HDDs were registered. This observed spatial climatic variability mirrors the geography of the country: northern Nigeria is part of the dry Sudan-savanna zones, while the southern region is mainly characterized by humid coastal weather conditions. In general, temperature decreases, and the length of the crop growing season increases in Nigeria from north to south.

5. Empirical Estimation Strategy

Building on the previous section, we investigate the effect of climate changes (temperature and precipitation fluctuations) on farmers' crop mix decisions and income share from different sources. We allow for nonlinearities of climate changes in our estimations by including both HDD and GDD change, and precipitation and precipitation change squared. We estimate the effect of farmers' crop mix decisions and income share from different sources using equ. 5:

$$SL_{itk} = \gamma_1 \Delta \mathrm{GDD}_{it} + \gamma_2 \Delta \mathrm{HDD}_{it} + \gamma_3 \Delta \mathrm{R}_{it} + \gamma_4 \Delta \mathrm{R}_{it}{}^2 + \gamma_5 X_{it} + \eta_{it} + \mu_i + \varepsilon_{itk} \ , \quad (5)$$

where SL_{itk} is farmers' crop mix decision of crop categories k or income share of main sources k by household i in year t. ΔGDD_{it} is deviation of log growing degree days from long-term average at household level i in year t. ΔHDD_{it} is deviation of log harmful degree days from long-term average at household level i in year t. ΔP_{it} is deviation of log precipitation from long-term average at household level i in year t. Similarly, X is a vector of household and community characteristics, including household size, age, gender of the household head, and household assets. State-year (η_{it}) captures aggregate shocks impacting the entire state and secular trends in outcome variables and individual (μ_i) fixed effects. ε_{itk} is the error term for which a strict exogeneity condition is assumed to hold; errors are independently and normally distributed with zero mean and constant variance and are assumed to be uncorrelated to all the explanatory variables.

However, factors affecting the intensity of a specific crop area planted could also affect the intensity of an area planted with other crop types, as well as cross-equation error terms, which may likely be correlated for the same household because the area planted with a specific crop by a household in a particular year is fixed. Similarly, factors affecting crop income share may affect the income share of livestock, nonfarm self-employment, wage employment, and income from other sources, as well as cross-equation error terms that may likely be correlated for the same household. Thus, a seemingly unrelated regression (SUR) model was developed to include joint estimates from several regression models, where the error terms associated with the dependent variables are assumed to be correlated across the equations (equ. 6). Therefore, the empirical model of farmers' crop mix decisions and income share from different sources is a set of five simultaneous equations as specified in equ. 6.

$$\begin{cases} SL_{it1} = \gamma_{11}\Delta\text{GDD}_{it} + \gamma_{12}\Delta\text{HDD}_{it} + \gamma_{13}\Delta\text{R}_{it} + \gamma_{14}\Delta\text{R}_{it}{}^{2} + \gamma_{15}X_{it} + \eta_{it1} + \mu_i + \varepsilon_{it1} \\ SL_{it2} = \gamma_{21}\Delta\text{GDD}_{it} + \gamma_{21}\Delta\text{HDD}_{it} + \gamma_{23}\Delta\text{R}_{it} + \gamma_{24}\Delta\text{R}_{it}{}^{2} + \gamma_{25}X_{it} + \eta_{it2} + \mu_i + \varepsilon_{it2} \\ SL_{it3} = \gamma_{31}\Delta\text{GDD}_{it} + \gamma_{32}\Delta\text{HDD}_{it} + \gamma_{33}\Delta\text{R}_{it} + \gamma_{34}\Delta\text{R}_{it}{}^{2} + \gamma_{35}X_{it} + \eta_{it3} + \mu_i + \varepsilon_{it3} \\ SL_{it4} = \gamma_{41}\Delta\text{GDD}_{it} + \gamma_{42}\Delta\text{HDD}_{it} + \gamma_{43}\Delta\text{R}_{it} + \gamma_{44}\Delta\text{R}_{it}{}^{2} + \gamma_{45}X_{it} + \eta_{it4} + \mu_i + \varepsilon_{it4} \\ SL_{it5} = \gamma_{51}\Delta\text{GDD}_{it} + \gamma_{52}\Delta\text{HDD}_{it} + \gamma_{53}\Delta\text{R}_{it} + \gamma_{54}\Delta\text{R}_{it}{}^{2} + \gamma_{55}X_{it} + \eta_{it5} + \mu_i + \varepsilon_{it5} \end{cases} \tag{6}$$

where SL_{it1}, SL_{it2}, SL_{it3}, SL_{it4}, and SL_{it5} are crop mixes of major crop categories to total area planted (of cereal crops, pulses, roots/tubers, tree crops, and other uses, respectively) or income share (of income share of crops, livestock, nonfarm self-employment, wage employment, and income from other sources, respectively) of household i in year t. As the sum of all areas planted and income share of household i is up to 100 percent at each household and the same regressors were used in each equation, the covariance matrix of the residuals becomes singular. Thus, SL_{it5} is dropped during the estimation procedure.

Second, we estimate the effect of climate changes on agricultural productivity. Given that factor markets are absent or imperfect in our rural settings, we employ a non-separable (between production and consumption decisions) farm household model (de Janvry et al., 1991; Singh et al., 1986) as the key conceptual framework. We measure agricultural productivity through analysis of the productivity of land. Application of inputs (e.g., seeds and fertilizer) is important for increasing productivity of land as land scarcity increases. We measure agricultural productivity (P_{it}) as the real net crop income per hectare. We use a Cobb-Douglas production function as in (equ. 7):

$$ln(P_{it}) = \alpha_1\Delta\text{GDD}_{it} + \alpha_2\ \Delta\text{HDD}_{it} + \alpha_3\text{RD}_{it} + \alpha_4\text{RD}_{it}{}^{2} + \alpha_5\ln(Z_{it}) + \eta_{it} + \mu_i + \varepsilon_{it}\ , \tag{7}$$

where Z_{it} is an agricultural input, including area planted, seeds, fertilizer, herbicides, and pesticides used at household level i in year t. We capture the nonlinear impacts of temperature by separately including ΔHDDs and ΔGDDs and allowing for nonlinear precipitation effects by including precipitation and precipitation squared (Schlenker and Roberts, 2006). We estimate a log-log linear fixed effects regression model. Thus, the coefficients α can be interpreted as elasticities for the agricultural productivity.

In addition to examining the impact of climate changes on agricultural productivity, we aim to examine the specific pathways that mediate such agricultural productivity, focusing on the impact of climate changes on input use. Climate changes are widely understood to have potentially serious adverse effects on agricultural productivity through reduced productivity-enhancing external input use. This is mainly because weather shocks increase the risk of farm technology adoption, particularly in rainfed, liquidity-constrained, and imperfect market settings (Barrios et al., 2010; Dercon and Christiaensen, 2011; Di Falco and Chavas, 2009). We specifically estimate a fixed effects specification (equ. 8) to investigate the effect of climate changes on input use:

$$Z_{it} = \beta_1 \Delta \mathrm{GDD}_{it} + \beta_2 \Delta \mathrm{HDD}_{it} + \beta_3 \Delta \mathrm{RD}_{it} + \beta_4 \Delta \mathrm{RD}_{it}{}^2 + \beta_5 X_{it} + \eta_{it} + \mu_i + \varepsilon_{it} \,, \tag{8}$$

where Z_{it} stands for input use, such as area planted, fertilizer application, purchased seed, and pesticide use for each household i and year t. The estimate for the area planted is carried out using a linear fixed effects regression model. Fertilizer use, purchased seed, and pesticide use are estimated using linear probability models. The coefficients β can be interpreted as the change in probability of fertilizer use, purchased seed, and pesticide use to relative changes in the corresponding weather variables.

The effects of climate changes are likely to vary with households' socioeconomic status, including differences in their underlying vulnerabilities. For instance, poorer households are likely to bear the consequences of climate changes, as they are likely to rely on rainfed agriculture and have limited access to farm technologies. We therefore estimate the main specification in equations (7) and (8) across several sample splits. In such circumstances, resource-poor farmers bear the high cost of climate changes and may find it difficult to adopt productivity-enhancing technologies and inputs or to diversify into high-value commodities (Shiferaw et al., 2015; Anderson and Feder, 2007). Thus, the effect of climate changes on farmers' crop mix decisions, income shares, input use, and agricultural productivity depend on households' risk-bearing capacities, level of assets, and perceptions of climate changes (Dercon and Christiaensen, 2011; Amare et al., 2021a). We use the first round (wave 1) value of assets, livestock ownership, and farm size as a proxy for wealth. We separate the sample by terciles and denote households in the bottom tercile as relatively "poor." We define binary wealth variables that take value 1 if value of assets, livestock holdings (TLU), and farm size for household i is in the bottom tercile based on wave 1 data, that is if the 2010/11 total value of household assets is less than US$175.51 in PPP, and livestock holdings are less than 0.08 TLU and 0 otherwise. We then estimate separately if the magnitude of the coefficient of changes in temperature and precipitation over time varies on agricultural productivity and farmers' input use decisions by initial wealth indicators.

6. Results and Discussions

In this section we report the main estimation results based on equations (6–8). Although some of the relationships we discuss may carry causal interpretations, we refrain from claiming clean causality. We first present estimation results based on the effect of climate changes on agricultural productivity in section 6.1 and on households' income sources in section 6.2. We then present the estimation results of the specific pathways that mediate agricultural productivity, focusing on the effect of climate changes on farmers' crop mix decisions (section 6.3) and input use (section 6.4). Estimation results of heterogeneous impact of climate changes is presented in section 6.5.

6.1. The effect of climate changes on agricultural productivity

We employ fixed effects regression models to estimate the effect of climate changes on agricultural productivity using both unconditional and conditional relationships. The estimated coefficients on climate changes remain sizable and strongly statistically significant even after controlling for these characteristics (Table 3). We focus on and report results from models controlling for covariates. The results in Table 3 show that the change in HDD has a negative effect on agricultural productivity.

The estimates confirm that the change in HDD has a significant and negative impact on agricultural productivity. Controlling for other factors, we find that a 15 percent (one standard deviation) increase in change in HDD leads to a decrease in agricultural productivity of 5.22 percent on average. Similarly, the estimates confirm that precipitation change has a significant and negative impact on agricultural productivity. A one standard deviation increases in precipitation change leads to a decrease in agricultural productivity of 1.23 percent on average. Similarly, several regression coefficients are statistically significant, and the signs of the estimated coefficients are in line with a priori theoretical expectations. Comparing the relative effects of the change in HDD and that of precipitation, we find that changes in HDD have a much larger effect on agricultural productivity than changes in precipitation. This may indicate that, in the context of our data in the study country, temperature variability plays a stronger role in influencing agricultural production and productivity.

6.2. The effect of climate changes on income sources

We now turn to an exploration of the effect of climate changes on farmers' income shares from their main income sources. We estimate the effect of climate changes on farmers' income shares with and without covariates. The effect of climate changes is substantially reduced when we control for household characteristics, but the estimated coefficients on climate changes remain sizable and strongly statistically significant (Table 4). The Breusch-Pagan (BP) test verifies the use of the SUR model, as it is statistically significant at the 1 percent level. The coefficients associated with extreme heat and second-order polynomial terms of precipitation show substantial nonlinearity in the relationship between climate changes and income shares.

The results indicate that the change in HDD decreases the income share from crops and nonfarm self-employment, while it increases the income share from livestock and non-agricultural wage income. A 15 percent (one standard deviation) increase in change in HDD leads to a reduction of 0.52 percentage points in the income share from crops, an increase of 0.19 in the income share from livestock, and an increase of 0.28 points in the income share from wage employment. Similarly, precipitation change decreases the income share from crops while it increases income shares from livestock and wage employment. A one standard deviation increase in change in rainfall leads to an increase of 0.97 percentage points in the income share from livestock and 0.62 percentage points in the income share from wages.

6.3. The effect of climate changes on farmers' crop mix decisions

We first report on the results of the effect of climate changes on farmers' crop mix decisions. We estimate the effect of climate changes on crop mix decisions with and without covariates. The fixed effect results control for household and year fixed effects, which can capture time-invariant community-level heterogeneity across households and time. Our results show that the effect of climate changes is substantially reduced when we control for household characteristics, suggesting that the effect of climate changes on farmers' crop mix decisions are mediated through these channels. Nevertheless, the estimated coefficients on climate changes remain sizable and strongly statistically significant even after controlling for these characteristics. We focus on and report results for models controlling for covariates. The coefficients associated with extreme heat and second-order polynomial terms of precipitation show substantial nonlinearity in the relationship between climate changes and farmers' crop mix decisions.

Table 5 reports the fixed effects estimates for effects of climate changes on farmers' crop mix decisions. The Breusch-Pagan (BP) test verifies the use of the SUR model, as it is statistically significant at the 1 percent level. We find that farmers use crop mix to respond to climate changes. This shows that the set of available adaptations differs by crop categories and there could be additional scope for adaptation with the "other crops" category, such as fishponds. This finding suggests that the capacity of the "other crops" category to absorb fluctuations may play an important role in mitigating the consequences of weather-driven changes in agricultural productivity. This is consistent with the literature, which indicates that changes in crop mix are as a possible way to increase food security and adapt to climate change (Harvey et al., 2014; Burke and Emerick, 2016).

The results indicate that the change in HDD reduces the share of land allocated to cereals and tree crops, while it increases the share of land allocated to legumes and tubers. For example, a 15 percent (one standard deviation) increase in change in HDD leads to a reduction of 1.16 percentage points in the land share of cereals and 0.28 percentage points in the land share of tree crops; it also leads to increases of 0.33 and 0.36 percentage points in the land share of legumes and tubers, respectively. The results indicate that farmers respond to extreme heat by making changes in crop choices, switching from cereals and tree crops to legumes and tubers. This finding may indicate that legumes and tubers are affected less by extreme heat. But farmers could prefer legumes and tubers for several reasons other than heat tolerance. Studies on food security highlight several advantages of tubers (like potatoes, cassava, and sweet potatoes) over other crops, as they have short maturity, sequential harvesting, low water and fertilizer requirements, more reliability, and high nutritional content (Devaux et al., 2014).

Similarly, precipitation change decreases the land share of cereals and legumes, while it increases the land share of tubers and tree crops. A 15 percent (one standard deviation) increase in precipitation leads to reductions of 16.46 and 5.34 percentage points in the land share of cereals and legumes, respectively, and to increases of 18.09 and 2.79 percentage points in the land share of legumes and tubers, respectively. This is consistent with the literature, which indicates that farmers tend to allocate land to crops that are comparatively less impacted by precipitation change (Ebanyat et al., 2010; Chalise and Naranpanawa, 2016; Asante et al., 2017).

6.4. The effect of climate changes on input use

To address the effect of climate changes on input use, we employ linear and probability fixed effects regression models. We estimate both unconditional and conditional relationships between climate changes and input use. The estimated coefficients on climate changes remain sizable and strongly statistically significant even after controlling for these characteristics. We focus on results for models controlling for covariates (Table 6). The estimated coefficients associated with extreme heat and second-order polynomial terms of precipitation show substantial nonlinearity in the relationship between climate changes and input use.

Area planted*:* The results show a positive and statistically significant effect of HDD on area planted. Controlling for other factors, we find that a 15 percent (one standard deviation) increase in HDD change leads to an increase in area planted of 1.17 percent on average. The results further show that a 15 percent (one standard deviation) increase in rainfall change leads to a decrease in area planted of 6.12 percent on average. The explanation for this may be related to the farmers' risk-aversion behavior and adaptation to climate shocks. With an increase in change in HDD, farmers may anticipate failures of crops that are susceptible to climate changes. So, to protect against such potential crop failures, farmers may cultivate more areas (possibly with diverse crops) so that households can minimize income losses and food insecurity.

Fertilizer, purchased seed, and pesticide use: We find that the change in HDD has a negative and significant effect on fertilizer use. Change in extreme heat also seems to decrease the likelihood of purchased seed use. The negative and statistically significant point estimate is consistent with the hypothesis that farmers reduce input expenditures. Controlling for other factors, we find that a 15 percent (one standard deviation) increase change in HDD decreases the probability of fertilizer use by roughly 3 percent. Our finding is consistent with the recent finding by Jagnani et al. (2021), who show that Kenyan farmers shift from productivity-enhancing fertilizer inputs to loss-reducing inputs such as pesticides as a response to temperature anomalies. Our results also show that a one standard deviation increase change in HDD decrease the probability of purchased seed use by 18 percent. This might suggest that, as liquidity constraints begin to bind for farmers, expenditure on loss-reducing adaptive inputs necessitates reduction in fertilizer use. This last result is consistent with findings in the literature on fertilizer use showing that households reduce fertilizer use when subject to negative income shocks (Bandara et al., 2015).

We also find that farmers increase pesticide use in response to extreme heat change. The increase suggests that farmers exposed to temperature shock may need to resort to more intensive land use and pesticide use to offset undesirable drops in output (Jagnani et al., 2021). In this sense, changes in input use are akin to other consumption-smoothing mechanisms, such as selling disposable assets or increasing off-farm work (Zimmerman et al., 2003). However, farmers may also be responding to changes in output risk from an increased incidence of pests, crop diseases, and weeds (Mubiru et al., 2018).

6.5. Heterogeneous effects by wealth

We hypothesize that farmers' wealth differential has led to heterogeneous effects (Asfaw et al., 2019) from climate changes on the outcome variables considered in the study. Poor households are more likely to face binding financial liquidity constraints and are more likely to be risk averse for a given increase in biotic risk exposure. This is due to farmers' differing ability and willingness to cope with weather-induced reductions in agricultural productivity and input use. We examine whether the magnitude of the coefficient of changes in temperature and precipitation over time varies by initial wealth indictors (asset holdings and livestock holdings) by estimating the agricultural productivity and input use model separately for "poor" and "non-poor" households. We define a binary variable (a 0–1 binary wealth variable). This variable takes the value of 1 if the value of assets and livestock (TLU) for a household is in the bottom tercile, that is if the 2010/11 total value of household assets is less than US$175.51 in PPP and livestock holdings is less than 0.08 TLU. If not, the variable takes the value of 0.

The results on the effect of climate changes on agricultural productivity by wealth indicators are reported in Table 7. Our findings highlight the importance of understanding the heterogeneity effect of change in heat stress and precipitation on agricultural productivity based on household assets and livestock holdings. We observe that change in HDD and precipitation have a negative effect on agricultural productivity for both asset poor and non-poor, and TLU poor and non-poor households, but it has a stronger impact for the poor households.

We also allow for heterogeneity in the impact of climate changes on input use by initial wealth indicators. The results are reported in Tables 8 and 9. The results in Table 8 show that extreme heat and precipitation have a significant effect only on area planted for non-poor households. In column (2), controlling for other factors, a one standard deviation increase change in HDD increases the area planted by 1.9 percent while a one standard deviation increases in precipitation would decrease the area planted by 6.5 percent, on average for non-poor households. The results in columns (3) and (4) show that the change in HDD and precipitation have a significant effect on fertilizer use for both poor and non-poor households. However, when we compare poor with non-poor households, the coefficients for the change in HDD and precipitation are higher for the poor households than the non-poor. The results in columns (5) and (6) show that changes in HDD have a significant effect only on purchased seed for poor households. The results in columns (7) and (8) show that changes in HDD have a significant effect only on pesticide use for non-poor households. These results indicate that poorer households are less likely to adapt to change in HDD. These effects are consistent with the binding liquidity constraints hypothesis, but less so with a risk-aversion story if pesticide purchases reduce risk and farmers exhibit constant or decreasing absolute risk aversion (Jagnani et al., 2021; Aragón et al., 2021). In Table 9, we further allow for heterogeneity in the impact of climate changes on input use by household livestock holdings. The results show that extreme heat and precipitation change have a significant effect only on areas planted for non-poor households. The results in columns (3)–(6) show that change in HDD and precipitation have a significant effect on fertilizer use for both poor and non-poor households. The results in columns (7) and (8) show that change in HDD has a significant effect only on pesticide use for TLU non-poor households.

7. Conclusions and Implications

This paper combines panel data from nationally representative household-level surveys in Nigeria with long-term satellite-based spatial data on temperature and precipitation using geo-referenced information related to households. The paper aims to quantify the effects of climate change on agricultural productivity and shares from sources of household income. The paper further explores the specific pathways that mediate changes in agricultural productivity and income sources, focusing on farmers' crop mix and input use decisions in response to climatic factors. We measure climate changes using long-term temperature and precipitation anomalies during the crop calendar months using 30 years of geo-referenced temperature and precipitation data. We employ fixed effects regression models to estimate the effect of climate changes on our outcome variables using both unconditional and conditional relationships. Our analysis results in several important findings.

First, we find that the change in HDDs has a negative effect on agricultural productivity. Controlling for other factors, we find that a 15 percent (one standard deviation) increase in change in HDDs leads to a decrease in agricultural productivity of 5.22 percent on average. Second, our estimates confirm that precipitation change has a significant and negative impact on agricultural productivity. Third, we find that the change in HDDs decreases the income share from crops and non-farm self-employment, while it increases the income share from livestock and non-agricultural wage employment.

Examining possible transmission channels for these effects, we find that farmers use crop mix to respond to climate changes, which means that crop diversification could be one potential adaptation strategy to climatic factors. Furthermore, the paper shows that changes in extreme heat led to an increase in the area planted, a decrease in fertilizer use, and a decrease in purchased seed. For instance, we find that a one standard deviation increases in HDD change leads to a 1.17 percent increase in area planted.

We also examine whether the magnitude of the coefficient of changes in climatic factors over time varies by initial wealth indicators (measured by asset and livestock holdings) by estimating agricultural productivity and the input use models separately for "poor" and "non-poor" households. We also allow for heterogeneity in the impact of climate changes on input use by initial wealth indicators. Our findings highlight the importance of understanding the heterogeneity effect of changes in heat stress and precipitation on agricultural productivity and input use based on initial wealth indicators. For example, we observe that changes in HDDs and precipitation have a negative effect on agricultural productivity for both poor and non-poor households but have a stronger impact for the poor households.

Based on our findings we suggest four key policy interventions. First, our empirical findings indicate the negative impacts of climatic factors on agricultural productivity. In the context of smallholders in SSA, who are already experiencing low agricultural productivity, climate change exacerbates the burden and tends to worsen livelihoods. Thus, targeted interventions that promote climate-resilient agricultural practices, for instance investment in water-storage infrastructure and small-scale irrigation systems, are imperative to mitigate the effects of climate change on poorer smallholder farmers. In the context of Nigeria, such measures focusing on agricultural water management align well with the country's National Agricultural Resilience Framework (NARF), which outlines sector-specific climate adaptation and innovative agricultural production strategies to enhance resilience in the agriculture sector. Second, our results suggest the changes in crop mix and agricultural input use are potential adaptation methods in response to climatic factors. However, smallholders often lack access to climate-resistant varieties and yield-enhancing agricultural inputs. Policy interventions that enhance access to these inputs are warranted in order to ensure crop diversification is a viable coping strategy for climate anomalies. Third, we found that the income shares from livestock and nonfarm activities increase with increases in climate shocks. Thus, we suggest that policy consider the development of the livestock sector and micro/small enterprises as a potential strategy for mitigating the impacts of climate change on farming communities. And finally, our analysis shows that climate change has heterogenous effects on poor compared with relatively non-poor households, measured in terms of differences in endowments of productive assets and livestock holdings. Accordingly, alongside national and regional climate-related policies, we suggest pro-poor interventions that specifically target disadvantaged households. These interventions should include low-cost financing options for climate-proof agricultural technologies and measures to reduce the inequality of access to livelihood capital, including land and other productive assets.

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Table 1: Summary Statistics on Climate Changes (Temperature and Precipitation Change)

Variable	Mean	Std. Dev.	Min	Max
Temperature and precipitation				
ΔHDD	0.02	0.02	-0.04	0.08
ΔGDD	0.07	0.33	-0.78	3.06
Total precipitation	1185.20	495.04	309.40	3416.18
ΔP	-0.04	0.09	-0.44	0.24

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm.

Table 2: Summary Statistics on Crop Mix, Income Share, Input Use, and Agricultural Productivity

Variable	Mean	Std. Dev.
Agricultural productivity and input use		
Agricultural productivity (Output per ha $US PPP)	3425.95	4756.65
Area planted (ha)	0.91	1.27
Fertilizer use (yes=1)	0.45	0.50
Purchased seed (yes=1)	0.32	0.47
Purchased pesticide (yes=1)	0.43	0.50
Income share		
Income shares of crop (%)	57.09	38.88
Income shares of livestock (%)	4.10	14.19
Income shares of self-employment (%)	26.91	34.37
Income shares of wage employment (%)	6.70	21.35
Other sources of income (%)	5.20	-8.79
Crop mix		
Area shares of cereals	36.03	41.48
Area shares of legumes	12.10	20.94
Area shares of tubers	32.79	42.27
Area shares of trees	4.75	12.42
Other crops	14.33	17.12
Control variables		
Household size (ha)	6.64	3.24
Female-headed (yes=1)	0.11	0.31
Household head age	49.25	14.63
Value assets ($US PPP)	621.46	906.26
Livestock (TLU)	1.78	17.48
Farm area	1.12	1.14
Distance to market (km)	74.25	38.95

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Table 3: Impact of Climate Changes on Agricultural Productivity

	(1)	(2)
	Agricultural Productivity	
ΔHDD	-0.391***	-0.348***
	(0.092)	(0.088)
ΔGDD	6.196***	6.360***
	(1.421)	(1.434)
ΔP	-0.087***	-0.082***
	(0.002)	(0.003)
ΔP sqr	-2.120	-2.273
	(1.582)	(1.601)
Household size		-0.001
		(0.051)
Female-headed		0.112
		(0.078)
Household head age		0.124
		(0.077)
Value of assets		0.051***
		(0.019)
Livestock (TLU)		0.027
		(0.060)
Distance to market		-0.240***
		(0.074)
HH fixed effect	Yes	Yes
Year Fixed Effect	Yes	Yes
N	6387	6387

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impact of Climate Changes on Farmers' Main Income Sources

	Income share from crops		Income share from livestock		Income share from self-employment		Income share from wage employment	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ΔHDD	-0.233*	-0.343**	0.150**	0.125**	-0.034	-0.054	0.203**	0.190**
	(0.145)	(0.142)	(0.059)	(0.582)	(0.139)	(0.143)	(0.081)	(0.083)
ΔGDD	5.567***	-5.354***	0.458	0.670***	-2.169**	-2.841***	2.131***	2.453**
	(1.198)	(1.329)	(0.268)	(0.213)	(0.801)	(0.935)	(0.552)	(1.172)
ΔP	1.130*	-2.045***	0.461*	0.643**	0.383*	0.413**	0.432	0.188
	(0.678)	(0.606)	(0.253)	(0.254)	(0.210)	(0.211)	(0.308)	(0.318)
ΔP sqr	-1.764	-2.524***	1.371**	1.232**	3.386**	3.020**	0.9.00	0.717
	0.834)	(0.713)	(0.503)	(0.556)	(1.431)	(1.420)	(0.630)	(0.601)
Household size		-0.472***		0.470		0.731***		0.251***
		(0.103)		(0.034)		(0.094)		(0.058)
Female-headed		-0.659***		0.171***		0.256		0.066
		(0.185)		(0.063)		(0.166)		(0.101)
Household head age		1.488***		0.036		-0.071		-0.070
		(0.107)		(0.034)		(0.098)		(0.063)
Value of assets		-0.334***		-0.034***		0.289***		0.179***
		(0.037)		(0.013)		(0.033)		(0.019)
Livestock (TLU)		-0.336***		1.009***		-0.484***		-0.151**
		(0.112)		(0.043)		(0.109)		(0.064)
Distance to market		0.884***		-0.027		-0.110		-0.131**
		(0.084)		(0.026)		(0.078)		(0.051)
HH fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6387		6387		6387		6387	

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of Climate Changes on Farmers' Crop Mix Decisions

	Area shares of cereals		Area shares of legumes		Area shares of Tubers		Area shares of trees	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔHDD	-2.121***	-0.771***	0.535***	.2.179**	0.334**	0.243**	-0.189***	-0.191***
	(0.195)	(0.165)	(0.087)	(0.088)	(0.131)	(0.114)	(0.048)	(0.051)
ΔGDD	1.540	2.307***	-8.057***	-13.339***	11.966***	9.383***	9.183***	8.376***
	(2.559)	(0.241)	(1.137)	(1.293)	(2.085)	(2.222)	(0.633)	(0.757)
ΔP	-8.646***	-10.971***	-2.932***	-3.559***	15.471***	12.060***	1.991***	1.861***
	(0.762)	(0.708)	(0.375)	(0.0382)	(0.635)	(0.629)	(0.220)	(0.227)
ΔP sqr	-8.747***	-3.505	-1.22	-1.644	24.178***	11.907***	4.223***	3.719***
	(3.184)	(3.228)	(1.632)	(1.744)	(2.747)	(2.831)	(0.959)	(1.041)
Household size		0.883***		0.254***		-0.587***		-0.187***
		(0.098)		(0.052)		(0.098)		(0.029)
Female-headed		-0.638***		-0.075		0.963***		-0.213***
		(0.181)		(0.096)		(0.176)		(0.055)
HH age		0.283***		0.032		0.845***		0.059**
		(0.100)		(0.053)		(0.101)		(0.029)
Value of assets		-0.066*		-0.024		0.212***		-0.004
		(0.038)		(0.020)		(0.036)		(0.011)
Livestock (TLU)		0.776***		-0.050		-0.910***		-0.055
		(0.125)		(0.067)		(0.118)		(0.038)
Distance to market		0.346***		0.142**		0.058		0.054**
		(0.773)		(0.040)		(0.079)		(0.022)
HH Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6387		6387		6387		6387	

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Impact of Climate Changes on Input Use

	Area planted		Fertilizer use		Purchased seed		Pesticide Use	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔHDD	0.096***	0.078***	-0.050**	-0.021**	-0.135***	-0.122***	0.104***	0.087**
	(0.033)	(0.030)	(0.021)	(0.010)	(0.031)	(0.024)	(0.036)	(0.036)
ΔGDD	-2.710***	-2.154***	-3.543***	-2.514***	0.640	0.591**	-2.758***	-2.278***
	(0.468)	(0.480)	(0.575)	(0.542)	(0.517)	(0.299)	(0.508)	(0.496)
ΔP	-0.515***	-0.408***	-0.778***	-0.604***	0.184*	0.174**	-0.360**	-0.275**
	(0.136)	(0.137)	(0.158)	(0.151)	(0.101)	(0.083)	(0.142)	(0.138)
ΔP sqr	-1.140**	-1.012**	-1.104*	-0.961	0.279	0.250	-0.585	-0.531
	(0.512)	(0.513)	(0.630)	(0.621)	(0.555)	(0.384)	(0.673)	(0.645)
Household size		0.107***		0.136***		0.020		0.091***
		(0.022)		(0.018)		(0.012)		(0.017)
Female-headed		-0.176***		-0.046*		0.060***		-0.127***
		(0.023)		(0.026)		(0.021)		(0.025)
Household head age		-0.082***		-0.110***		0.005		-0.143***
		(0.030)		(0.031)		(0.021)		(0.030)
Value of assets		0.011*		0.029***		0.006		0.028***
		(0.006)		(0.007)		(0.005)		(0.007)
Livestock (TLU)		0.095***		0.045*		-0.062***		0.056**
		(0.023)		(0.027)		(0.017)		(0.024)
Distance to market		0.104***		-0.135***		-0.075***		0.075***
		(0.025)		(0.026)		(0.010)		(0.025)
HH fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6387		6387		6387		6387	

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. Standard errors, clustered at household level, are given in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 7: Impact of Climate Changes on Agricultural Productivity, by Asset and TLU

	(1)	(2)	(3)	(4)
	Asset poor	Asset non-poor	TLU poor	TLU non-poor
ΔHDD	-0.358***	-0.281***	-0.202	-0.358***
	(0.110)	(0.105)	(0.145)	(0.093)
ΔGDD	6.591***	6.105***	8.784***	5.823***
	(2.035)	(1.656)	(2.147)	(1.528)
ΔP	-0.434**	-0.213	-0.397**	-0.340**
	(0.213)	(0.434)	(0.201)	(0.179)
ΔP sqr	-3.621	-1.151	-4.886*	0.069
	(2.752)	(1.654)	(2.496)	(1.859)
Control variables	Yes	Yes	Yes	Yes
HH fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	2129	4258	2129	4258

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. We define a binary variable (a 0-1 binary wealth variable) which takes value 1 if value of assets, livestock (TLU) and farm size for household is in the bottom tercile, that is if the 2010-11 total value of household assets is less than 175.51 $US in PPP; livestock holdings (TLU) are less than 0.08 TLU; and 0 otherwise. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Impact of Climate Changes on Input use, by Asset Holdings

	Area plated		Fertilizer use		Purchased seed		Pesticide use	
	Asset-Poor	Asset Non-poor	Asset-Poor	Asset Non-poor	Asset-Poor	Asset Non-poor	Asset-Poor	Asset Non-poor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔHDD	0.050	0.126***	-0.024**	-0.017**	-0.056	-0.183***	0.066	0.104***
	(0.033)	(0.034)	(0.011)	(0.008)	(0.048)	(0.040)	(0.047)	(0.038)
ΔGDD	-1.939***	-2.652***	-2.090***	-3.230***	1.131*	0.231	-1.627**	-3.131***
	(0.614)	(0.565)	(0.688)	(0.615)	(0.647)	(0.601)	(0.725)	(0.615)
ΔP	-0.312	-0.434***	-0.940***	-0.593***	0.270	0.098	0.049	-0.454***
	(0.206)	(0.158)	(0.232)	(0.171)	(0.199)	(0.137)	(0.224)	(0.153)
ΔP sqr	-0.698	-1.307**	-1.986	-0.822	0.666	0.115	0.201	-0.886
	(0.861)	(0.576)	(1.247)	(0.683)	(0.852)	(0.571)	(0.995)	(0.741)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2129	4258	2129	4258	2129	4258	2129	4258

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. We define a binary variable (a 0-1 binary wealth variable) which takes value 1 if value of assets household is in the bottom tercile, that is if the 2010-11 total value of household assets is less than 175.51 $US in PPP and 0 otherwise. Standard errors, clustered at household level, are given in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 9: Impact of Climate Changes on Input Use, by TLU

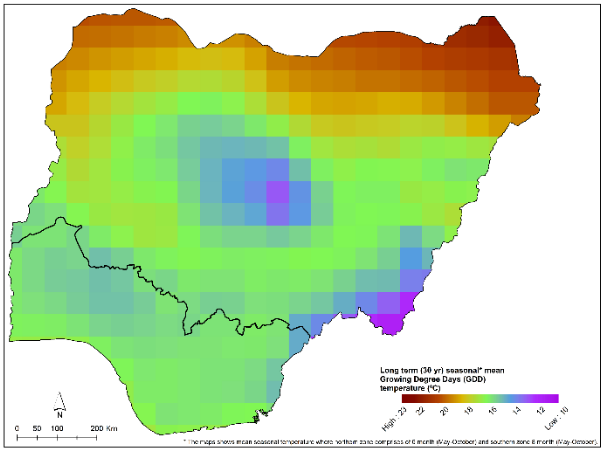
	Area plated		Fertilizer use		Purchased seed		Pesticide use	
	TLU-Poor	TLU Non-poor	TLU-Poor	TLU Non-poor	TLU-Poor	TLU Non-poor	TLU-Poor	TLU Non-poor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔHDD	0.080	0.105***	-0.009**	-0.008**	-0.118*	-0.140***	0.018	0.141***
	(0.057)	(0.032)	(0.004)	(0.003)	(0.068)	(0.036)	(0.054)	(0.041)
ΔGDD	-2.933***	-2.348***	-2.261***	-3.211***	1.955***	0.174	-4.015***	-2.065***
	(0.597)	(0.568)	(0.725)	(0.652)	(0.752)	(0.555)	(0.641)	(0.638)
ΔP	-0.208	-0.440**	-0.758***	-0.638***	0.090	0.228	-0.380**	-0.135
	(0.173)	(0.200)	(0.192)	(0.192)	(0.159)	(0.169)	(0.162)	(0.193)
ΔP sqr	0.029	-1.560**	-0.237	-1.370*	0.132	0.590	0.026	-0.410
	(0.557)	(0.706)	(0.896)	(0.745)	(0.852)	(0.628)	(0.739)	(0.887)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2129	4258	2129	4258	2129	4258	2129	4258

Source: Authors' calculations based on Uganda LSMS-ISA 2010, 2012, and 2015.

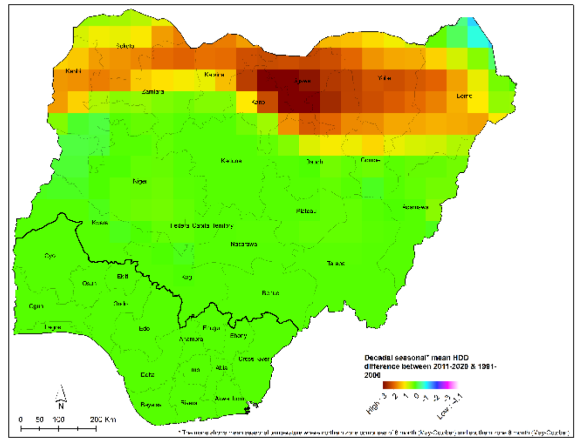
Note: ΔHDD is deviation of log HDD from long-term average. ΔGDD is deviation of log GDD from long-term average. ΔP is deviation of log precipitation from norm. We define a binary variable (a 0-1 binary wealth variable) which takes value 1 if livestock (TLU) for household is in the bottom tercile, that is if the 2010-11 household livestock holdings (TLU) are less than 0.08 TLU and 0 otherwise. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Distribution of Historical Average Growing Degree Days and Harmful Degree Days

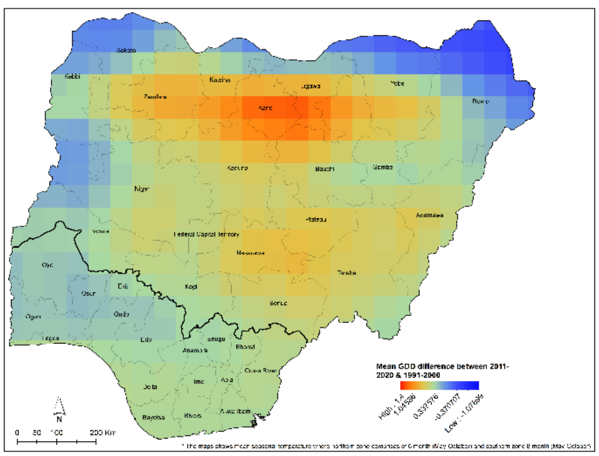
a) Growing Degree Days



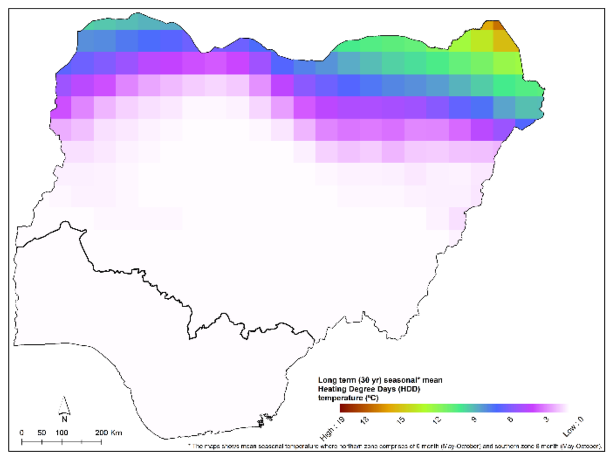
b) Harmful Degree Days



c) Difference Growing Degree Days



d) Difference Harmful Degree Days



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