Climate Variability and its Effects on Agricultural Yields in Sub-Saharan Africa

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This research project examines the relationship between short-run climate variability in the form of temperature and rainfall anomalies and agricultural yields. Utilizing data from longitudinal surveys conducted by the World Bank (LSMS-ISA), I investigate how short-run temperature and rainfall anomalies affect plot-level yields in Ethiopia, Mali, Nigeria, Malawi, and Tanzania.

Previous literature provides strong evidence that climate variability affects agricultural productivity. A study indicates that negative rainfall shocks (drought like conditions) reduce household consumption and agricultural yields (Amare et al. 2018). Additional evidence indicates that temperature has non-linear effects on the yields of staple crops (Schlenker and Lobell 2010).

I hypothesize that negative rainfall anomalies and extreme temperature shocks decrease yields, particularly in regions that are highly dependent on rainfall. To test this, I constructed standardized rainfall and temperature anomaly measures and estimated ordinary least squares, household fixed effects regressions, and a series of extreme shock models that estimated droughts, heat shocks, flood shocks and frost shocks along with positive and negative rainfall and temperature shocks. Extreme shocks are defined as being ±1.5 standard deviations from the mean and the positive and negative rainfall shocks are defined as being ±0.5 standard deviations from the mean.

The results are consistent for rainfall shocks, an increase in rainfall across the specifications is associated with higher yields, ranging from 5% to 9% (around 7% in the household- fixed effects model), while temperature effects range from 9% to 19%. Temperature effects decline when enumeration area (EA) fixed effects are included; this indicates that cross location differences are driving the temperature coefficients up. These findings remain robust under the household fixed effects specifications. Quadratic forms of the rainfall and temperature z-scores were found to be insignificant across the specifications. Additional specifications indicate that a negative rainfall shock leads to a 7% reduction in yields, while positive rainfall shocks display positive effects, but lose their significance when EA fixed effects are included.

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1. Introduction

I. State of Agriculture in Sub-Saharan Africa

Agriculture occupies a central role in the African economy and society. Approximately 80% of agricultural land in Sub-Saharan Africa (SSA) is managed by smallholders, and 94.5% of it is rainfed (FAO 2012). To compound these structural adversities, there are additional deficiencies such as low levels of mechanization, and limited access to credit, inputs, and irrigation (Nyoni et al. 2024).

About half of the African population lives in arid, semi-arid, or hyper-arid areas and is dependent on farming as the primary source of their livelihood (Biteye 2016; FAO 2024). Despite SSA having a quarter of the world's arable land, it only produces up to ten per cent of its output (IFAD n.d.).

Given these factors, agriculture in SSA is highly exposed to the climate, and variations in temperature and rainfall cause meaningful impacts that extend beyond yields.

II. Climate Exposure and Regional Vulnerability

The major climatic risks that are faced by farmers in SSA are droughts, floods, and severe storms (One Acre Fund 2023). Climatic trends indicate that there has been an increased variability in the precipitation levels. This has subsequently led to frequent and intense droughts and floods. The magnitude of these changes is not projected to be even across the region. East Africa is at a much higher risk of flooding, while West Africa is projected to experience severe declines in food productivity due to declines in oceanic productivity (Serdeczny et al. 2016).

III. Economic Growth and Conflict Implications

A study conducted in 20 fragile countries in SSA by Maino and Emrullahu (2022) utilized a panel fixed effects model and found that an increase of the mean temperature by one degree celsius decreased the income per capita growth by 1.8 percentage points. Fragility in this context is defined as countries that have weak governance or the presence of a UN or regional peacekeeping operation in the last ten years.

This was corroborated by Hendrix and Glaser (2007), who found that fragile states in SSA are most susceptible to climate change and its subsequent conflicts. Regions with higher rainfall are associated with less conflict in the following year. Any change in the precipitation levels can cause a reduction in economic growth, which may increase the risk of civil war (Boko et al. 2007). Changes in precipitation levels also expedite the risk of soil degradation and water scarcity, which have led to armed conflicts in the past.

IV. Health and Social Consequences

The variabilities caused by climate change in SSA are associated with multiple healthcare challenges. Periods of drought lead to malnutrition, disproportionately affecting young children and women. It also imposes strict restrictions on the use of water, leading to a decrease in certain hygienic practices like handwashing and bathing. This can increase the prevalence of diseases such as typhoid. The stunted growth of children has been associated with droughts in Mali, Kenya, Ethiopia, and Ghana (Opoku et al. 2021).

Floods, on the other hand, have prolonged and severe effects. They disrupt sewage systems and lead to water contamination. Stagnant water serves as a breeding ground for anopheles mosquitoes, which propagate malaria (Moyo et al. 2023). The spread of malaria is also dependent on temperature, peaking at 25ºC. With an increased variation in temperature, diseases such as malaria are projected to increase their morbidity rates (Opoku et al. 2021).

V. Fiscal Burden

Limited steps have been taken towards the mitigation of these climate anomalies. It is estimated that countries lose around 5% of their Gross Domestic Product (GDP) responding to climate disasters. Encouraging sustained investments in meteorological and hydrological early warning systems could potentially save the lives of millions of people in the region (World Meteorological Organization 2023).

VI. Scope and Motivation of this Study

With this broader context, this study aims to examine how short-run deviations in temperature and rainfall affect agricultural yields in rainfed smallholder systems across SSA. To do this, I obtain all agricultural data from the Living Standard Measurement Survey - Integrated Surveys on Agriculture (LSMS-ISA), which is a longitudinal survey conducted by the World Bank across eight SSA countries. Rainfall data is extracted from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), and temperature data is extracted from European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA5).

The analysis examines how temperature and rainfall anomalies during the growing season impact agricultural yields per hectare. Irrigated crops are excluded from the analysis since they can navigate anomalies by changing their levels of irrigation. Instead, the study focuses on rainfed crops, including maize, cassava, sorghum, and millet. Climate anomalies are captured using rainfall and temperature z-scores during the growing season, which captures how unusual the temperature or rainfall is this year compared to its long-term mean. Additional nonlinear specifications and extreme shock indicators, such as drought, heat, flood, and frost shock events are included. This analysis is conducted using OLS models that include country level fixed effects and enumeration area fixed effects. A household fixed effects model is included to isolate the impact of short-run climate variability on household-level agricultural yields.

2. Current State of Agriculture

Across the countries examined in this study, there is substantial heterogeneity in the agricultural systems. This arises from the differences in agroclimatic zones, the crops grown, and the rainfall received. The empirical analysis in this thesis relies on country and enumeration area fixed effects to account for these differences; however, it is important to acknowledge this underlying variation. This section describes the different agricultural systems across Ethiopia, Mali, Malawi, Nigeria, and Tanzania.

I. Ethiopia

Ethiopia is a landlocked country in the Eastern part of Africa, also referred to as the horn of Africa. It is the second most populous country in the continent, with a population of approximately 128 million (World Health Organization 2024).

The country hosts five major agroclimatic zones, namely, Wurch, the cold and moist zone; Dega, the cool and humid zone; Wenya Dega, the cool sub-humid zone; Kola, the warm semi-arid zone; and Berha, the hot arid zone (Dixon 2018). The zones are visually depicted in Figure 1. Approximately 80% of the population is dependent on agriculture, and a large number of those involved in agriculture are also semi-nomadic pastoralists (Tsegaye et al. 2013).

Smallholder farms in Ethiopia produce around 90% of the agricultural output, and the main crops grown are corn, wheat, sorghum, barley, and millet (Foreign Agricultural Service 2025, Aweke 2017). There are two major seasons of crop cultivation, the Meher, which runs between September and February, and the Belg, which runs from March to August. (Taffesse et al. 2012). Recent years have experienced lower than average rainfall, leading to a depleting water table

(FAO 2025). Average plot sizes in Ethiopia are around a hectare and land degradation remains a serious constraint to economic growth (Jayne, Chamberlin, and Headey 2014; Lemenih et al. 2004).

Droughts have had a strong impact on agricultural output. The drought of 1985 led to a 21% reduction in agricultural output (Mera 2018). This is a substantial decline, and the increasing frequency of droughts is contributing to severe food security in the East Hararghe region of Ethiopia (Baker et al. 2025). A study of farmer perceptions revealed that farmers who produced wheat, barley, and potato indicated they experienced improving yields and believed non-climate factors such as improved seed and better production technologies, contributed. On the contrary, most farmers who grew maize and horse beans reported that climate change has adversely impacted their yields and they believe that this situation will get worse (Habtemariam et al. 2016).

II. Mali

Mali is a landlocked country in western Africa. It has a population of approximately 24 million (World Health Organization 2023). The country has three major agroclimatic zones. They are the tropical savanna in the south, the warm semi-arid region in the center, and the warm desert region in the north, and the primary growing season is from May to October (Red Cross Red Crescent Climate Centre and International Committee of the Red Cross 2021; Salifou et al. 2018). The agroclimatic zones are visually depicted in Figure 2. The average plot sizes are around 4.1 ha, and staple crops produced are corn, rice, millet, and sorghum (Jayne, Chamberlin, and Headey 2014; Foreign Agricultural Service 2025).

Farming and fishing employ nearly 80% of the workforce in Mali and also form a significant chunk of the GDP. As it stands currently, agricultural production in Mali is insufficient to feed its growing population, leading to widespread malnutrition and hunger (Ebi et al. 2011).

Agriculture in Mali is extremely dependent on rainfall. Several droughts have occurred from 1910 to 2022, causing substantial negative impacts on agriculture. The occurrence of droughts becoming more common is expected to have significant negative impacts on food security (BenYishay et al. 2024; FAO 2022). Additional evidence suggests that under future projections of climate change, yields for major crops like maize and sorghum are likely to decline by 11% to 17% (Butt et al. 2005).

III. Malawi

Malawi is also located in the Eastern part of Africa, adjacent to Tanzania. It has a population of 21.7 million (World Bank 2019). There are four major agro-ecological zones. These are the Lower Shire Valley, the Lakeshore Plains and Upper Shire Valley, the mid-altitude plateau, and the highlands. They are depicted visually in Figure 3. The growing season varies across agroecological zones. The highlands, the mid-altitude plateau, and the Lower Shire Valley receive most of their rainfall between December and March. The lakeshore plains and Upper Shire valley receive the maximum of their annual rainfall between the months of December and April (Nalivata et al. 2017).

The major food crops produced are potato, maize, rice, cassava, and legumes. The agricultural sector employs 80% of the population and contributes around 30% to the GDP of the country. Smallholder farming is widespread in the region. Lack of irrigation is a major problem in Malawi, as only 4% of the cultivated land is irrigated; the rest relies heavily on rainfall. Malawi is also one of the most land constrained countries in Africa, as more than 20% of its land is covered by Lake Malawi (World Bank 2018). Existing land has come under pressure as Lake Malawi's surface area has increased in the past decade, and plot sizes in Malawi are small, averaging at 1.4 ha (Department of Climate Change and Meteorological Services 2025; Jayne, Chamberlin, and Headey 2014).

Despite the abundance of water resources, droughts are a major problem in Malawi. In 2023 to 2024, Malawi experienced acute drought conditions during its growing season in January and February, which led to severe damage to crops and negatively affected several households (United Nations Office for the Coordination of Humanitarian Affairs 2024). Estimates show maize production has been impacted by both floods and droughts in the past, with losses averaging at 32 to 48 per cent. Intercropping with legumes was provided as a solution against floods and droughts (McCarthy et al. 2021).

IV. Nigeria

Nigeria is the most populous country in western Africa with a population of nearly 228 million (World Health Organization 2023). The main agricultural zones are the mangrove forest and coastal vegetation, freshwater swamp forest, lowland rainforest, derived savannah, Guinea savannah, Jos plateau, montane forest, Sudan savannah, and Sahel savannah (FAO 2020). These are depicted visually in Figure 4. The agricultural sector constitutes around 21% of its GDP. Around 70% of the rural dwellers are subsistence farmers (IFAD 2014). The average farm sizes are around 1.4 ha (Jayne, Chamberlin, and Headey 2014). The major food crops produced are rice, maize, soybean, sorghum, cassava, and yam (Chiaka et al. 2022). The rainy season usually runs from April to September (Takeshima 2016). The heterogeneity in agroclimatic zones in

Nigeria also means that different regions face different climate risks. The Northern savannah regions are more at risk for droughts, while the southern regions are more susceptible to flooding and heavy rainfall.

A study conducted in the Enugu region of Nigeria, studied the effects of variable rainfall patterns, noted that all traditional crops, with the exception of cassava and peppers, had a significant decrease as rainfall patterns became more erratic (Enete 2014).

V. Tanzania

Tanzania is located in East Africa with a population of nearly 61.7 million (World Health Organization 2024). There are seven main agro-ecological zones, namely the coastal zone, the arid zone, the semi-arid zone, the plateau, the southern and western highlands, the northern highlands, and the alluvial zone (Africa Kilimo 2023). These are depicted visually in Figure 5.

Northern regions of Tanzania have a two-phase rainfall season and receive rainfall between March and May and again from October to December, while other regions experience rainfall between December and May (Rowhani et al. 2011). Staple crops grown here include maize, sorghum, rice, sweet potatoes, bananas, beans, sorghum, and sugarcane (International Trade Administration 2022).

Agriculture remains predominantly rain-fed, making it susceptible to rainfall timing and variability (Mkonda 2021). The agricultural sector in Tanzania contributes approximately 28% to its GDP and employs around 61% of the workforce. Within this sector, around 80% of the farming is subsistence farming, which is particularly dependent on rainfall and is vulnerable to climate change (IFAD 2019). Smallholder farming often dominates the agricultural landscape in Tanzania, with plots averaging 2.4 ha (Jayne, Chamberlin, and Headey 2014). Droughts in the region disproportionately affect arid and semi-arid zones, while the river basins are at high risk of flooding (Rowhani et al. 2011). Additional evidence indicates that due to climate change, grain production in Tanzania will decrease, leading to poverty and hunger (Ahmed et al. 2011).

3. Climate Sensitivity of Major Crops

Yield responses to climate variability differ by crop due to different temperature and irrigation thresholds. The empirical analysis utilised in this thesis uses a crop fixed effects approach to control for time-invariant characteristics across crops. However, it is necessary to see how crop-specific responses to temperature and climate variabilities may be different in practice.

Maize is the staple crop of SSA. Schlenker and Roberts (2009) reported that, on average, the optimal temperature to grow corn is 29º C, and any temperature increase beyond that proves to be extremely harmful for yields. For each degree day that is spent above 30ºC, corn yields decrease by 1% (Lobell et al. 2011). Climate change projections reveal that in Eastern Africa, maize yields will decline by 40%. This decline comes from rising temperatures during the growing season, which exceed the optimal threshold (Adhikari, Nejadhashemi, and Woznicki 2015).

Sorghum is a widely grown, drought-resistant crop across the semi-arid regions of the world. The main optimal temperature to grow sorghum is 25° to 28°C for reproduction. Future projections indicate that rising temperatures will adversely affect sorghum yields (Prasad et al. 2008). Floods and droughts significantly reduce sorghum yields in SSA, leading to food insecurity, with past droughts continuing to negatively influence sorghum yields in subsequent seasons (Akpa 2024).

The other crop examined in this study is cassava. It is a drought-resistant root crop grown in SSA. Temperatures of 25° to 29°C are the most favorable for growing cassava, with the crop performing well in rainfall as little as 500 mm per annum (Nyakauru et al. 2025). Even though cassava is generally drought-resistant and produces large yields in SSA, Schlenker and Lobell (2010) predict that, due to rising temperatures, cassava yields will decline by approximately 8%.

Millets are sustenance crops categorized into pearl millet, finger millet, fonio, and teff (Ramashia et al. 2025). Pearl millet, the most prevalent species of millet commonly found in Africa, is able to grow in temperatures as high as 42°C and sustain rainfall as low as < 250 mm. Despite its drought resistance, higher temperatures are related to lower pearl millet yields, and higher rainfall has been associated with a higher yield (Satyavathi et al. 2021). This suggests that despite the overall climate resistance of millets, any temperature and rainfall variability still have impacts on their yields.

4. Literature Review

Existing literature suggests that temperature and rainfall shocks do not have uniform effects on yields; rather, their effects depend on the timing of the shock within the growing season and the crop types. Global literature evidence on staple crops is generally well developed; little attention has been paid to regionally important crops like millets and localized smallholder contexts, particularly in Africa. This review classifies the literature into seven broad themes. These themes are the general vulnerability of rainfed smallholder systems and projected climate impacts, country-level panel regressions linking temperature and precipitation to crop yields, household and plot-level fixed effects models using LSMS-ISA data, rainfall anomaly indices, and IV strategies for causal identification, farmer-reported shocks, disaster databases, and imputation methods, effects of rainfall variability on consumption, food security, and prices, and sector-level and macroeconomic growth effects of temperature and precipitation. The literature presents its applications in a variety of contexts; this thesis primarily focuses on their applications to climate variability and its effects on agricultural yields in Sub-Saharan Africa.

Building on these threads, the paper examines the micro-level relationship between rainfall variability and agricultural productivity using data from LSMS-ISA surveys in Ethiopia, Mali, Nigeria, Malawi, and Tanzania. Broadly, the literature examined utilized a household, country, or district-level fixed effects model. This thesis examines the relationship between rainfall and temperature shocks and the natural logarithm of the agricultural yields per hectare.

I. General vulnerability of rainfed smallholder systems and projected climate impacts

A number of papers have highlighted that climate variables exhibit threshold behavior; that is, yields increase with temperature and precipitation to a certain extent, after which they sharply decline. In a review article, Carleton and Hsiang (2016) state that the effects of temperature are often more important than precipitation in the production of staple crops. They have stated that extremely hot days cause the most amount of losses in crops. Even though temperature effects outweigh precipitation, previous research has stated that both low and high seasonal rainfall damage yields. Within a growing season, a small number of extreme rainfall days can cause several problems for a farm's yield. This relationship has been documented for major global crops like maize, rice, soy, and wheat, but less is known about the effects on regional crops like millet and cassava.

Regional evidence derived from East and West Africa suggests the vulnerability of rainfed systems and the differential effects of rainfall across agro-ecological zones. In a review of climate change and food security in Nigeria, Durodola (2019) observed that the body of literature indicated that the effects of climate change, in the form of temperature and rainfall variability, differ by climatic zones and crops produced, with some crops potentially benefiting. Maize and sorghum production in the Southern Guinea savanna zone could increase by approximately 2% to 6%. However, in Northern Guinea, yield could decline by 2% to 20% due to climate change. The authors noted that since Nigerian agriculture is highly rainfed, it would suffer setbacks due to climate change. An example of this is that Nigeria is projected to experience low crop yields as a result of intermittent droughts.

Micro-level evidence from Tanzania further illustrates the variability of yields with climate. A study conducted in the Kongwa District of central Tanzania by Mkonda and He (2018) combined meteorological data collected by the Tanzania Meteorological Agency (TMA) collected between 1980 to 2015, along with qualitative data collected from the Participatory Rural Appraisal method (PRA) and group discussion collected between June and September 2016. They used Pearson's moment correlation coefficient and simple regression analyses to compare the trends of rainfall and temperature versus crop yields. The crops under consideration were maize, sorghum, and millet. Maize had the highest overall yields. Most participants were in agreement that climate change is a real threat and would affect their livelihoods. They found that there has been a dramatic decrease in the rainfall in the region along with an increase in temperature. It was also found that temperature is negatively correlated with yields, and rainfall is positively correlated with yield amounts.

The literature is indicative of some consistent patterns. Extreme temperature shocks may cause large yield losses.

II. Country-level panel regressions linking temperature and precipitation to crop yields

Some branches of literature estimate climate impacts on agriculture by using country-level panel regressions that link historical weather to crop yields and attempt to extrapolate future yield amounts from climate projections. Some of the studies exploit the within-country variation over time to isolate the short-run responses of yields to temperature and precipitation shocks while controlling for time-invariant heterogeneity.

One of the key studies in this area has been conducted by Schlenker and Lobell (2010). Using panel data from Sub-Saharan Africa, they investigated the negative effects of climate change on African agriculture. They combined data about yields from the FAO with gridded climate data from National Centers for Environmental Prediction (NCEP) reanalysis dataset and the Climatic Research Unit of the University of East Anglia (CRU), using which they estimated log crop yields as a function of multiple weather specifications. Their baseline model was a country fixed effects model that included a quadratic time trend and precipitation along with degree day measures capturing crop exposures to moderate (10–30°C) and extreme (>30°C) heat. This allowed them to control for time-invariant country characteristics such as soil quality and geography, as well as technological progress over time, while identifying the effects of climate variables by using within-country variation over time.

Most importantly, the authors in this study excluded irrigated crops like wheat and instead focused the analysis on rain-fed staple crops such as maize, sorghum, millet, groundnuts, and cassava. Less work has focused on investigating the impacts of weather shocks on these crops. The results from this study indicate that the authors estimated declines of −22%, −17%, −17%, and −8% for maize, sorghum, millet, and cassava, respectively, using degree day specification. Another key finding they discovered is that countries with higher yields displayed larger losses in their crops, indicating that well-fertilized systems are more vulnerable to extreme heat patterns.

Similarly, Blanc (2012) estimated the impact of climate change on yields for millets, maize, sorghum, and cassava for 37 countries in Sub-Saharan Africa from 1961 to 2002. This study is novel in the sense that the author goes beyond regular climate variables used and incorporates evapotranspiration, the standardized precipitation index (SPI), droughts, and floods. Crop supply functions were constructed using an error correction model built on panel data, and crop yields were estimated through 2100 using General Circulation Models (GCMs). Evapotranspiration refers to the loss of water through evaporation from land and plants. The SPI measures how rainfall deviated from its long-term mean over a specific time period. A GCM is a model that examines how the ocean, air, and land interact using inputs like greenhouse gases to see how Earth's climate might change (USDA, n.d.). The panel model used controls for time-invariant country characteristics through its panel structure. Panel estimations assume all parameters to be equivalent, however farming conditions differ across countries, therefore the authors included an indicator variable to distinguish between countries with less favorable agricultural conditions (LFACs), with zero indicating a non LFAC and one indicating an LFAC country. In addition, time dummy variables are included to account for any shocks that vary over time but affect all countries.

Their results revealed that for the time period considered, cassava had the highest yields. Yields increased for all crops except millets. Temperatures generally increased over the time period. The highest evapotranspiration rates were observed in millet areas, and the lowest were observed in maize areas. Annual precipitation decreased, and the region where cassava is grown generally observed a higher rate of precipitation compared to the three other crops. The Standardized Precipitation Index (SPI) generally decreased compared to the 1901-2002 average. Each General Circulation Model (GCM) is simulated under a different range of greenhouse gas assumptions.

Relative to a case without climate change, yield changes in 2100 are near zero for cassava. For maize, these changes are between -19% and +6%; for millets, they range between -38% and -13%; and for sorghum, they range from -47% to -7%.

Expanding beyond Africa, Lobell, Schlenker, and Costa-Roberts (2011) examined yield response models to see the effects of climate change on major crop yields in all countries with available data for the time period of 1980 to 2008. They examined wheat, maize, rice, and soybeans by conducting a panel regression analysis that included quadratic temperature and precipitation terms, country-specific intercepts, and country-specific time trends of historical data to relate past yield outcomes to weather realizations. This allowed them to control for time-invariant country characteristics, technological progress, and quadratic climate effects.

The results indicated that at the global scale, maize and wheat exhibited negative impacts for several major global producers and a global net loss of 3.8% and 5.5%, respectively, compared to what would have been achieved without these trends. The majority of these impacts are driven by trends in temperature rather than precipitation.

Additional global evidence is provided by Parry et al. (2004). They simulated the global consequences of crop yields, production, and risk of hunger linked to several climate-related scenarios. This study combines climate projections from a general circulation model, a statistical crop yield transfer function derived from dynamic crop simulations, and the Basic Linked System, an economic food trade model. The objective of the paper is to not only estimate impacts on crop yields but also to see how these changes translate into food production changes and the number of people at risk for hunger. To translate the climate projections into agricultural impacts, the authors used yield transfer functions.

The results show that global cereal changes are not affected by the different climate changes. The increase in production in developed countries makes up for the decline in developing countries; however, this masks the regional disparity. Under extremely high emission scenarios, developing countries experience the largest yield declines.

The literature consistently shows strong effects of temperature and precipitation on yields, both in the Sub-Saharan and global contexts. While temperature and precipitation both influence yields, the literature has shown that in some contexts temperature may have a more dominant effect on yields as compared to precipitation. Overall, both econometric and simulation models point out that climate change will likely impact yields differentially, with small rain-fed farms facing the brunt of climate change.

III. Household and plot-level fixed effects models using LSMS-ISA data

Empirical studies that have used LSMS-ISA data rely on fixed effects frameworks to estimate the impact of weather variability on agricultural productivity in Sub-Saharan Africa. These approaches utilise the variation in weather over time while controlling for unobserved heterogeneity. These studies attain their results by examining the LSMS-ISA data, which is the same dataset that will be used in this study. The LSMS-ISA data provides detailed information on agricultural inputs, household characteristics, geographic variables, credit information, and climate information. This study builds on the framework developed by prior literature.

Jithitikulchai (2023) investigated the effects of temperature and precipitation on the total value of agricultural outputs using repeated cross-sections from the LSMS-ISA across six Sub-Saharan countries, namely, Ethiopia, Malawi, Niger, Nigeria, and Tanzania. The study used a fixed country and fixed year effects model and regressed the total agricultural output on temperature and rainfall and a vector of control variables that included spatial and temporal dummy variables. The regression included quadratic terms for precipitation and temperature to capture the nonlinear nature of their interactions with the explanatory variables. The model controls for unobserved country characteristics using country fixed effects and for common time shocks using year fixed effects. It also includes household, geographic, and production input variables to account for observable heterogeneity across farms.

Climate variables were taken as exogenous, and standard errors were clustered at the country-specific survey strata levels. The results revealed that a one-degree Celsius increase is associated with approximately a 14% decline in agricultural output for all households. Overall, rainfall has a positive effect on agricultural outputs; however, the squared term of rainfall has decreased marginal returns to agricultural outputs. They also found that households that diversify their agricultural activities experience less sensitivity to changes in temperature and rainfall.

IV. Rainfall Anomaly Indices and IV Strategies for Causal Identification

Another branch of the literature advances these causal identification strategies by constructing rainfall anomaly indices and using an instrumental variables (IV) approach.

Utilizing data from the Nigeria LSMS-ISA waves conducted in 2010, 2012, and 2015, Amare et al. (2018) calculated the rainfall shock variable by measuring the log deviation of the previous year's rainfall during the wet season during the crop-growing season from the 30-year average. This measurement has been previously referred to as the rainfall anomaly index. For the core analysis, the authors used an instrumental variables regression approach, where agricultural land productivity is instrumented using rainfall shocks. Since the paper's main domain is in rural areas and factor markets are practically absent in such areas, they adopted the farm household model as their key framework. The study estimates a two-stage fixed effects model: in the first stage, rainfall shocks predict agricultural productivity, and in the second stage, the value of that predicted productivity is used to estimate its causal impacts on household consumption measured as the real consumption per adult equivalent unit. The first stage included household and time fixed effects, and the second stage included household and state fixed effects, and identification relies on within-household variation while controlling for time-invariant characteristics.

The findings of the first stage concluded that a negative rainfall shock strongly affects agricultural productivity, decreasing it by 38%. A positive rainfall shock has a positive and significant impact on agricultural productivity. It was also found that negative rainfall shocks have a stronger impact on the southern part of Nigeria, as the region is dry and has a shorter rainy season. In terms of crop-specific effects, it has a more negative impact on maize and millets and a less negative impact on cowpea and yam productivity, indicating that these crops may be more weather resistant. Since the main objective of this thesis is to estimate the causal effects on consumption, relying on an instrumental variables approach is justified; however, in this study this approach will not be used and a fixed effects approach will be used to control for time-invariant unobserved heterogeneity across units.

Similar rainfall anomaly indices are employed by Kakpo, Mills, and Brunelin (2022). They studied the semi-arid regions of Niger to identify the impacts of climate shocks on millet production and price seasonality. The same constructs for a rainfall anomaly index are used in this study. A fixed effects regression was employed in two parts: a district-level fixed effects regression was used to quantify rainfall shock effects on millet production. Then, the rainfall shock variables are used as covariates in the second level of district-level fixed effects regression with the monthly millet prices as the dependent variable. The ultimate effect of rainfall shocks on price seasonality is determined by interacting rainfall shocks with month indicators to quantify impacts in all of the twelve months following a shock. The results are consistent with what has been discovered in the literature. A positive rainfall shock has been associated with increasing production, and a negative rainfall shock decreases production. The largest price decreases occur during the growing season of June to August, relative to the baseline of October. Production responses to mild and moderate rainfall shocks are proportional; however, large negative rainfall shocks generate production decreases that are far greater than the increases that occur from large positive rainfall shocks.

These studies demonstrate how the inclusion of a rainfall anomaly index can provide a credible source of exogenous variation for identifying the causal effects of climate shocks. Taken together, both papers have demonstrated that negative rainfall shocks have nonlinear effects on production, with implications for prices and household consumption.

V. Farmer-reported shocks

A large body of literature heavily relies on taking precipitation variation as exogenous. The LSMS-ISA dataset also provides data about self-reported shocks by farmers.

Wollburg et al. (2024) incorporate a novel approach by identifying climate-related losses using farmer-reported shocks as controls at the plot-level. This study used microdata collected from six African countries: Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania to consider the effects of climate shocks on smallholder African agriculture. The study estimates agricultural productivity using various models. The first model is an ordinary least squares (OLS) model in which plot-level yields are regressed on an annual time trend and country fixed effects. The second model is the baseline model, which takes in a vector of input variables and a vector of household and plot controls and weather variables that are selected by the least absolute shrinkage and selection operator (LASSO) algorithm and crop types controls. Unobserved heterogeneity is accounted for by aggregating data at the household and plot-level, and employing fixed effects models, and the intercept varies across different units.

The main finding is that across the sample, there is no evidence of productivity growth. Most specifications indicate a declining -3.5% per year. Results are different across the countries, with significant declines in Nigeria and Malawi and no significant changes in Ethiopia, Mali, and Tanzania and apparent growth in Niger.

VI. Effects of rainfall variability on consumption, food security, and prices

Literature has shown that exogenous rainfall has been used to estimate not only its effects on yields but also more downstream effects such as per capita consumption, crop income, and Body Mass Index (BMI).

Randell, Gray, and Shayo (2022) provide additional indirect effects from Tanzania. Food security is another lens through which impacts on yields can be discerned. They link nationally representative longitudinal data from the Tanzania National Panel Survey, which is a part of the LSMS-ISA. Climate data is obtained from CHIRPS and $CHIRTS_{MAX}$ data. They then estimated three multivariate binary logistic regression models of the probability of being food secure. The estimated variables are Food Consumption Score (FCS) and Reduced Coping Strategies Index (rCSI), and simultaneously estimating FCS and rCSI. Control variables included demographic controls such as the gender, age, and education of the head of the household, socioeconomic factors such as housing quality index, poverty status, and income source, farm characteristics such as the farm size and seasonal indicators. Additional precipitation during the rainy season has been positively associated with all three measures. It has also been found that higher precipitation is positively linked with per capita consumption, crop income, and BMI category among children aged 2-4 years. Moving from a typical rainfall year to a dry year increases the risk of being food insecure by 13 percentage points. This means that households have reduced food security through reduced yields and increased agricultural prices.

This price and welfare transfer mechanism is also validated in Amare et al. (2018) and Kakpo, Mills, and Brunelin (2022). Amare et al. (2018) show that negative rainfall shocks negatively influence agricultural productivity, which lowers household consumption. Kakpo, Mills, and

Brunelin (2022), show that rainfall shocks reduce millet production and generate price fluctuations.

This demonstrates that the impacts of climate change go further beyond yields. Rainfall shocks propagate themselves through production, income, and price channels. These effects alter household consumption and food security in regions where agriculture is primarily rainfed.

VII. Sector-level and macroeconomic growth effects of temperature and precipitation

Beyond household and sector-specific outcomes, climate change also has impacts on aggregate growth. Chamma (2024), utilises a panel dataset comprising 43 SSA countries with data spanning from 1970 to 2019 to investigate the impact of climate change on aggregate economic growth and sectoral growth.

It identifies factors that affect economic growth at the regional climate using variables such as temperature, precipitation, the coefficient of variations in precipitation and their square conditional on macroeconomic variables such as human capital. The study applies a country and year fixed effects model. It also estimated the effects of climate change on sector-level growth of several major sectors, like agriculture, and industry manufacturing using a seemingly unrelated regression (SUR) model. The findings revealed that climate change hinders aggregate and sector-specific growth. Variations in the temperature and squared precipitation are inversely related to aggregate growth across all model specifications. A decline in precipitation adversely impacts economic growth, while excessive precipitation causes flooding and substantial economic losses. The agriculture sector's growth is negatively affected by increased temperatures and decreased precipitation. It was found that the squared term for precipitation does not hold a significant effect despite the overall negative association. Based on the current data, increased temperatures negatively affect GDP growth. The region's aggregate GDP was positively associated with average annual precipitation, and the squared coefficient of variations in precipitation negatively impacted GDP growth.

VIII. Gap in Previous Literature

The literature is extensive in identifying the economic impacts of climate variability on agricultural outcomes. Existing literature relies heavily on country- and household-level fixed effects models. These approaches provide insight, but they also have drawbacks in relation to climate data. Country-level aggregation is a coarse measure of aggregation as it may obscure actual variation in climate. Rainfall is highly localized, and aggregating at the country-level may mask the inherent heterogeneity that exists across regions.

Analyses conducted at the household or plot-level rely on climate variables that are measured at a broader scale, as temperature and rainfall do not meaningfully vary across individual plots within the same geographic location.

This thesis contributes to existing literature by using a spatially refined approach. The LSMS-ISA surveys for each country provide detailed plot and household-level data which are matched with high-resolution climate data at the enumeration area (EA) level. This EA usually corresponds to the census-based clusters that are small geographical units such as villages or neighbourhoods. The analysis retains plot and household-level observations while incorporating

EA fixed effects to control for time-invariant local characteristics such as soil quality, mineral content in soil, etc. This approach allows capturing local variation in climate over time while maintaining consistency between the spatial resolution of climate data and agricultural yields.

5. Data & Methodology

I. Agricultural Data

The data used in this study comes from the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). The data has been collected by the World Bank in conjunction with the national statistical agencies in each country to provide nationally representative panel household surveys with an emphasis on agriculture from eight countries in Sub-Saharan Africa. The LSMS-ISA collects information about yield amounts across the countries examined in this thesis. The smallest unit that is repeated through the surveys is the household. These datasets are designed to be representative of agricultural systems in the countries.

The LSMS also contains detailed information about household characteristics such as the gender of the head of the household, their educational levels, the number of people in the household, and so on. It also includes information about the plot-level yields, the kind of crops farmed, and extensive information about input usage. These surveys span several waves. Therefore, before modeling, each of the datasets had to be harmonized. The harmonized datasets were available through the World Bank website. The analysis dataset contains information about household, plot, and crop data using the unique identifiers for the country, wave, household, and plot.

Plot-level agricultural yields are calculated from the analysis data by dividing the harvest amount (In kilograms) by the plot area. The yield variable is then transformed using the natural

logarithm, allowing changes to be interpreted as percentage changes. Observations with missing values for harvest and plot area were excluded to ensure consistency across the analysis.
The final analysis examined rainfed crops, including maize, sorghum, millet and cassava. Mixed-category crops are excluded to ensure consistency in the sample. Irrigated crops were excluded from the sample, as irrigation can be used to mitigate the rainfall anomalies.

II. Climate Data

To measure rainfall variability, I matched all the survey clusters (enumeration areas, EAs) to monthly precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). This data is derived from rain gauge and satellite data and has been used widely in previous research. Using the GPS coordinates from the LSMS-ISA dataset, each EA was matched to the corresponding climate grid-cell, and rainfall was aggregated over the growing season. Rainfall anomalies were constructed following the approach from the literature (Amare et al. 2018, Kakpo, Mills, and Brunelin 2022). The main measure of the weather deviation is the standardized rainfall anomalies (z-score), which shows how much rainfall in a year deviated from its long-term average rainfall within each EA, scaled by the standard deviation. This approach allowed for comparability across different ecological environments, which is essential in this study as several countries are examined.

Temperature data was extracted from ERA5, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). Similar to the rainfall data, I matched each enumeration area to the corresponding climate grid cell. Temperature anomalies were constructed in a manner similar to rainfall anomalies to capture how the temperature deviates from its long-term mean.

III. Variable Construction

The primary outcome variable in this study is the agricultural yield at the plot-level. Yields are calculated by dividing the harvested quantity by the plot area and then log-transformed. This transformation allows coefficients to be interpreted as approximate percentage changes. The main explanatory variables are rainfall and temperature anomalies, which capture how the current season differs from the long-run average climatic conditions. This has been previously used in the literature (Amare et al. 2018; Kakpo, Mills and Brunelin 2022). The rainfall anomalies are described as:

$$Z_{it}^{\text{Rain}} = \frac{R_{it} - \mu_i^{\text{Rain}}}{\sigma_i^{\text{Rain}}} \qquad (1)$$

Where Z_{it}^{Rain} represents the rainfall anomaly in cluster *i* in year *t*. μ_i^{Rain} represents the long-run mean rainfall at cluster *i* and σ^{Rain} measures the standard deviation of the rainfall in that cluster. R_{it} represents the rainfall received in the growing season in location *i* in year *t.* Temperature anomalies are constructed in the same manner. They are described as:

$$Z_{it}^{Temp} = \frac{Temp_{it} - \mu_i^{Temp}}{\sigma_i^{Temp}} \qquad (2)$$

Where Z_{it}^{Temp} represents the temperature anomaly in cluster *i* in year *t*. μ_i^{Temp} represents the long-run mean temperature at cluster *i* and σ^{Temp} measures the standard deviation of the temperature in cluster *i.* Temp_{it} represents the temperature during the growing season in location *i* in year *t.*

IV. Control variables

In order to isolate the effects of temperature and rainfall, a set of control variables was included in the regressions. The controls can broadly be divided into plot, household and input controls. Household controls include the household size as a proxy for seeing the labor availability within the household, as bigger households might have more people available to work on the farm. The dependency ratio is included to capture how many people from the household are of working age; a higher dependency ratio signals less availability of household labor. Household-level formal education is added to examine if any member of the household has been exposed to education. This is a useful control as a higher level of education could indicate that more resources are being diverted to education instead of agriculture. The household asset index is also included as a proxy for seeing the wealth of the household, as wealthier households may have better access to inputs and hybrid varieties of seeds.

Farm controls include the age of the plot manager to see how experience levels may yield amounts. The gender of the plot manager is included to examine if there are any constraints due to gender that may affect the yield amounts. Number of plots is included, as that may influence yields. Bigger farms could benefit through the creation of economies of scale.

Irrigation is included to account for access to water, and irrigated plots may be less susceptible to climatic variation. Livestock ownership is also included as a proxy for household wealth and productive assets. Seed use (in logarithmic form), fertilizer use, and pesticide use are also included in capture input use, as these directly affect agricultural productivity.

Hired labor is the total expenditure on labour (in USD). Higher spending on labor signals intensive labor use and as higher labor may improve cultivation and yields. Labor values cleaned by non-numeric entries are top-coded at the 99th percentile to control for the influence of extreme outliers. The natural log of labor is then taken and included across specifications. The summary statistics for these variables are presented in Table 1.

V. Regression Methods Considered

To estimate the relationship between climate variability and yields, this thesis uses two main econometric specifications. Across the specifications, the main dependent variable is the logarithm of plot-level agricultural yield, constructed as the log of harvested quantity in kilograms divided by the plot size.

The first model considered is the Ordinary Least Squares model (OLS). This has been widely used as the baseline model in literature. The logarithm of the plot-level yields per hectare is the response variable, estimated as a function of rainfall anomalies, temperature anomalies, and control variables. Two specifications of this model are included to test the effects of temperature and rainfall. The first specification includes the z-score of the temperature and the rainfall with country, crop, and year fixed effects. A version of this specification is added with the quadratic forms of the rainfall and temperature z-scores to capture potential non-linear effects of temperature and rainfall on yields. This specification controls for differences across countries but examines the variations within the country over time.

The second specification of this model includes the z-score of the temperature and the rainfall with year, crop, and EA fixed effects. Following from the first specification, a version of this specification is also created with the quadratic form of z-scores of temperature and rainfall are also included. This specification controls for time-invariant differences in an EA, such as soil quality, geographic conditions, and infrastructure differences. The identification here comes from within-EA variation over time, allowing for how deviations in temperature and rainfall affect yields in the same location over time.

For the OLS specifications standard errors are clustered at the EA-level. All regressions are estimated using sampling weights to ensure representativeness of the underlying population.

In addition to these, a household fixed effects model is also considered. This specification further controls for household-level unobserved heterogeneity such as household wealth, ability, and farming practices. Following from the OLS specifications, a version of this specification is also created with the quadratic form of z-scores of temperature and rainfall are also included. Errors are clustered at the household-level, and sampling weights are used to ensure representativeness of the underlying population.

VI. Additional Specifications Considered

Schlenker and Roberts (2009), Carleton and Hsiang (2016), and Adhikari, Nejadhashemi, and Woznicki (2015) state that after temperature and rainfall exceed a certain threshold their impacts affect yields more. I include these in additional specifications; extreme climate shocks are defined as using threshold indicators based on these standardized anomaly values. Rainfall anomalies below -1.5 standard deviations are classified as drought shocks, while values above +1.5 standard deviations are classified as flood shocks. Similar thresholds are applied to temperature, where temperature anomalies +1.5 standard deviations are classified as heat shocks and values below -1.5 standard deviations are classified as frost shocks.

Amare et al. (2018) and Kakpo, Mills, and Brunelin (2022) examined how positive and negative rainfall shocks affect productivity. I also include these as an additional specification. Since

Amare et al. (2018) uses a classification of ±0.5 standard deviations, the same specifications are used in this thesis.

6. Results

This section examines the results related to the central research question of the paper: How do rainfall and temperature affect agricultural yields?

I. Ordinary Least Squares (OLS)

Table 2 presents the ordinary least squares estimates of rainfall and temperature variability affecting yields. Rainfall exhibits a positive and statistically significant relationship with yields throughout all OLS specifications, with a one standard deviation increase in rainfall increasing the yields between approximately 5% to 9%. Temperature effects are larger in magnitude. A one standard deviation increase in temperature is associated with a 9% to 19% increase in yields. The squared terms of neither temperature nor rainfall are statistically significant in any specifications, indicating that there is no statistically significant nonlinear relationship in the observed data range.

The specifications with EA, crop, and year fixed effects models see how climate variation in the same location over time affects agricultural yields. In these specifications, the rainfall coefficient remains positive and statistically significant, with a one standard deviation increase in rainfall resulting in a 5% to 5.4% increase in agricultural yields. Rainfall coefficients remain stable at the EA-level, which suggests that within-location variability is an important driver of these coefficients.

Temperature coefficients decline significantly when EA fixed effects are included instead of country fixed effects. The coefficient falls from approximately 19% to approximately 9%. This indicates that a significant portion of temperature effects observed are driven by cross-location differences rather than within-location variation.

Across the specifications, the controls behave as expected. Irrigation, fertilizer use, seed use, pesticide use, and household asset index are positively associated with yields. This reflects the role of productive inputs in agricultural yields. Household size and dependency ratio are negatively associated with yields, suggesting that additional members of the household are associated with lower yields. These effects are diminished and lose their significance in specifications with EA fixed effects, suggesting that they are primarily driven by cross-sectional differences rather than within-location differences over time. The coefficient on log labor is positive and statistically significant across all specifications, indicating that higher labor input is associated with higher yields.

Age of the plot manager is also negatively associated with yields, indicating that ageing managers are associated with lesser yields; this may be due to a few reasons. Ageing managers are less likely to take risks and adopt newer agricultural practices. Female plot managers also have a negative and significant coefficient across the specifications. This may indicate some structural barriers that are outside the scope of this study. The number of plots is negatively associated with yield amounts, indicating that households that manage more plots have lower yields.

II. Household Fixed Effects

Table 3 presents the results of the household fixed effects model. By controlling time-invariant characteristics, this model isolates how changes in climate conditions affect household yields. By collapsing data to the household-year level, this model exploits within-household variation over time and controls for time-invariant characteristics.

Rainfall is positive and statistically significant, with a one standard deviation increase in rainfall associated with an approximately 7% increase in average household yields. This suggests that rainfall variability remains an important predictor of yields even after controlling for household-level heterogeneity. Temperature shocks also remain positive and significant at the one per cent level. A one standard deviation increase in temperature leads to between an 8.3% and 8.5% increase in average household yields. This suggests that warmer than average conditions are associated with higher yields in the short-run.

The non-linear specification shows no evidence of curvature in rainfall effects, as the coefficient is close to zero and not statistically significant. The squared temperature coefficient is also not statistically significant, indicating no statistically significant nonlinear relationship between temperature and rainfall on yields in the observed data range.

In comparison to the OLS specifications, several of the control variables lose their significance. This is expected as the household fixed effects absorb much of the household time-invariant characteristics such as household size, the gender of the plot manager, the age of the plot manager, the number of plots, irrigation, livestock use, pesticide use, and labor use.

Among the inputs, fertilizer use remains positive and significant, and seed use remains weakly significant. The education variable is negative and statistically significant in the household fixed effects specification. Since this measure captures if any household member has formal education, it can vary over time with changes in household structure and size. The negative coefficient suggests that households with greater access to education may allocate labor to non-farm activities associated with lower agricultural yields. Household asset index also remains positive and statistically significant as household's assets may change over time and higher assets are indicative of a higher ability to invest in inputs. The dependency ratio also remains negative and statistically significant, indicating a higher dependency ratio is associated with lower yields.

III. Additional Climate Specifications

To further examine the relationships between climate variability and agricultural yields, additional specifications are included to capture threshold and extreme climate shocks.

The extreme shock specification examines the impact of severe climate shocks on agricultural yields. Across both specifications, drought shock is negative; however it is not statistically significant. Heat shocks are associated with an approximately 32% to 34% increase in yields. While this may be a counterintuitive result, this variable captures relative deviations from the typical climate conditions rather than absolute temperature levels. The positive and significant coefficient suggests that years with warmer than average temperatures are associated with higher yields. It may also mean that despite this deviation the temperature may still be in the optimal growing range for crops. Flood shocks and frost shocks are insignificant in both specifications.

The second specification focuses on weather asymmetries by looking at positive and negative shocks to temperature and rainfall. Positive rainfall shocks are associated with an 11% increase in yields in the specification with country, year, and crop- fixed effects. However, once the country fixed effects are replaced with EA effects, this effect decreases in magnitude and does not remain significant. Negative rainfall shocks result in a decrease in yields by approximately 7%, and these effects are significant at the 5% level across both the specifications.

Negative temperature shocks are also robust across specifications. A negative temperature shock is associated with a 8.3% to 20.4% decrease in agricultural yields and these shocks are significant. A positive temperature shock is associated with a 13.7% increase in the specification with country fixed effects; however, this effect declines in magnitude and significance in the specification with EA fixed effects.

IV. Comparison to previous literature

The results from the OLS model indicate that a one standard deviation in rainfall is associated with a 5% to 9% increase in yields that is consistent with magnitude and direction across the literature. Amare et al. (2018) and Kakpo, Mills and Brunelin (2022) both find that positive rainfall shocks increase agricultural productivity, while Randell, Gray and Shayo (2022) document the effects of rainfall on food security measures in Tanzania and find similar positive effects.

Both Amare et al. (2018) and Kakpo, Mills and Brunelin (2022) construct rainfall shock variables by utilizing a standardized anomaly index, which is also calculated in this thesis. However, a key methodological difference is that Amare et al. (2018) and Kakpo, Mills and Brunelin (2022) convert their continuous z-scores to binary dummy variables for positive and negative rainfall shocks. Amare et al. (2018) utilizes a threshold of ± 0.5 standard deviations to define positive and negative shocks whereas Kakpo, Mills and Brunelin (2022) utilise a ± 1 threshold for the same. This thesis retains the continuous z-scores to capture the full magnitude of rainfall effects in the main specifications. In the additional specifications, positive and negative rainfall anomalies are also examined.

Therefore directionally the results are the same; however, their magnitude is different due to the difference of the type of climate variable used. Additionally, direct comparison of results is not possible as the dependent variables in Amare et al. (2018) and Kakpo, Mills and Brunelin (2022) are agricultural land productivity measured as real net crop income per hectare and millet production and price seasonality, respectively. These measures are related to agricultural yields but not the same. Blanc (2012) also uses a Standardized Precipitation Index to examine the effects of rainfall on crop-specific yields and finds positive and significant effects of above-average rainfall on maize, millet, and sorghum yields, providing direct methodological evidence for the methods considered here. The squared rainfall coefficient is not statistically significant in either of the specifications.

Household fixed effects in Table 3 confirm the rainfall effects persist even after controlling for time-invariant household characteristics, with a one standard deviation increase associated with an approximately 7% increase in average household yields. This is consistent with Amare et al. (2018), who similarly find that rainfall shocks retain their significance within a household fixed effects framework, confirming that rainfall variation rather than time-invariant household characteristics drives the relationship.

Kakpo , Mills and Brunelin (2022) used district fixed effects with millet production and price seasonality as their dependent variable and also found that rainfall shocks retain their significance within a fixed-effects framework. This corroborates the rainfall effects identified in this study. Direct comparisons are not possible given that the dependent variables in these studies are not the same. However, directional consistency across specifications provides support for robustness of the rainfall findings in this thesis.

The positive and negative binary indicators for rainfall in Table 5 provide additional support for the rainfall results. Negative rainfall shocks are associated with lower yields in both specifications with coefficients of -0.069 and -0.067, both statistically significant. This result is consistent with Amare et al. (2018), who documented that negative rainfall shocks have a negative and statistically significant impact on agricultural outcomes. Positive rainfall shocks are associated with higher yields, with a coefficient of 0.112 in the country fixed effects, although the coefficient declines to 0.041 and becomes statistically insignificant in the EA fixed effects model.

Temperature results in this thesis require more careful interpretation as they diverge from the literature. Schlenker and Lobell (2010) use degree days that capture exposure of crops to temperatures above 30ºC and find large negative yield effects across crops in Sub-Saharan Africa. Similarly, Blanc (2012), Jithitikulchai (2023), and Mkonda and He (2018) found that increases in temperature are associated with reductions in agricultural productivity, food security and consumption. Chamma (2024) documents the negative impacts of temperature on the agricultural sector performance.

However, the temperature coefficients in this model across specifications are positive and statistically significant. In Table 2, the coefficient on temperature z-score is 0.187 and 0.181 in the country fixed effects specifications and declines to 0.096 and 0.087 in the EA fixed effects specifications. This is indicative that the relationship between temperature and yields remains positive and significant. This difference primarily arises from the way temperature is constructed in this study. Instead of taking absolute temperature, this study uses the z-score, which captures deviation from the local mean as compared to absolute temperature. Therefore, the specifications do not capture whether temperatures exceed critical thresholds. In this context a positive deviation may reflect a more favorable growing season or indicate a higher number of sunny days, which do help crops. Additionally, these deviations may still be in the optimal growing range for crops and therefore not damage them.

Table 3 depicts household effects that reinforce the main findings. The coefficient on temperature remains positive and statistically significant at 0.085 and 0.083, indicating that temperature deviations continue to affect yields even after controlling for time-invariant characteristics.

The shock models further highlight asymmetry in temperature effects. Heat shocks are positive and significant (0.339 and 0.323), while frost shocks are insignificant. Negative temperature shocks reduce yields with coefficients of -0.204 and -0.083, but positive shocks increase yields with coefficients of 0.137 and 0.056; however, the effect weakens under EA fixed effects. This is consistent with Schlenker and Lobell (2010), who document nonlinear effects and show that deviations below optimal conditions are particularly harmful.

V. Connections to Climate

The results show that agricultural yields are responsive to short-run deviations in rainfall and temperature, with rainfall shocks remaining robust across specifications and negative shocks consistently reducing yields. The persistence of these effects under the EA and household fixed effects suggests that agricultural production is closely tied to within-location variability in the climate. Short-term deviations in climate cause meaningful changes in agricultural yields.

This context is important when talking about climate change. The empirical specifications in this thesis capture short-run changes rather than long-run changes in average climate conditions. The result is that in this thesis the estimated coefficients are the effects of climate variability, not the long-term effects in temperature and rainfall levels.

Existing evidence from literature shows that climate variability is already associated with more intense rainfall anomalies and widespread droughts and the frequency of these events is expected to increase over time (Boko et al. 2007). In this context, the results suggest that the types of climate shocks both positive and negative are likely to occur more frequently and with greater magnitude.

As climate change is expected to increase the frequency and severity of these deviations, the short-run effects are likely to become more pronounced over time. This thesis identifies the short-run mechanism through which climate change might affect productivity through increased variability in temperature and rainfall rather than changes in their long-term means.

7. Conclusions

The primary goal of this thesis was to examine the relationship between short-run temperature and rainfall variability and agricultural yields for rainfed crops in SSA. This was achieved by constructing the rainfall and temperature z-scores as predictors and control variables to estimate this relationship. This relationship was then estimated across OLS and household fixed effects models, with additional specifications. One of the additional specifications tested for major shocks such as drought shocks, flood shocks, heat shocks, and frost shocks. Another specification created binary indicators for positive and negative rainfall and temperature shocks, as has been done in prior literature.

The results indicate that higher rainfall is always associated with higher yields across the specifications. This is a result corroborated by previous literature. Additional levels of rainfall are positively associated with yields for rainfed crops in SSA, resulting in a nearly 5% to 9% increase in yields across all specifications tested. The shock models do find a negative relationship between a flood shock and agricultural yields, in the model with EA fixed effects; however, this effect is not statistically significant.

Temperature results are more interesting here. In climate literature, usually the temperature examined is in terms of the absolute temperature; however, this thesis examined the short-run deviations in contrast to the absolute form of temperature. Positive associations have been found between temperature and agricultural yields. While on the surface this may seem contradictory to previous literature, it is not. The difference in results comes from the way that temperature is constructed in this thesis. The z-score estimate of temperature only accounts for short-run deviations rather than long-term changes in the mean of temperature. Therefore, in this context, the positive association may also come from the fact that these deviations may still lie in the optimal ranges for growing these crops. Temperature results also widely vary by the chosen specification. In the OLS specification the results range from a one standard deviation resulting in an approximately 19% increase in yields when country, crop, and year fixed effects are included, and substantially decline to approximately 9% when the country fixed effects are replaced with EA fixed effects. The results of the household fixed-effects are similar to the EA fixed effects.

The magnitude difference in the results for temperature suggests that temperature effects are sensitive to the spatial variation at which they are modeled. The within-location variation in the context of temperature effects is relatively small compared to cross-sectional differences.

Future directions of this thesis should focus on seeing these effects at the plot-level. The way the LSMS-ISA dataset is currently structured, plots cannot reliably be tracked across survey waves; the smallest unit of tracking is the household-level. The magnitude of short-run deviations in temperature and rainfall would be even more reliable if the same plots could be tracked across time. However, understandably, there are challenges to producing such a panel dataset. Over time, plots get sold, divided, and reallocated to different households, and consistent tracking of them may not be possible. Despite these limitations, constructing a plot-level panel dataset remains crucial to stronger identification of these effects.

Another future direction could extend this analysis to see how these climate shocks may translate to crop prices, input costs, and household income. Accounting for these channels will help understand how climate variability impacts agricultural welfare as a whole.

To help mitigate the effects caused by variations in climate a few measures may be adopted by farmers in SSA. McCarthy et al. (2021) suggest intercropping with legumes as a potential solution to these variabilities. Growing legumes enriches the soil through nitrogen fixation making the yields more bountiful. World Meteorological Organization (2023), suggests that government-wide solutions to mitigate these variabilities should include sustained investments in meteorological and hydrological early warning systems. These systems will have the ability to reliably detect seasonal temperature and rainfall and in case they are not optimal for crop growth, farmers can have time to plan their mitigation strategies accordingly.

Tables

Table 1 : Summary Statistics

Variables	mean	sd	min	max	count
Log Yield (kg/ha)	7.017	1.405	-5.510	20.438	48013
Rainfall (z-score)	-0.108	0.905	-3.319	3.652	48013
Temperature (z-score)	0.118	0.613	-2.289	2.431	48013
Household Size	6.268	3.573	1	25.000	48013
Dependency Ratio	1.142	0.889	0	11.000	48013
Any Formal Education	0.889	0.314	0	1	48013
Asset Index	-0.243	0.739	-1.470	9.996	48013
Female Manager	0.210	0.407	0	1	48013
Manager Age	47.066	15.101	0	100	48013
Number of Plots	5.935	6.141	0	60.000	48013
Irrigated Plot	0.018	0.135	0	1	48013
Livestock Ownership	0.771	0.420	0	1	48013
Log Seed Use	1.900	1.374	0	13.816	48013
Fertilizer Use	0.423	0.494	0	1	48013
Pesticide Use	0.063	0.244	0	1	48013
Log Labor Input	1.670	2.911	0	10.208	48013

Notes: This table reports the summary statistics for all variables examined in the study. Rainfall and temperature anomalies are reported as z-scores. The sample consists of 48013 observations.

Table 2 : OLS Models

	(1)	(2)	(3)	(4)
	log_yield	**log_yield**	**log_yield**	**log_yield**
Rainfall anomaly (z-score)	0.087***	0.086***	0.054**	0.049**
	(0.017)	(0.017)	(0.023)	(0.021)
Temperature anomaly (z-score)	0.187***	0.181***	0.096***	0.087***
	(0.023)	(0.024)	(0.027)	(0.027)
Household size	-0.013***	-0.013***	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Household dependency ratio	-0.017*	-0.017*	-0.008	-0.008
	(0.009)	(0.009)	(0.008)	(0.008)
Household has formal education	-0.021	-0.021	-0.031	-0.031
	(0.027)	(0.027)	(0.025)	(0.025)
Household asset index	0.167***	0.167***	0.112***	0.112***
	(0.016)	(0.016)	(0.015)	(0.015)
Female plot manager	-0.037*	-0.036*	-0.071***	-0.071***
	(0.020)	(0.020)	(0.017)	(0.017)
Age of plot manager	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.000)	(0.000)
Number of plots under household management	-0.004	-0.004	-0.008***	-0.008***
	(0.003)	(0.003)	(0.002)	(0.002)
Plot is irrigated	0.176**	0.177***	0.223***	0.224***
	(0.069)	(0.069)	(0.082)	(0.082)
Household has livestock	0.044**	0.043**	0.066***	0.066***
	(0.021)	(0.021)	(0.018)	(0.018)
Seed Use (Log)	0.019**	0.019**	0.001	0.001
	(0.009)	(0.009)	(0.008)	(0.008)
Plot uses fertilizer	0.293***	0.293***	0.212***	0.212***
	(0.024)	(0.024)	(0.020)	(0.020)
Plot uses pesticides	0.125***	0.124***	0.061*	0.061*
	(0.045)	(0.045)	(0.032)	(0.032)
Labor input (log)	0.010**	0.010**	0.008**	0.007**

	(0.004)	(0.004)	(0.003)	(0.003)
Rainfall anomaly (z-score) Squared		0.003		-0.011
		(0.012)		(0.014)
Temperature anomaly (z-score) Squared		0.020		0.008
		(0.023)		(0.025)
Constant	8.178***	8.128***	7.116***	7.123***
	(0.098)	(0.110)	(0.040)	(0.046)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	No
Crop FE	Yes	Yes	Yes	Yes
EA FE	No	No	Yes	Yes
Observations	48013	48013	47804	47804
R-squared	0.221	0.222	0.380	0.380

Note: The dependent variable is the log agricultural yield (kg/ha). Rainfall and temperature anomalies are reported as z-scores. Columns (1)-(2) include country, crop and year fixed effects. Columns (3)-(4) include EA, crop and year fixed effects. Additionally, columns (2) and (4) include the quadratic terms of temperature and rainfall. Standard errors are clustered at the EA-level and included in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Table 3: Household Fixed Effects

	(1)	(2)
	(mean) log_yield	**(mean) log_yield**
Rainfall anomaly (z-score)	0.066***	0.066***
	(0.017)	(0.017)
Temperature anomaly (z-score)	0.085***	0.083***
	(0.022)	(0.024)
Household size	0.009	0.009
	(0.010)	(0.010)
Household dependency ratio	-0.033*	-0.033*
	(0.017)	(0.017)
Household has formal education	-0.155***	-0.154***
	(0.052)	(0.052)
Household asset index	0.064*	0.064*
	(0.034)	(0.034)
Female plot manager	-0.050	-0.049
	(0.042)	(0.042)
Age of plot manager	-0.001	-0.001
	(0.002)	(0.002)
Number of plots under household management	-0.007	-0.007
	(0.005)	(0.005)
Plot is irrigated	0.131	0.131
	(0.123)	(0.123)
Household has livestock	0.032	0.032
	(0.031)	(0.031)
Seed Use (Log)	0.023*	0.023*
	(0.013)	(0.013)
Plot uses fertilizer	0.211***	0.211***
	(0.035)	(0.035)
Plot uses pesticides	0.038	0.038
	(0.056)	(0.057)
Labor input (log)	0.007	0.007
	(0.007)	(0.007)

Rainfall anomaly (z-score) Squared		-0.001
		(0.010)
Temperature anomaly (z-score) Squared		0.006
		(0.020)
Constant	7.204***	7.193***
	(0.114)	(0.119)
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	29763	29763
Within R-squared	0.0329	0.0329
Between R-squared	0.0278	0.0299
Overall R-Squared	0.0390	0.0406
F-Stat	16.84	15.55
P-value	0	0

Note: The dependent variable is the log agricultural yield (kg/ha). Rainfall and temperature anomalies are reported as z-scores. Columns (2) include the quadratic terms of temperature and rainfall. Standard errors are clustered at the HH-level and included in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Table 4: Shock Models

	(1)	(2)
	log_yield	**log_yield**
Drought Shock	-0.100	-0.146
	(0.081)	(0.091)
Heat Shock	0.339**	0.323**
	(0.139)	(0.141)
Flood Shock	0.015	-0.026
	(0.056)	(0.068)
Frost Shock	0.022	-0.082
	(0.093)	(0.089)
Household size	-0.015***	-0.000
	(0.003)	(0.003)
Household dependency ratio	-0.015*	-0.008
	(0.009)	(0.008)
Household has formal education	-0.023	-0.032
	(0.027)	(0.025)
Household asset index	0.169***	0.112***
	(0.016)	(0.016)
Female plot manager	-0.035*	-0.072***
	(0.020)	(0.017)
Age of plot manager	-0.003***	-0.003***
	(0.001)	(0.000)
Number of plots under household management	-0.001	-0.008***
	(0.003)	(0.002)
Plot is irrigated	0.184***	0.225***
	(0.068)	(0.083)
Household has livestock	0.035*	0.064***
	(0.021)	(0.018)
Seed Use (Log)	0.020**	0.003
	(0.009)	(0.008)

Plot uses fertilizer	0.289***	0.211***
	(0.025)	(0.021)
Plot uses pesticides	0.113**	0.058*
	(0.044)	(0.032)
Labor input (log)	0.009**	0.007**
	(0.004)	(0.003)
Constant	7.978***	7.130***
	(0.106)	(0.041)
Year FE	Yes	Yes
Country FE	Yes	No
Crop FE	Yes	Yes
EA FE	No	Yes
Observations	48013	47804
R-squared	0.217	0.380

Note: The dependent variable is the log agricultural yield (kg/ha). Drought, heat, flood and frost shocks are binary indicators that equal one when temperature or rainfall exceed their predefined thresholds. Column (1) include the year, country and crop fixed effects and column (2) include EA, crop and year fixed effects. Standard errors are clustered at the EA-level and included in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Table 5: Positive and Negative Binary Indicators

	(1)	(2)
	log_yield	**log_yield**
Negative Rain Shock	-0.069**	-0.067**
	(0.030)	(0.033)
Positive Rain Shock	0.112***	0.041
	(0.031)	(0.039)
Negative Temperature Shock	-0.204***	-0.083**
	(0.037)	(0.040)
Positive Temperature Shock	0.137***	0.056
	(0.031)	(0.043)
Household size	-0.013***	-0.000
	(0.003)	(0.003)
Household dependency ratio	-0.016*	-0.008
	(0.009)	(0.008)
Household has formal education	-0.025	-0.031
	(0.027)	(0.025)
Household asset index	0.169***	0.112***
	(0.016)	(0.016)
Female plot manager	-0.039*	-0.072***
	(0.020)	(0.017)
Age of plot manager	-0.003***	-0.003***
	(0.001)	(0.000)
Number of plots under household management	-0.003	-0.008***
	(0.003)	(0.002)
Plot is irrigated	0.172**	0.224***
	(0.067)	(0.082)
Household has livestock	0.046**	0.066***
	(0.021)	(0.018)
Seed Use (Log)	0.018**	0.001
	(0.009)	(0.008)

Plot uses fertilizer	0.290***	0.212***
	(0.024)	(0.020)
Plot uses pesticides	0.123***	0.060*
	(0.045)	(0.032)
Labor input (log)	0.009**	0.007**
	(0.004)	(0.003)
Constant	8.052***	7.130***
	(0.101)	(0.046)
Year FE	Yes	Yes
Country FE	Yes	No
Crop FE	Yes	Yes
EA FE	No	Yes
Observations	48013	47804
R-squared	0.221	0.380

Note: The dependent variable is the log agricultural yield (kg/ha). Negative and positive rainfall and temperature shocks are binary indicators for deviations below −0.5 and above +0.5 standard deviations. Column (1) include the year, country and crop fixed effects and column (2) include EA, crop and year fixed effects. Standard errors are clustered at the EA-level and included in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Literature Review Table

Paper	Context	Regressions Used & Dependent Variable (Y)	Control Variables	Variables	Countries	Datasets Used
Rainfall shocks and agricultural productivity: Implication for rural household consumption Amare et al. (2018)	Rainfall shocks, agricultural productivity, and consumption	Productivity estimated using Cobb-Douglas production function with household and time fixed effects; Consumption estimated using household and state fixed effects; IV-FE model where agricultural productivity is instrumented using rainfall shocks Agricultural productivity: real net crop income per hectare Household consumption: real consumption per adult equivalent unit (AEU)	Negative rainfall shock, Positive rainfall shock, HH Age, Family size, Dependency Ratio, Land size, Total livestock- tropical livestock unit (TLU) , Assets, Wage income, Self-employment income, Remittance, Fertilizer use, Pesticide and herbicide, Extension, Finance, Distance to road, and crop fixed effects	Rainfall anomaly index (log deviation from 30-year monsoon avg). Shock dummies (≥1 SD). Cobb-Dougl as production function.	Nigeria	Nigeria LSMS-ISA (2010–2015); ARC2; NOAA (For weather data)

Crop yields fail to rise in smallholder farming systems in sub-Saharan Africa Wollburg et al. (2024)	Agricultural productivity trends over time	Uses OLS and multiple fixed effects models (household, plot manager, cluster) to estimate agricultural productivity (yield per hectare) as a function of inputs, controls, weather, and time trends across	Land area (hectares), Family and exchange labor days per hectare, Value of seeds per hectare, Value of hired labor per hectare, Value of inorganic fertilizer per hectare, Pesticide use, Organic fertilizer use, Intercropping, Irrigation, Plot ownership, Crop shocks (drought, flood, fire), Age of plot manager, Gender of plot manager, Education of plot manager, Household size, Recent household shocks, Livestock ownership, Household electricity access, Urban/rural status, Indicator for missing harvest values, Agricultural assets index, Year (time trend)		Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania	LSMS-ISA; European Centre for Medium-Range Weather Forecasts' ERA5, Chirps weather data World Bank CPI

Climatic conditions and household food security: Evidence from Tanzania Randell, Gray & Shayo (2022)	Rainfall variability & food security	Multivariate logistic regressions. Y: FCS, rCSI, food security status.	Female-headed household, age of household head, education of household head, number of members ages 0–6, number of members ages 7–15, number of members ages 16–64, number of members ages 65+, housing quality index, poverty status (under $1.90/day), primary income source, farm size, head resident in EA < 10 years, interview season.	CHIRPS rainfall deviations.	Tanzania	Tanzania LSMS-ISA; CHIRPS; CHIRPSMAX

Weather shocks and food price seasonality in Sub-Saharan Africa: Evidence from Niger Kakpo, Mills & Brunelin (2022)	Rainfall shocks, millet production & price seasonality	District FE regressions. Y1: Millet production. Y2: Millet prices (shock × month).	Positive rainfall shock, Negative rainfall shock, District Fixed Effects, Month indicators, year fixed effects	Rainfall anomaly index (≥1 SD), Positive and negative rainfall anomalies.	Niger	Niger Ministry of Agriculture; Market data; NOAA

The effect of climate change and agricultural diversification on the total value of agricultural output of farm households in Sub-Saharan Africa Theepakorn Jithitikulchai (2023)	Climate, diversification & output resilience	Country & year FE (Ricardian-style). Y: Total agricultural output.	Number of agricultural workers and its squared term, Land used for agriculture (hectares) and its squared term, Agricultural wealth index, Index of access to infrastructure, Female head (relative to male head), Age of head and its squared term, if the Household has a cell phone, EA latitude and its squared term, EA longitude and its squared terms, Log of elevation (m) and its squared term, Rural (relative to urban), Country and year controls, Two activities (both crop and livestock), Livestock only and mixed activities.	Temperature & rainfall (quadratic terms). Diversification indicator.	Ethiopia, Malawi, Niger, Nigeria, Tanzania, Uganda	LSMS-ISA

Robust negative impacts of climate change on African agriculture Schlenker & Lobell (2010)	Climate impacts on staple crop yields	Country FE panel. Y: Log crop yields (maize, cassava, sorghum,millets ,groundnuts)	Country fixed effects,quadratic time trend	Degree days; quadratic precipitation ; seasonal averages.	Multiple SSA countries	FAO; NCEP (National Centers of Environmental Prediction); CRU(Climatic Research Unit of the University of East Anglia)

The Impact of Climate Change on Crop Yields in Sub-Saharan Africa Blanc (2012)	Climate scenarios & crop yields	Panel regressions by crop. Y: National yields for millets, maize, sorghum, and cassava	All models: Area harvested, error correction term, time dummies, country fixed effects (except cassava) T-P specific: Average temperature, precipitation, squared precipitation, temperature-precipitation interactions, LFAC (less favorable agricultural conditions) interactions ET-SPI specific: Evapotranspiration (ETo), standardized precipitation index (SPI), flood dummies, ETo-flood interaction CO2 specific: no weather variables (multicollinearity)	Temperature, precipitation, evapotranspiration, SPI. 20 GCM scenarios.	37 SSA countries	FAOSTAT; CSIRO2 HadCM3 CGCM2 ECHAM4 and PCM - all climate change models

Climate change and economic growth in sub-Saharan Africa: an empirical analysis of aggregate- and sector-level growth Chamma (2024)	Climate change & macro growth	Country & year FE; Seemingly Unrelated Regression (SUR). Y: GDP growth (aggregate & sectoral).	Human capital (HC) measured as gross secondary school enrollment ratio, sourced from Penn World Table	Avg temperature; precipitation; CV of precipitation.	43 SSA countries	CRU; WDI; Penn World Table

Climate Trends and Global Crop Production Since 1980 Lobell, Schlenker & Costa-Roberts (2011)	Global crop yield response to climate trends	Yield regressions on weather. Y: Maize, wheat, rice, soy yields.	Country specific intercepts, country specific time trends	Monthly temperature & precipitation trends.	Global	FAO; global climate data

Effects of climate change on global food production under SRES emissions and socio-economic scenarios Parry et al. (2004)	Climate scenarios, yields & hunger risk	Transfer functions + economic trade model. Y: Crop yields; hunger risk.	None	HadCM3 climate projections; IPCC SRES scenarios.	Global	HadCM3; crop simulation models

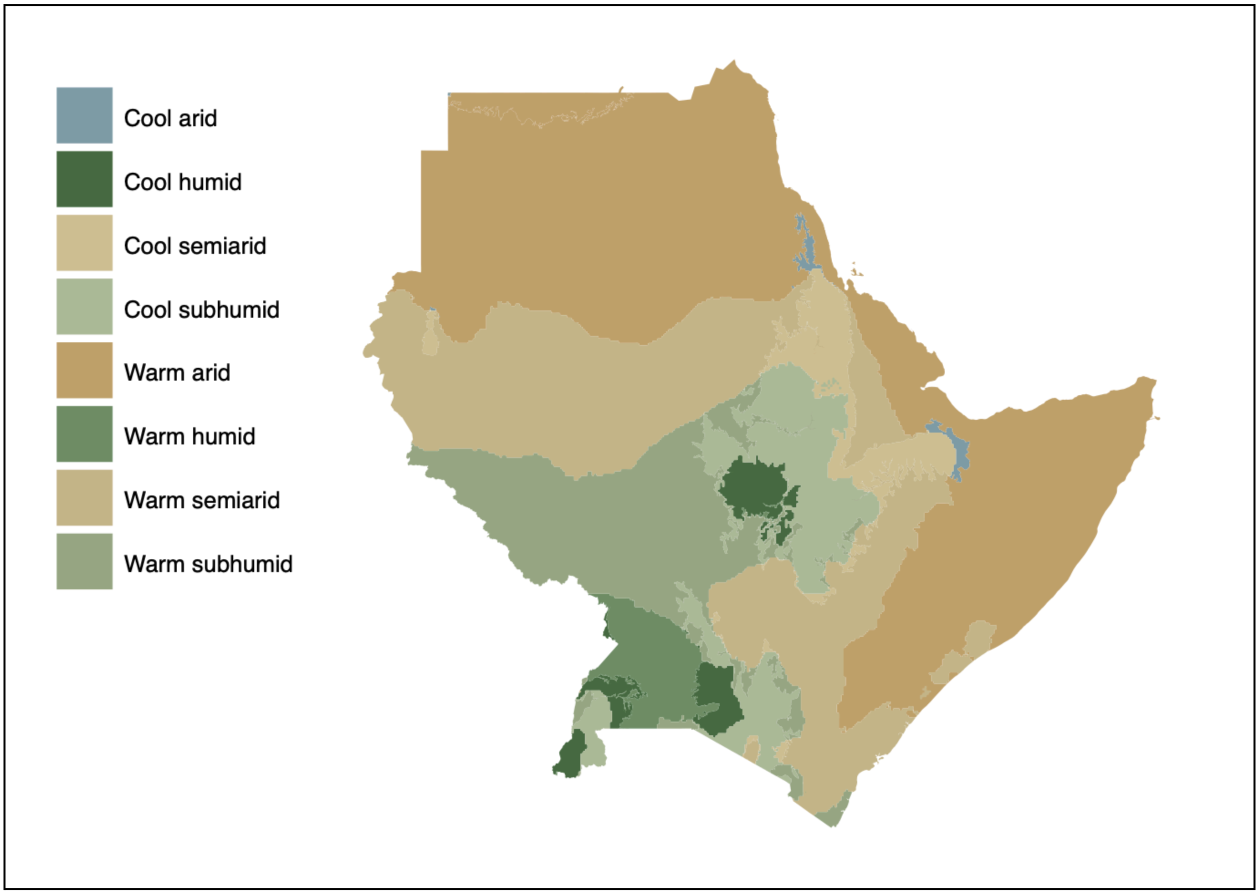
Social and economic impacts of climate Carleton & Hsiang (2016)	Review of climate impacts	Review Article (No data collected, no regressions estimated)	None	Emphasis on nonlinear temperature & precipitation effects.	Global	Secondary review

The Impact of Climate Change Induced Extreme Events on Agriculture and Food Security: A Review on Nigeria Durodola (2019)	Review of climate change & Nigerian agriculture	Review Article (No data collected, no regressions estimated)	None	Summary of rainfall & yield impacts.	Nigeria	Secondary sources

Climate variability and crop yields synergies in Tanzania's semiarid agroecological zone Mkonda & He (2018)	Climate change & yields in Tanzania	Pearson's moment correlation coefficient and Correlation regression analysis. Y: Crop yields (maize, sorghum, and millet)	None	Meteorological rainfall & temperature data.	Tanzania	Local meteorological data; PRA survey

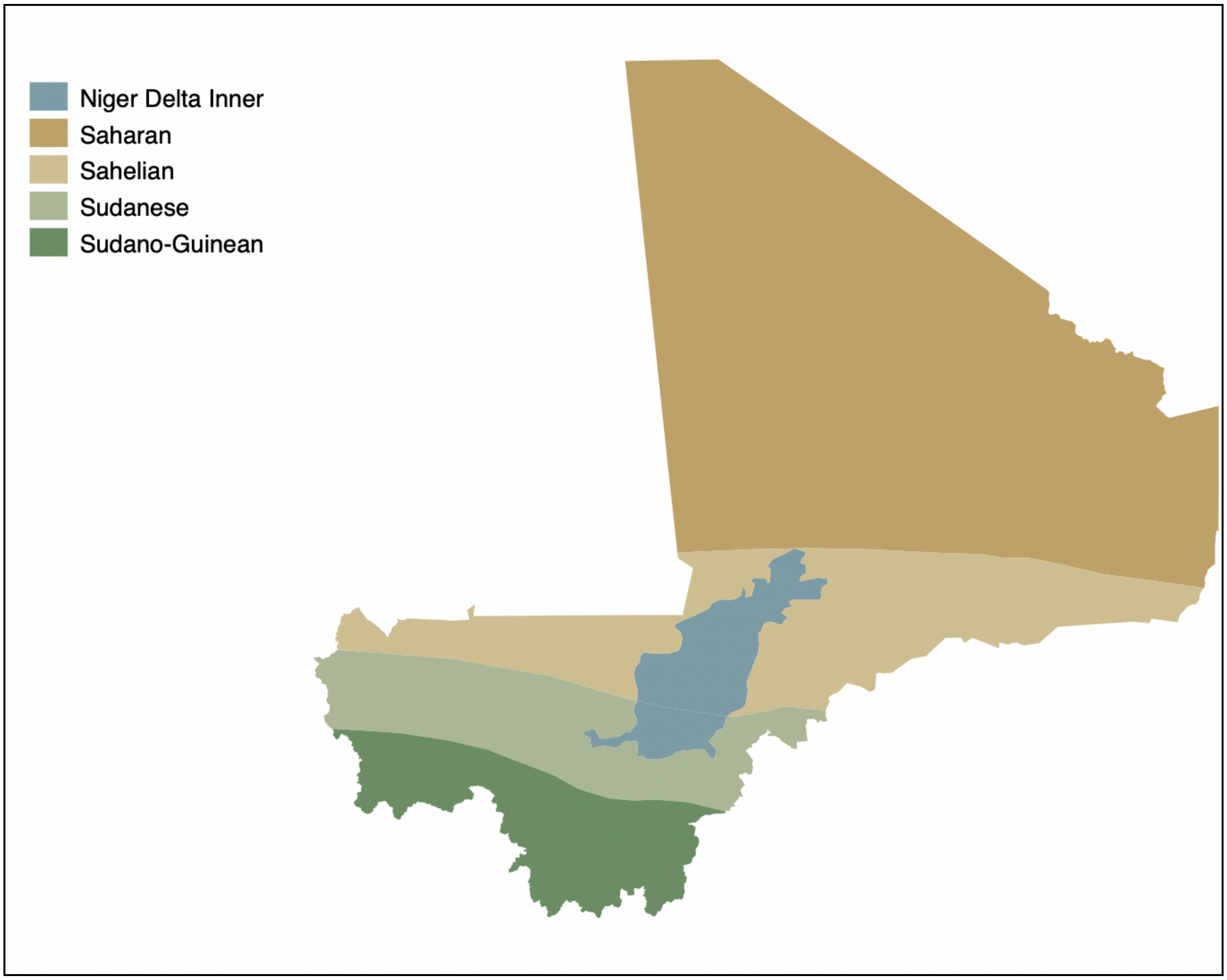
Figures

Figure 1: Ethiopia Agroclimatic Zones



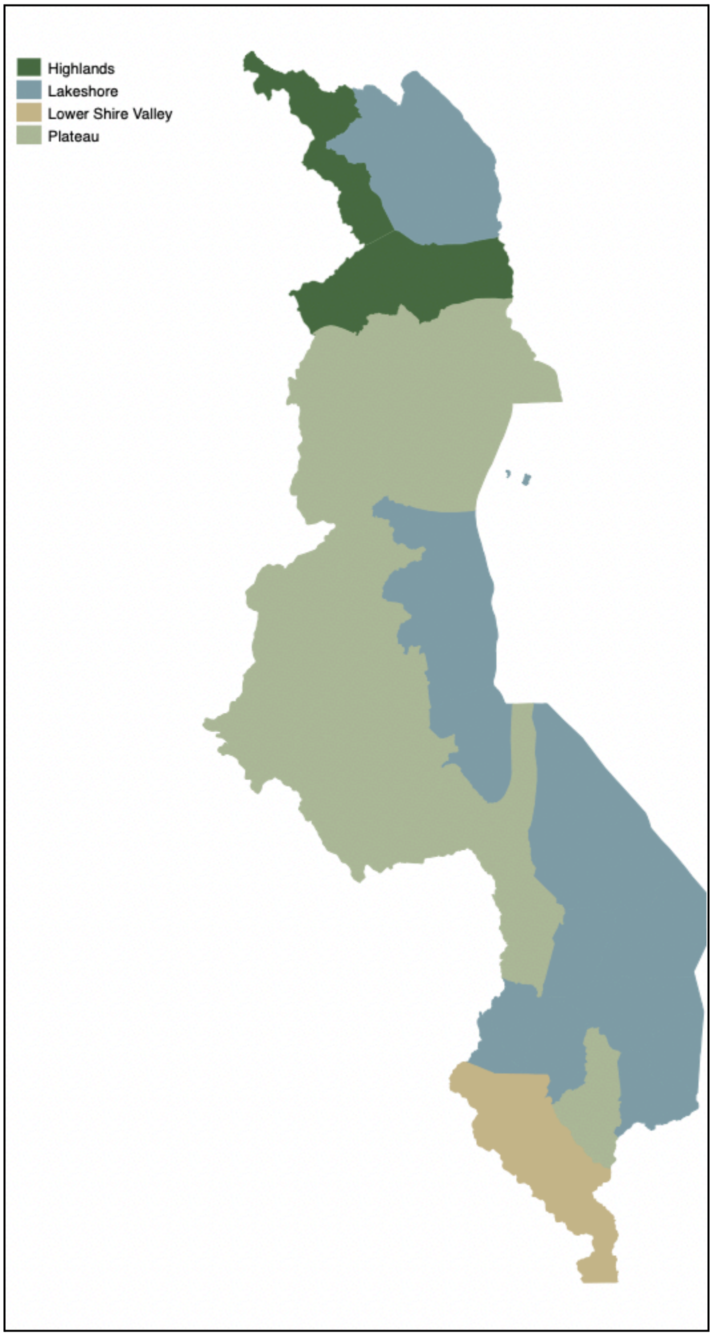
Notes: Administrative boundaries are derived from the Global Administrative Areas (GADM) database. Agroclimatic zones are sourced from the RCMRD dataset.

Figure 2: Mali Agroclimatic Zones



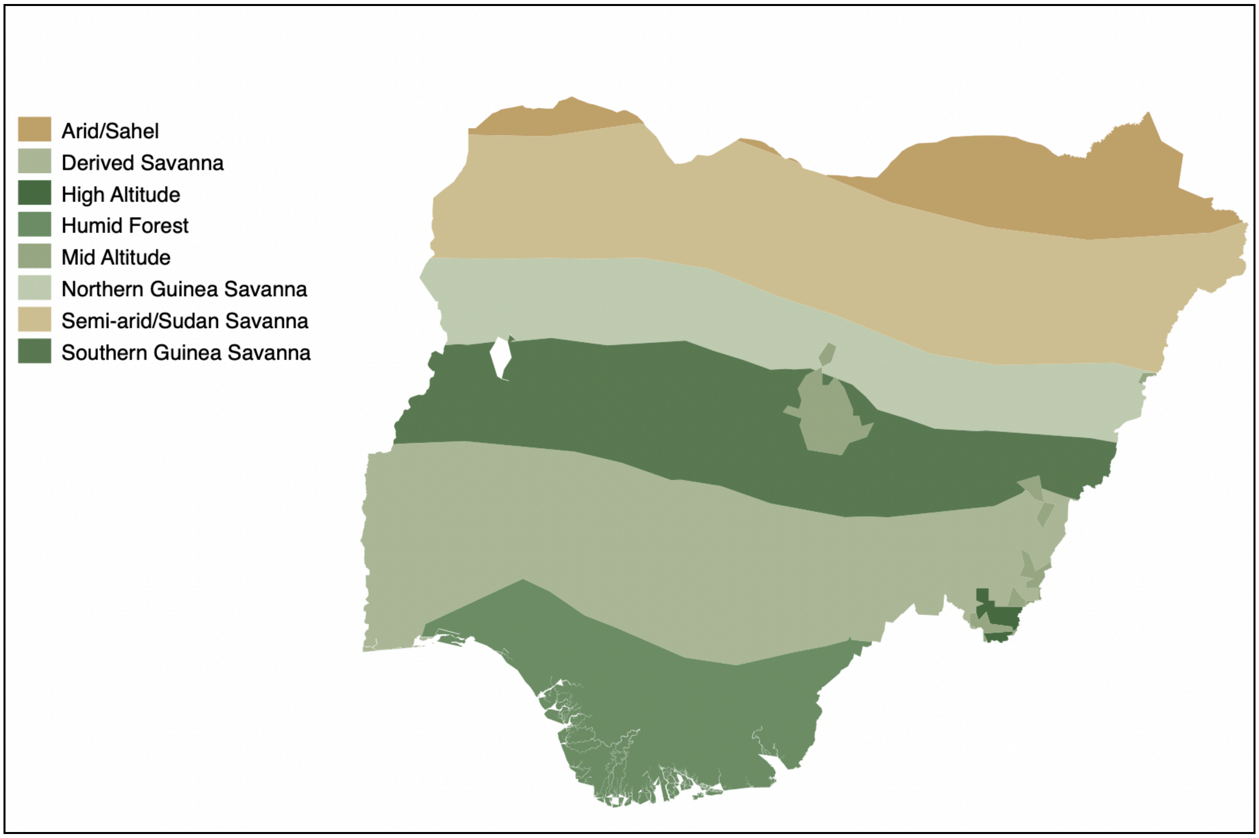
Notes: Agroclimatic zones are sourced from the "*Zones Agroclimatiques De Mali"* accessed from the FAO Global Agro-Ecological Zones (GAEZ) portal.

Figure 3: Malawi Agroclimatic Zones



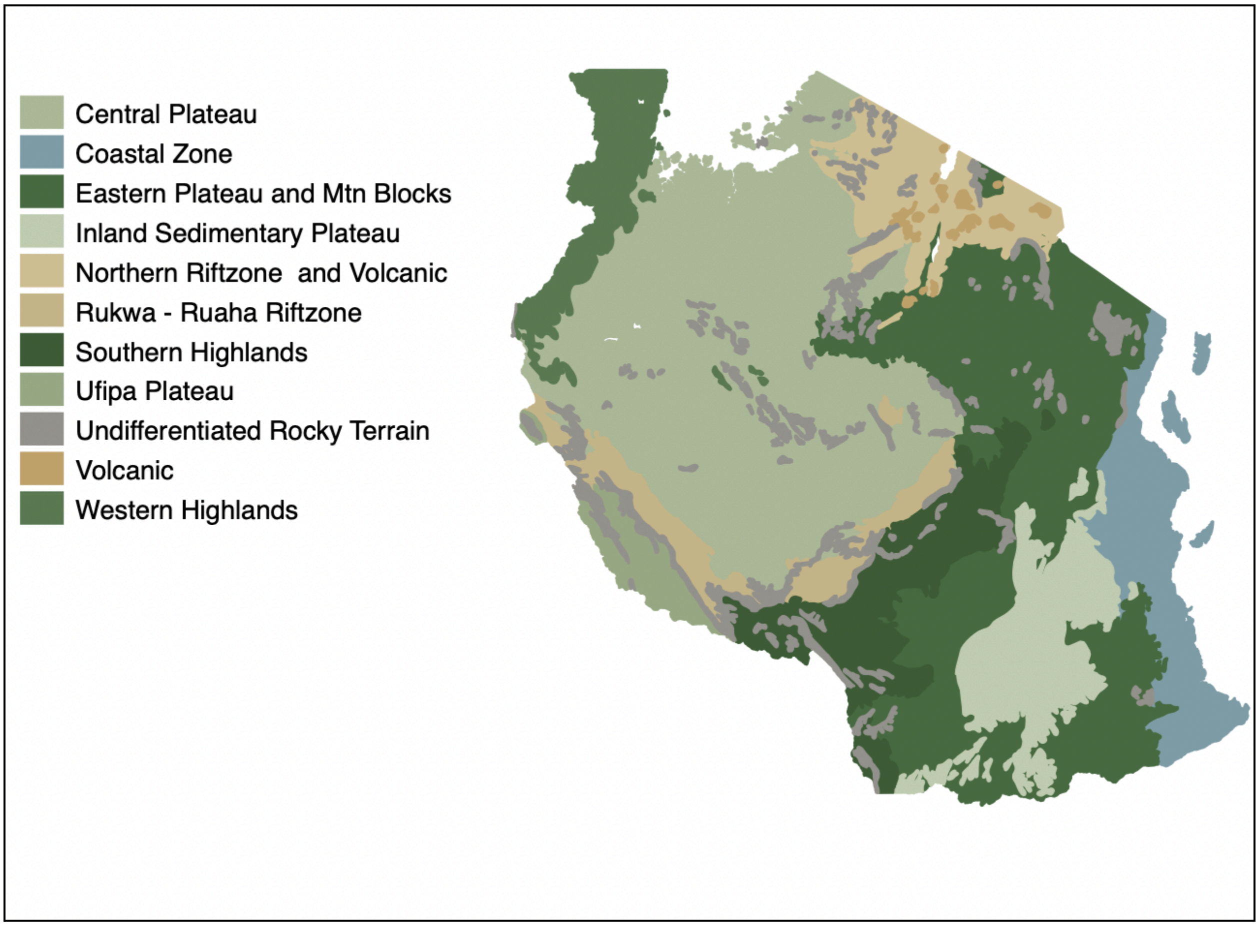
Note: Administrative boundaries are derived from the [Global Administrative Areas (GADM)] database. Agroclimatic zones are sourced from the [Malawi Segmentation Tool.]

Figure 4: Nigeria Agroclimatic Zones



Note: Agroclimatic zones are derived from the Nigeria Agroecological Zones dataset, accessed via the [Africa GeoPortal.]

Figure 5: Tanzania Agroclimatic Zones



Notes: Administrative boundaries are derived from the [Global Administrative Areas (GADM)] database. Agroclimatic zone classifications are derived from the FAO Global Agro-Ecological Zones (GAEZ) [portal.]

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