June 2026

Working Paper

19.2026

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Summary

Weather shocks increasingly threaten agricultural productivity in Sub-Saharan Africa. While the negative effects of drought on production have been documented in numerous studies, the behavioral dimension of adaptation, particularly how households perceive drought and what shapes these perceptions, remains less explored. The study focuses on Uganda to distinguish between self-reported drought (subjective) and data-driven drought (objective) and how their divergence is associated with agricultural outcomes. The study relies on four waves of household surveys (UNPS for 2009/10, 2010/11, 2011/12, and 2013/14) with historical re-analysis data on temperature and precipitation from 1981 to 2015. Log-linear and logit models are applied to estimate the association between drought, perception, and household characteristics on production and drought perception formation. Objective drought is negatively associated with total value of production. Subjective drought perception has a positive association with production. Self-reported drought captures differences in households' behavioral responses or preparedness, rather than observed weather shocks. Households that underestimate drought conditions tend to exhibit lower production outcomes, while households reporting a drought when this is not observed in objective data tend to maintain their production levels. Access to the Drought Early Warning System (DEWS), technology adoption, higher education levels, farming experience, and greater off-farm assets are positively associated with higher production. Conversely, lower production is associated with a higher share of female labor, female-headed households, and poverty. The results highlight the importance of distinguishing between perceived and observed drought and improving households' access to timely information to plan adaptation strategies.

Keywords: Drought perception, objective drought, agricultural production, Uganda, early warning systems, climate change adaptation

JEL Classification: Q01, Q12, Q16, Q54, O13

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Distinguishing drought experiences: From perception to measurement and their significance on productivity value in Uganda

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Abstract

Weather shocks increasingly threaten agricultural productivity in Sub-Saharan Africa. While the negative effects of drought on production have been documented in numerous studies, the behavioral dimension of adaptation, particularly how households perceive drought and what shapes these perceptions, remains less explored. The study focuses on Uganda to distinguish between self-reported drought (subjective) and data-driven drought (objective) and how their divergence is associated with agricultural outcomes. The study relies on four waves of household surveys (UNPS for 2009/10, 2010/11, 2011/12, and 2013/14) with historical re-analysis data on temperature and precipitation from 1981 to 2015. Log-linear and logit models are applied to estimate the association between drought, perception, and household characteristics on production and drought perception formation. Objective drought is negatively associated with total value of production. Subjective drought perception has a positive association with production. Self-reported drought captures differences in households' behavioral responses or preparedness, rather than observed weather shocks. Households that underestimate drought conditions tend to exhibit lower production outcomes, while households reporting a drought when this is not observed in objective data tend to maintain their production levels. Access to the Drought Early Warning System (DEWS), technology adoption, higher education levels, farming experience, and greater off-farm assets are positively associated with higher production. Conversely, lower production is associated with a higher share of female labor, female-headed households, and poverty. The results highlight the importance of distinguishing between perceived and observed drought and improving households' access to timely information to plan adaptation strategies.

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Introduction

Agriculture is mainly dependent on weather conditions in Sub-Saharan Africa, where more than 60% of the population relies on farming activities as its primary source of income and food security. However, farming systems are predominantly rain-fed, and highly vulnerable to climate variability. Drought remains one of the most destructive and frequent weather shocks significantly reducing crop yields, and consequently rural incomes (Akwango et al., 2017; Twongyirwe et al., 2019). Projections indicate that climate change will intensify drought frequency and duration which will increase livelihood insecurity among smallholder households (Kakeeto et al., 2019). Therefore, because of weather shocks, the relationship between drought and crop yield remains a crucial concern for the continent's future (Girard et al., 2021).

Uganda ranks 155 out of 181 in the NG-GAIN[1] vulnerability index (World Bank, 2018) due to high climate sensitivity and limited level of adaptation. Within the country, drought has been recognized as the most destructive and frequent weather shock (Twongyirwe et al., 2019). Rural households are deeply dependent on rain-fed farming, especially rain patterns and temperature levels, which drastically constrain yield and hence income (Hübler et al., 2025). Approximately half of Ugandan households are currently income insecure due to crop failure and reduced production diversity in agriculture-dependent rural areas (Girard et al., 2021). By 2050, in many parts of the world as a result of population growth, rising income, and changes in climate conditions, mean temperature could rise by up to 2.5°C even in years with near-normal rainfall (World Bank, 2018; González et al., 2017). The situation is likely to exacerbate evaporation and soil moisture loss and leading to crop failure (IPCC, 2014).

To cope with the situation, the perception of drought at the household level is associated with drought adaptation. Based on individual perceptions, different households perceive drought differently and undertake local adaption. In other words, the way local farmers perceive drought is associated with their adaptation measures and coping strategies. For designing and implementing climate adaptation policies, understanding households' perceptions of, or concern about, of drought is very important (Karanja et al., 2017& Ricart et al., 2025). To assess how households'

[1] Notre Dame Global Adaptation Initiative (NG-GAIN)

perceptions toward climate change are influenced by their socio-economic and institutional factors, weather and climate perceptions are modeled as a function of these proxies. According to Feng and Arora (2024), households' social characteristics, such as age, literacy, income level, farm-size, off-farm assets, and their motivation to mitigate weather shocks all impact whether they perceive the climate is changing.

Several studies (e.g., see Akwango et al., 2017; Kakeeto et al., 2019; Ojara et al., 2019) have attempted to investigate the primary impacts of climate-related shocks (e.g., drought) on agriculture. Only a limited number of studies have explicitly focused on the distinct effects of households' perception and physical exposure to drought on crop failure. This study addresses this gap by systematically comparing objective drought (measured through satellite-based climate records) and self-reported drought (as perceived by households) measures. Additionally, a fundamental question is whether the self-reported shocks align with what is measured through secondary data, and if not, how the key differences between these two dimensions are, and how these typologies of shocks are associated with production outcomes. The main contributions lie in explicitly quantifying the perception-record gap through accuracy indicators (match and mismatch). In addition, studying perception formation is needed to facilitate resilience processes and improve adaptation strategies. So, the study examines the role of institutional, technological, and socio-economic characteristics of households in shaping both perception and production outcomes.

Through focusing on observed drought and self-reported drought, this study investigates three key research questions: 1) How do objective drought conditions relate to agricultural Total Value Production (TVP) in Uganda? 2) How is

households' self-reporting of drought associated with their production outcomes?, and 3) Which factors shape households' likelihood of self-reporting drought, and how closely do these perceptions align with objective drought indicators? By combining household-level data with observed climate records, this study contributes to literature by distinguishing the effect of actual drought exposure and self-reported drought on households' behavioral responses and agricultural outputs.

Section 2 reviews the literature on drought and production losses and on households' perception of drought. The conceptual framework is described in section 3. Data, variable definitions and site-study discussion are provided in section 4. The methodology and the findings are extended to section 5. The manuscript ends with conclusions, policy implications, study limitations and propositions for the future agenda.

What we already know

This section reviews the studies on weather shocks, households' perceptions, and the role of socio-demographic and economic factors on crop production. We focus on how households perceive and respond to drought effects on crop production. Reviewing studies allows us to identify key research gaps and to position the contributions of the study within the broader literature. The literature review is organized into four strands: (i) self-reported and subjective perception of drought, (ii) perception formation and behavioral responses, (iii) objective measurement of weather shocks, and (iv) systematic comparisons between subjective and objective measures. Additionally, Table (1) provides a summary of related studies' data in terms of sources, methodological approaches and key findings. The provided table illustrates the diversity of approaches to measuring drought (both subjective and objective), perception formation, and adaptation strategies, and their impact on households' welfare. Taken together, the studies highlight the critical evidence gaps, most notably the lack of systematic comparisons between perceptions and scientific records, which motivates the present study.

Drought remains a major source of undermined agricultural crop production and poses a huge threat to households' income, especially in developing countries (Sunday et al., 2021). Within the literature on drought impacts and crop production, several studies focus on African countries and Uganda. Most of these studies use open-ended questionnaires, interviews, and group discussions to characterize drought factors. They measure household perceptions as a weather shock observation, subjective drought, on a binary scale, either observed or not observed. Akwango et al. (2017) comprehensively examine the quality, relevance and dissemination of information produced by the Drought Early Warning System (DEWS) in Uganda, and how it meets the needs of households. Crop failure, malnutrition, and hunger are reported as the most severe drought effects. While DEWS information is useful and understandable, it is often not timely. Most households receive drought information through communication channels, radio, parish chiefs. Socioeconomic status, including land size, education, gender, significantly influence the households' preferred channels of information. In other study, Twongyirwea, et al. (2019) analyze the perceived effects of drought on household food security in southwest Uganda. About 95.6% of households perceive drought as a major contributor to food insecurity, while the remaining households, typically those with higher off-farm incomes and larger farm sizes, did not consider drought as a problem. Similarly, Kakeeto et al. (2019) determine how smallholder farmers perceive and cope with drought in Uganda. The major reported impact of drought is reduced yield. Farmers, especially in the northern and mid-western regions, respond by growing landraces and adopting early planting strategies to cope with drought. Recently, Oriangi et al. (2020) investigate how households in Mbale Municipality, Uganda, perceive prolonged droughts and erratic rainfall levels. About 63% of households identify both drought and erratic rainfall as a crucial problem. Household size, gender, higher income, access to social, government, and NGO networks improve households' preparedness for and recovery from drought. In the case of Asian countries, Nguyen et al. (2020) examine the impact of weather shocks on rural household welfare in northeast Vietnam and Thailand. Drought, the most significant shock, has strong effects on household income, poverty and consumption. Improving access to networks, such as the internet, can help enhance households' welfare. More recently, Nalwanga et al. (2025) evaluate the effectiveness of drought and gendered adaptation strategies in enhancing resilience and reducing vulnerability to drought in Rakai, Nakasongola, and Nabilatuk regions of Uganda. The results highlight gender-differentiated impacts of drought; female-headed households are more affected by food shortages, poor health, and increased workloads, whereas men are more affected by crop losses and social distress. In addition, there are significant gender differences in strategy adoption and perceived benefits.

Considerable research has been devoted to specifically describing factors influencing household's drought perception. Karanja et al. (2017) investigate Kenyan households' perceptions of drought and the factors that influence formation of such perceptions. The results show that farm households perceive drought. A wide range of sociodemographic and economic factors, including age, income level, and type of land ownership are associated with households' perceptions of climate change. In the case of Ethiopian corn and soybean farmers, Khan et al. (2021) study stakeholders' perceptions of climate change and how misperceptions influence past decisions. Farm households perceive higher temperature, reduced rainfall, and changes in rainfall patterns. Climate adaptation strategies are strongly linked to socio-demographic and economic characteristics. In the case study of Sanliurfa, Turkey, Sevinc et al. (2021) investigate whether farmers observe drought as fate, and the factors driving drought perception. Land size, age, household size, settlement location, and religious and social context shape farmers' perceptions, whereas education and income level are found to be insignificant. Sunday et al. (2021) study Uganda's household resilience capacities with a special focus on drought. As households exhibit low and nearly static resilience capacities, the study recommends the adoption of EWS and broader dissemination of climate-related information. To evaluate the validity of the assumed direct linkage between drought and household perception in a global context, Kchouk et al. (2022) review more than 5000 scientific studies and highlight the role of DEWS in shaping household perceptions of drought. Similarly, Abdulahi et al. (2023) determines the variables influencing households' perceptions of drought in Ethiopia. Gender, severity of drought, water shortage, temperature levels, and drought frequency all show positive effects on households' perceptions of drought, whereas household size, food availability and rainfall levels show negative effects.

In parallel, objective measures of drought have been shown to be important drivers of malnutrition in Sub-Saharan Africa/Uganda through their impact on agricultural production. Attempts have been made to investigate the general primary effects of objective drought. Ojara et al. (2024) analyze the temporal and spatial characteristics of drought events in southwestern Uganda, focusing on how different sociodemographic features respond to drought over time. The results show frequent and severe droughts during the periods, 1983/4, 1991/2, 1999-2008, and more recently in 2010-2014 which affected crop yields like such as maize and beans. In a case study of the Solomon Islands, Becchetti et al. (2024) evaluates the impact of weather shocks, including drought, on household well-being. The findings support the hypothesis of a strong correlation between weather shocks, low crop yields, malnutrition, and household well-being. More recently, Hübler et al. (2025) assess the impact of weather shocks on food security of household in Uganda. Weather shocks unequivocally reduce households' crop production. Large and female-headed households, and those lacking literacy or assets, as well as households residing in northern Uganda and rural areas, tend to suffer from greater food shortage and insecurity.

However, there is a very limited number of studies that have focused attention on the cross-category effects by combining perceived and observed weather shocks. Osbahr et al. (2011) investigate farmers' perceptions of climate change and variability in Uganda and confirm that farmers recognize regional climate change. However, discrepancies emerge between reported and observed climate records due to differences between farmers’ expectations of ideal and actual amounts of rainfall and temperature levels. FAO (2016) assesses how weather shocks affect household welfare in rural Uganda and find a weak direct impact of weather shocks. Higher temperature levels are associated with lower incomes. Socio-demographic and economic factors, including farm size, education, and access to irrigation, improve household well-being. Recently, Kraehnert et al. (2024) study how drought conditions affect farmers’ intentions to purchase land ownership rights in Uganda. The results indicate that drought (low SPI values) reduces willingness to buy land, whereas wetter conditions have the opposite effect. In addition, no significant effects are found across sociodemographic or economic characteristics. Arora and Feng (2024) assess systematic biases in farmers’ local climate change perceptions among corn and soybean farmers in the USA. About 70% of farmers misperceive past weather changes. Among them, three-fourths over-estimate temperature, while 40% under-estimate precipitation levels.

Consistent with the literature studies (e.g., Osbahr et al., 2011; Twongyirwe et al., 2019; Kakeeto et al., 2019; Nguyen et al., 2020; Becchetti et al., 2024), our study primarily focuses on drought as a key climate shock affecting household welfare and examines the role of socio-demographic and institutional factors in shaping responses. We recognize that both subjective perceptions and objective climate indices are essential for understanding the impact of climate variability. Despite advancements in estimating the global and local impact of climate change on crop yields and characterizing changes in societal perceptions, the evidence to quantify the gaps between perceptions and scientific records and the direct effects of misperception on production remains limited. This study addresses that gap by systematically comparing subjective drought perception with objective drought measures. Our main contribution lies in explicitly quantifying the extent of match and mismatch between perceived and observed drought conditions and the implications of such perception accuracy measures for agricultural production outcomes. In addition, previous case studies have the advantage of providing insights into households' perception formation, coping strategies, and the role of institutional factors in adaptation, but they rarely quantify how Early Warning System (EWS) and technology adoption moderate the impact of drought. Our second contribution bridges subjective and objective measures of drought to agricultural production values by linking the mediating role of EWS and institutional factors. Lastly, we contribute to literature, as our study accounts for spatial-temporal heterogeneity. This allows us to identify how the impact of drought shocks and perception accuracy varies across Uganda's diverse regions and over time.

Table (1): Overview of related studies in terms of data, methods, and findings

Authors(year)	Data & Method	Main findings
Osbahr et al., 2011	• Farmer survey (1990-2009) and historical weather records (1960-2009) • Descriptive and inferential statistics	• Farmers perceived regional climate to have changed in the past 20 years. • There are some differences between farmers perceptions and observed climate data.
FAO, 2016	• Uganda National Panel Survey (UNPS) (2009–2011) combined with NOAA and ECMWF reanalysis datasets • Generalized Least Squares (GLS) random effects and quantile regression	• Higher temperature reduce income, while rainfall variability shows inconsistent effect. • Access to irrigation and larger farm size increase income and crop production.
Akwango et al., 2017	• Household survey (2004–2014) • Linear Regression	• Drought mainly causes crop failure, hunger. • DEWS information is useful and understandable, but not timely. • Most households receive info from parish chiefs, though radio, or traditional methods.
Karanja et al., 2017	• Survey of 180 household • Logistic regression	• About 52.8% of household report that the 2009 drought was moderate and 42.7% was sever. • Age, income, type of land ownership are shaped farmers perceptions.
Twongyirwea, et al., 2019	• Survey of 140 households (September 2017) • Binomial and multinomial logistic regression models	• Drought is widely perceived; however, farmers with higher off-farm incomes and large size farms do not perceive food insecurity as a problem. • Coping strategies are mainly included by combination of size of farmland, total income from crops, number of livestock and marital status.
Kakeeto et al., 2019	• Survey of households • Descriptive and inferential statistics	• The major impact of drought is low yields. • Farmers in the northern and mid-western regions grow landraces and use early planting to cope with drought.

Oriangi et al., 2020,	• Survey of households • OLS regression	• About 63% of households perceive droughts and erratic rainfall as a serious problem. • Key resilience factors are household size, gender, social and NGO networks.
Nguyen et al., 2020	• Panel dataset of about 4000 rural households (2010/13/16) • Panel data regression	• Drought is the most significant weather shock that effects on household income, consumption, and poverty. • Accelerating internet access and supporting production would contribute to increasing household welfare.
Khan et al., 2021	• Survey of 397 households • Descriptive and inferential statistics and logit Model	• Farm households perceive higher temperature, reduced rainfall, and changed rainfall patterns. • Climate adaptation strategies are strongly linked to socio-demographic and economic characteristics.
Sevinc et al., 2021,	• Farmer surveys (2020) • Ordinal logit regression	• Settlement location, land size, age, and household size are significant for belief that drought is fate, while education and income are not significant. Religious and social context strongly shapes perceptions.
Sunday et al., 2021	• Uganda National Panel Survey (UNPS) (2010/11-2018/19) combined with objective measure of drought from the global SPEI database • TANGO framework and two-step factor analysis	• Households in Uganda exhibit low and nearly static resilience capacities. • Improving resilience requires investment in early warning systems and wide dissemination of climate related information, etc.
Kchouk et al., 2022	• Review of 5000+ scientific studies on drought indices, impact and geographical distribution	• Literature tends to focus on drivers of drought, with the preferred use of meteorological and remotely sensed drought indices. • Authors arguing for using of drought indices associated to sustainable development and household welfare, and the role of DEWS.
Abdulahi et al., 2023, PrePrint	• Survey of 200 households combined with drought classifications • Heckman two-stage probit model	• Gender, severity of drought, water shortage, temperature, drought frequency, and long dry season all have a positive effect, while age, household size, food availability and rainfall have a negative effect on adaption of resilience mechanism to drought hazards.
Ojara et al., 2024	• Objective data from CHIRPS rainfall and temperature (1981-2017) combined with soil characteristics • Quantitative agro-climatological approach combined with soil hydrological modeling	• Frequent and severe droughts are observed in 1983/84, 1991/92, 1999–2008, and 2010–2014. • The SPEI-3 index shows strong seasonal drought patterns affecting crops like maize and beans. • Soil properties like available water capacity (AWC) and infiltration rate significantly affect drought susceptibility.
Kraehnert et al., 2024	• Household panel survey (2005/06, 2009/10, and 2010/11) combined with CHIRPS & CHIRTS weather data (1983–2016) • Fixed effects model	• Drought (low SPEI) reduces willingness to buy land and lowers the price farmers are willing to pay, while wet conditions have the opposite effect.

		• No significant variation found across poverty status, gender of household head, or farm size.
Becchetti et al., 2024	• Survey of 1300 farmers (July-Oct 2021) combined with objective data on annual drought length • OLS regression	• Results confirm a strong correlation between weather shocks, household well-being, and nutrition.
Arora and Feng, 2024	• Spatially-delineated farmer survey (2004-2014) combined with 825 weather station records on temperature and precipitation	• About 70% of farmers misperceive past weather changes; three-fourths over-estimate temperature, while 40% under-estimate precipitation.
Hübler et al., 2025	• Panel UNPS data (2013/14, 2015/16, and 2019/20) with the total number of 3935 observations. • Poisson and logit fixed effects panel regressions	• Weather shocks unequivocally reduce households' food security. • Large female-headed, less educated, and asset-poor households in Northern and rural Uganda are most vulnerable. • Households with low assets ownership are hit hardest by weather shocks in terms of the number of meals, while households with middle asset ownership are hit hardest regarding food shortages.
Nalwanga et al., 2025	• Primary survey and focus group data from Rakai, Nakasongola, and Nabilatuk distinct. • Mixed-methods cross-sectional study	• Drought impacts are gender-differentiated: women are more affected by food shortages, poor health, and increased workload; men by income loss and social distress. • Significant gender differences in strategy adoption and perceived benefits.

Source: Author Elaborations

A 4-dimensions conceptual framework

To analyze the impact of weather shocks on welfare, we follow the conceptual framework proposed in Seo's (2015) micro-behavioral economics model of climate adaptation. This paper refers to a conceptual framework assuming that households are decision-makers who respond to weather shocks by adjusting their production portfolio, adopting technologies, and seeking information. Objective drought is an exogenous weather signal and household perception influence households' responses, which in turn are linked to agricultural production outcomes. Put differently, perceptions and behavioral changes are the core mechanisms that translate weather shocks into households' welfare (see Figure A-1 in the APPENDIX). The framework relies on four components: 1) Objective drought (exogenous climate signal), 2) subjective drought (households' perceptions), 3) behavioral responses (technology and information access), and 4) production outcomes (TVP). These dimensions would allow us to examine how the gap between objective and subjective drought relates to variation in agricultural productions. In what follows we delve on the literature that has addressed these aspects. Agricultural production is highly sensitive to weather shocks, with droughts among the most disruptive shocks. Following Decron et al. (2005) and Seo (2015), we define shocks as "bad events" and model them as exogenous disturbances that shift the production frontier and lead to the loss of household income or a loss of productive assets within the constraints of land, wealth, and knowledge. We assume that weather shocks, and in particular droughts, are associated with a reduction in agricultural yields and therefore in household welfare. The Total Value Production (TVP) reflects the monetary value of all crops' outputs produced by households and its changes capture the economic effects of weather shocks [1].

Waibel et al. (2018) highlight that households act not only on objective data but also on their perception and expectations of weather shocks which are shaped by information availability, social connections, and past experiences. Accordingly, the weather shock indicators, measured as the occurrence of drought reported by a household and weather station information, both objective and subjective exposure measures, are key independent variables. We quantify objective drought using the Standardized Precipitation Index (SPI), defining drought as periods when SPI is less than or equal to -0.5, which is calculated from long-term rainfall records. The index enables us to identify periods of meteorological stress, and it provides a normalized measure of drought intensity in relation to long-term historical norms (Svoboda & Fuchs, 2016). This objective drought index serves as the exogenous climate signal against which household perception and behavioral responses are compared.

Perception is the first and most critical step in the adaptation pathway (Seo, 2015), which is shaped by both objective exposure and socio-cognitive factors such as education, prior exposure, and local knowledge (Duinen et al., 2015). In this study, we measure subjective drought as a household's self-reported drought experience. To assess the relationship between objective and subjective drought, we construct perception accuracy indicators, Match and Mismatch (including Over_report, and Under_report), to capture whether households recognize drought conditions

[1] Consistently with recent findings from Uganda, accurate perception combined with timely behavioral responses is linked to lower production losses and greater resilience (Kraehnert et al., 2024; Becchetti et al., 2024).

accurately, underestimate, or overestimate them (see Arora and Feng, 2024). This comparison is crucial because it allows us to examine whether households accurately perceive drought conditions, which may either delay adaptation or engage them in unnecessarily costly actions. Evidence from Uganda (see Osbahr et al., 2011 & Mfitumukiza et al., 2020) highlights that farmers' perceptions of rainfall often diverge from observed rainfall trends, and such mismatches can drive delayed adaptation or lead to maladaptation.

Behavior represents a channel through which perception may translate into action. Households that perceive shocks are more likely to translate this information into behavioral responses or adopt strategies (Seo, 2015). We capture behavior through focusing on technology adoption, such as applying organic fertilizers, certified seeds, and erosion control techniques, as well as information seeking, using communication channels such as cellphones and internet connections to access the National Early Warning System (NEWS). These variables indicate channels through which perception translates into adaptive actions. Evidence from Uganda show that having access to extension, training, and EWS services significantly improves the uptake of adaptive technologies and minimizes production losses (FAO, 2018; OECD, 2012).

Further explanatory variables that affect TVP include socio-demographic factors and are specified as household- and household head-related characteristics, institutional factors, and location variables. According to Gbetibouo, (2009) and Kakeeto et al., (2019), the ability to perceive weather shocks accurately and respond effectively is heterogeneous. Wealth indices, land ownership, education of the household head enhance both perception and capacity to adopt technologies. Additionally, institutional access, like distances from service centers, influences the timeliness of information flow and support services (Oriangi et al., 2020).

Data

The study is conducted for Uganda due to its high dependence on rain-fed agriculture and its exposure to weather shock, in northern and northeastern regions. Uganda is a landlocked country with a total population of 49,238,041 (2024 est.) that is located in East-Central Africa and lies almost near the Nile basin and the equator (see Figure 1). In the country major population centers as well as parts of surrounding countries are located near Lake Victoria. Population density is relatively high in comparison to other similar nations, and most of the population is settled in the central and southern parts of the country, particularly along the shores of Lake Victoria. The population structure is young as 50.60 % of total population falls between 15-60 range, and the gender ratio is almost equal between two sexes. Urban population take 26.8% of the total population in 2023. Kampala, the capital city, with 3.84 million has the highest share. Social indicator for health reflects how the country has one of the highest annual population growth rates, the second highest fertility rate, and continues to be one of the poorest nations in the world (CIA, 2025 & FAO, 2016).

From a geographical perspective, the country has benefited from diverse climate patterns, several large rivers, and mountain ranges. Precipitation varies throughout the country: in the south rain spread throughout the year, in the southwest rain falls from March to June, and November/December near Lake Victoria, in the north, from November to February it experiences a dry season, and the northeastern regions have the driest climate and are prone to drought. Reports indicate that several natural hazards, including floods, drought (e.g., 2011/2012, 2013, and 2016/2017), landslides, etc., have affected the country's welfare (Oriangi et al. 2020; Kraehnert et al. 2024; NIDIS, 2025).

Around 71.9% of the land is cultivated, and this share has steadily increased to continue by diminishing forest covers. Agriculture accounts for a core sector of the economy as well as the main employer of the population. About 70% (2015 est., FAO) and 66% (2023 est., World Bank) of the total population were employed in the agriculture sector, and the sector contributes 23% to annual GDP. More than 80% of the annual total agricultural output, mainly tea, tobacco, and coffee, is delivered by small family farmers who account for 89% of all Uganda farmers (FAO, 2018 & World Bank, 2025).

The average farm size of a small family in Uganda was 1.35 hectare (2015 est.) and 1 hectare (2017 est.) in 2015 and 2017, respectively. An average small family farm is predominantly a male-headed and less than one third are female-headed, implying that agriculture remains a men-domain. A substantial proportion of smallholders (est. 27%) living below the national poverty line and a low level of education (with an average schooling of 5 years) remains to be serious obstacles to productivity and competitiveness (FAO, 2018 & Kraehnert et al. 2024).

Figure 1: Country Map
Source: CIA, 2025

The study combines historical time-series data on precipitation levels and temperature from the Climate Hazard Center (CHIRPS) and socio-economic data from the Uganda National Panel Survey (UNPS) to examine the impact of perceived and observed drought conditions, household socio-economic characteristics on agricultural total value production within a unified framework. The households -level data are obtained from multiple waves of the Uganda National Household Survey (UNHS) administered by the Uganda Bureau of Statistics (UBoS) between 2009/10 and 2013/14 (See Table 2). These surveys are part of the Living Standards Measurement Study-Integrated Survey on agriculture practices, technology adoption, access to services, labor allocation, household assets, demographic features, and climate-shocks which provide detailed information. To complete the dataset, we integrate climate re-analysis records on precipitation levels and temperature from Climate Hazard Group InfraRed Participation with Station Data (CHIRPS), covering the period 1981-2015 (see Figure 2). Using these series, we construct the Standardized Precipitation Index (SPI) based on deviations from long-term precipitation patterns, which allows for objective identification of drought episodes consistent with the thresholds following the standard classification of the National Integrated Drought Information System (NIDIS)[1] (refer to Table 3). To assess the spatial precision of objective drought measures, we calculate each households' distance to the nearest weather station. Figure A-1 (in the APPENDIX) shows most households are located between [20-60] km of a station (right skewed), with a maximum distance beyond 150 km.

Table (2): List of waves of the Uganda National Household Survey (UNHS)

Period	Wave	Households (Total OBS)
2009/2010	1	2653
2010/2011	2	2450
2011/2012	3	2525
2013/2014	4	3114

Table (3): Classification of objective drought Based on SPI Thresholds

Proxy	Classification	SPI Threshold
Objective drought=0	Near-normal	$-0.5 < SPI < 0.5$
Objective drought=1	Abnormally dry to Moderate drought	$-1.2 < SPI \leq -0.5$
Objective drought=2	Severe to Extreme drought	$-1.9 < SPI \leq -1.2$
Objective drought=3	Exceptional drought	$SPI \leq -1.9$

[1] https://www.drought.gov/

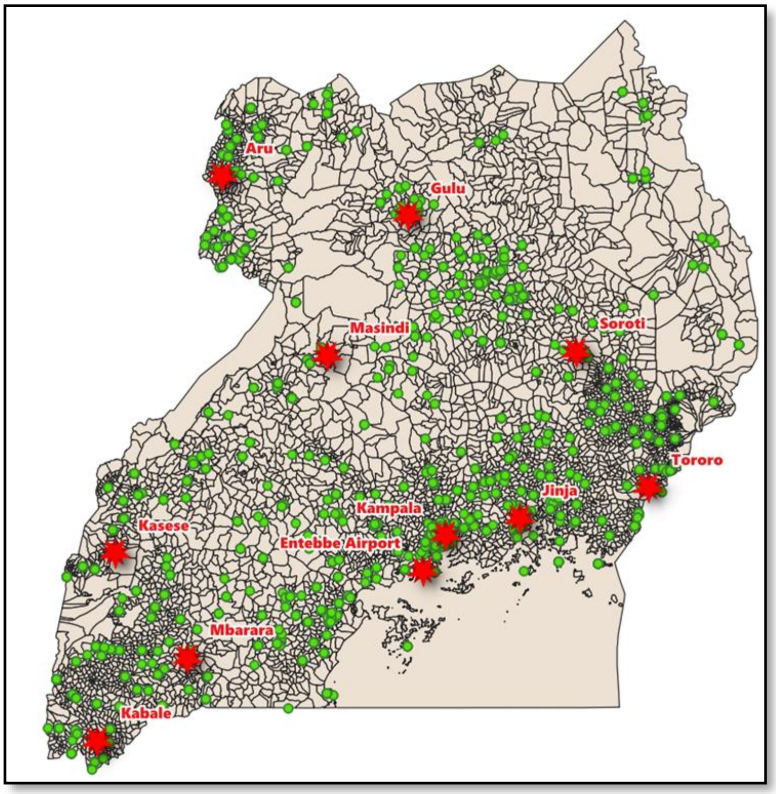

Figure 2. Households' distribution (green circles) and weather stations (red stars) in Uganda.
Source: Author's findings based on household's centroids and Uganda_ARC2_CHIRPS shapefiles. Map created using QGIS (V: 3.40).

Our analysis relies on two complementary indicators of drought: i) a self-reported measure, based on household reporting experiences of drought shocks, and ii) an objective measure, derived from the SPI classification. These variables enable us to capture potential mismatches in perception and measured exposure. Each household is matched to the nearest weather station to improve the spatial precision of climate exposure measures. From this comparison, we build two indicators to determine whether the self-reported measure match the measure obtained through the weather data. A first binary indicator, under_reporting, takes value equal to 1 if the household is not reporting a drought but this is observed in the data. A second dummy, over_reporting, is to 1 if the household is reporting a drought but this is not identifiable in the data. The household characteristics include demographic indicators, such as the gender, age, education of the household head, and labor composition by gender. Socio-economic variables capture land ownership, wealth indices (rural and urban agricultural and non-agricultural), poverty status, and distances to population and government centers. Agricultural technology variables capture household adoption of productivity-enhancing inputs or risk-mitigating practices. Technology-related variables include Fertilizer (distinguishing between organic and inorganic fertilizer use), Seed (use of certified or improved varieties), and soil and water management practices captured through erosion problem, erosion control strategy, and Extension Services and Advisory Technologies which include Agricultural Production Information, Agricultural Processing Information, and Agricultural Information. Together, these variables track input adoption, conservation practices, and access to agronomic and processing advice that can shape adaptation and productivity under climate stress. In addition, we incorporate access to Early Warning Systems (EWS) measured through Internet and cellphone access and household distance from local government officials (KM). We interpret Internet and phone access as channels through which alerts and advisories are received, while distance from local government officials proxies the household's proximity to institutions that disseminate warnings and coordinate responses (larger values indicate greater remoteness). A complete list of variables, their definitions, and data sources is presented in Table 4.

Table (4): List of variables definition and data sources

Variable Name	Label	Definition/Coding	Source
TVP	Total value of crop production	The total value of crop production of the household residing in village ($)	Uganda National Household Survey (UNHS), UGANDA BUREAU OF STATISTICS (2009/10, 2010/11, 2011/12, 2013/14)
Subjdrought	Subjective drought	Reported drought by Households (Yes=1, No=0)	Uganda National Household Survey (UNHS), UGANDA BUREAU OF STATISTICS (2009/10, 2010/11, 2011/12, 2013/14)[1]
Temp	Temperature	Temperature (C^0)	Climate Hazards Group InfraRed Precipitation with Station Data, from 1981 to 2015[2]
Precipitation		Total Precipitation level (mm)	
Objdrought	Objective drought	SPI index build based on total precipitation level and NIDIS drought spectrums	National Integrated Drought Information System (NIDIS)[3]
Over_report	Overestimate drought	Subjective drought is equal to1 and objective drought show neutral condition	Uganda National Household Survey (UNHS), UGANDA BUREAU OF STATISTICS (2009/10, 2010/11, 2011/12, 2013/14)
Under_report	Underestimate drought	Subjective drought is equal to 0 and objective drought show drought	

[1] *Available at: https://www.ubos.org*
[2] *Available at: https://www.chc.ucsb.edu/data/chirps*
[3] *Available at: https://www.drought.gov/*

Matchdrought	Match between subjective and objective drought	Both subjective and objective drought confirm drought condition	Climate Hazards Group InfraRed Precipitation with Station Data, from 1981 to 2015
Femhead		Female household head (Yes=1, No=0)	Uganda National Household Survey (UNHS), UGANDA BUREAU OF STATISTICS (2009/10, 2010/11, 2011/12, 2013/14)
ageeduhead	agehead	Age of household head	
	eduhead	Average years of education among household member (15-60)	
malelaborshare		Male labor share in household	
femlaborshare		Female labor share in household	
EWS	Internetacc	Household access to Internet (Yes=1, No=0)	
	cellphone	Household access to cellphone (Yes=1, No=0)	
	disGovCenter	Household distance from local government officials (KM)	
Technology	Fertilizer	Organic Fertilizer use (Yes=1, No=0)	
	Fertilizer	Inorganic Fertilizer use (Yes=1, No=0)	
	Seed	Certified/Improved Seed use (Yes=1, No=0)	
	Erosion Control (Soil and Water management)	Erosion problem (Yes=1, no=0)	
		Erosion control Strategy (Applied=1, not applied=0)	
	Extension Services and Advisory Technologies	Agricultural Production Information	
		Agricultural Processing Information	
		Agricultural Information (Received=1, not received=0)	
Reduction_tvp		Reduction in output values (lost income)	
Landownha		Household owns land per ha	
Wealth Index	Agwealthrural	Rural Agricultural Wealth Index	
	Agwealthurban	Urban Agricultural Wealth Index	
	nagwealthrural	Rural Not-Agricultural Wealth Index	
disPopCenter		Household distance from population center over 20000 people (KM)	
Poverty		Poverty status (Yes=1, No=0)	

Source: Author elaborations

Methodology

This section sets up the econometric regressions to estimate the effects of independent variables, including weather shocks and households' socio-demographic and economic factors, on the dependent variables: total value of production (TVP) and households' perception of drought. The econometric models are specified in Eqs. (1) and (2).

$$TVP = f(W, H, C) \qquad \text{Eq(1)}$$

$$P = f(T, H, C) \qquad \text{Eq(2)}$$

where TVP (total value of production) and P (perception of drought, match drought, and mismatch drought) are the dependent variables; W is a vector of weather shocks (either subjective or objective drought measures); T is a vector referring to temperature; H is a vector of household characteristics such as age, education, land ownership, and wealth indicators; and C is a vector capturing socio-demographic, economic, and institutional conditions at the country level.

To examine the relationship between weather shocks and household TVP, we employ a Fixed Effects Regression (FE) based on panel data in Table (3) (see Eq.3). The FE specifications are designed to separately examine the production outcomes using distinguish between objective and subjective droughts. The FE is preferable to Random Effects Regression (RE) because it controls time-invariant household characteristics that may be correlated with the explanatory variables. The approach allows the inclusion of time by region shocks by incorporating time fixed effects that capture spatially correlated shocks each year. In addition, the model accounts for econometric challenges, such as heteroskedasticity and serial correlation as well, by employing cluster-robust standard errors. Since the number of explanatory variables is high the Variance Inflation Factor (VIF) test is conducted to detect multicollinearity (Nguyen et al., 2020; Kraehnert et al., 2024).

The second set of dependent variables is derived from self-reported information on household's perception of drought and climate records. Considering the binary nature of the subjective drought and perception accuracy measures (match drought and mismatch drought), a fixed effects logit model is employed to estimate the determinants of drought perception and perception accuracy. The model is frequently used in similar previous studies (e.g. Khan et al., 2021; Sevinc et al., 2021; Hübler et al., 2025) due to its advantages over other models, such as the Linear Probability Model.

In this framework, households are assumed to either perceive drought or not, and this perception is modeled as a latent probability influenced by socio-demographic, economic, institutional, and environmental factors. The analysis is further extended to perception accuracy by constructing binary outcomes for match drought (consistency between household perception and climate records) and mismatch drought (inconsistency between household perception and climate records). Separate binary fixed-effects logit models are estimated for these outcomes, which allow us to identify the main determinants. Finally, post-estimation diagnostic tests are also conducted, and the final specification is reported in Eq(4) [1].

$$\begin{aligned} Ln\,TVP_{it} = {} & \beta_1 + \sum_{j=1}^{J} \beta_2 W_{j,it} + \beta_3 Temp_{it} + \beta_4 EWS_{it} + \beta_5 Technology_{it} \\ & + \beta_6 malelaborshare_{it} + \beta_7 femalelaborshare_{it} + \beta_8 Landownha_{it} \\ & + \beta_9 ageeduhead_{it} + \beta_{10} Femhead_{it} + \beta_{11} Poverty_{it} + \beta_{12} Wealthindex_{it} + \alpha_i \\ & + \gamma_i + \varepsilon_i \end{aligned} \qquad \text{Eq(3)}$$

$$\begin{aligned} Ln\left(\frac{\Pr(P_{it}=1)}{1-\Pr(P_{it}=1)}\right) = {} & \theta_1 + \theta_2 reduction\_tvp_{it} + \theta_3 Temp_{it} + \theta_4 EWS_{it} + \theta_5 Technology_{it} + \\ & \theta_6 malelaborshare_{it} + \theta_7 femalelaborshare_{it} + \theta_8 Landownha_{it} + \theta_9 ageeduhead_{it} + \\ & \theta_{10} Femhead_{it} + \theta_{11} Poverty_{it} + \theta_{12} Wealthindex_{it} + \mu_i + \sigma_i \end{aligned} \qquad \text{Eq(4)}$$

---

[1] Since both Eqs. (3) and (4) combine continuous and binary dependent variables, the coefficients are interpreted in ways consistent with the underlying estimation framework. For the fixed-effects log-linear models, coefficients are interpreted as semi-elasticities or elasticities. Each estimated coefficient indicates approximately the percentage change in agricultural production given a one-unit or one-percent change in the respective explanatory variable while holding other factors constant. To express these effects, the continuous regressors are multiplied by 100 and for dummy or binary regressors the exponential transformation [exp(β)-1]×100 is used to compute the accurate estimate. In addition, the fixed-effects logit models capture the change in the odds of the event occurring. Therefore, the results are presented and discussed in terms of odds ratios, Exp(β) or e^{β_j}, which give the multiplicative change in the odds of the outcome for a one-unit increase in an explanatory variable.

Where *LnTVP* refers to the natural logarithm of total value of crop production for household i in period t. P is the binary dependent variable refers to subjective drought and perception-accuracy for household i in survey wave t. *reduction_tvp* indicates whether the household experienced a reduction in the value of crop production. W denotes the vector of drought-related variables (objective, subjective, and perception-accuracy categories). *Temp* denotes temperature, *EWS* and *Technology* captures access to early warning system and agricultural technology adoption, respectively. Furthermore, *malelaborshare* and *femalelaborshare* indicate the share of male and female labor in the household. *Landownershipha* measures land owned by the households in hectares. *ageeduhead* captures age and education characteristics of household head. *Femhead* is a dummy variable equal to one if the household head is female and zero otherwise. *Poverty* and *Wealthindex* capture household poverty and wealth status, respectively. α_i, γ_i, and ε_i denote household and time fixed effects and the error term, respectively.

Results and Discussion

The summary statistics of the main variables describe substantial heterogeneity in household production, climate exposure, socio-economic and institutional characteristics in Uganda (Table 5). The log of household total value of production production (LnTVP) shows significant dispersion around the negative mean, with values of SD: 2.37 and mean: -0.73, reflecting heterogeneity in production capacity across Ugandan households. The distribution of LnTVP is slightly right skewed, which witnesses the minority of highly productive households driving much of the aggregate outcomes. About one-third of household's report that they have experienced drought, while around one-quarter of them are objectively classified as drought affected based on the SPI index which indicates a neutral condition. Both subjective and objective drought measures are unevenly distributed, with most households reporting no drought experience. This pattern indicates that most of the households do not report or experience drought in each period. Moving forward to control variables, average temperature falls within [24.33-27.93], and the EWS and technology variables show relatively low means and moderate dispersion. In addition, their distribution indicates moderate kurtosis with most values clustering at low adoption levels, which means asymmetric or unequal distribution of production potential and adaptive resources across households in the country. Regarding labor composition, production in Uganda remains male-dominated; however, female participation is significant. Around 25% of the sample falls below the poverty line, which is consistent with the national rural poverty figure. The wealth index distribution points to mild inequality rather than extreme polarization.

Table (5): Summary statistics of household characteristics and their hypothesized impact

	Effect*	Mean	Std. dev.	Min	Max	SK	KU
Dependent Variables							
LnTVP		-0.73	2.37	-10.81	7.67	0.45	2.91
Subjdrought	+/-	0.30	0.45	0	1	0.86	1.75
Matchdrought	+/-	0.04	0.21	0	1	4.25	19.06
Mismatchdrought		0.41	0.49	0	1	0.35	1.12
Weather Measures							
Objdrought	-	0.23	0.48	0	3	2.02	6.56
Over_report	+	0.25	0.43	0	1	1.13	2.28
Under_report	-	0.15	0.36	0	1	1.86	4.48
Control Variables							
Reduction_tvp	+/-	0.20	0.40	0	1	1.46	3.13
Temperature	-	26.13	1.80	21.27	31.61	0.20	2.76
EWS	+	8×10^{-10}	1.26	-2.55	2.93	0.06	2.36
Technology	+	6×10^{-10}	1.26	-1.33	5.30	1.90	6.04
Malelaborshare	+	0.45	0.34	0	1	0.19	1.96
Femalelaborshare	+	0.40	0.34	0	4	0.54	3.72
Landownha	+	1.52	7.6	0	330.26	27.78	951.86
Ageeduhead	+	181.6	185.34	0	1564	1.26	5.94
Femhead	+	0.30	0.45	0	1	0.87	1.75
Poverty	-	0.25	0.43	0	1	1.10	2.22
Wealth Index	+	1×10^{-10}	0.75	-1.16	17.04	5.28	64.07

* Effect or expected sign: + means that the dependent variable improves, – indicates the opposite effect, and +/- refers to ambiguous effect.
Source: Authors findings based on UNPS (2009/10–2013/14) and CHIRPS (1981-2015) data.

The comparison between self-reported and objective drought measures in Table 6 indicates a considerable mismatch between perceived and observed conditions. Results in Panel A indicate a considerable mismatch between the two measures of drought. Households that did not report drought (subjective = 0), about 77%, actually resided in non-drought areas, but approximately 20% of them did indeed experience mild to moderate drought according to the SPI index. Among those who reported drought (subjective > 0), only about 12% are found in objectively drought-affected areas, whereas the majority (around 84%) over-reported drought conditions. The small share of correctly matched cases, around 4% of the overall sample, shows that perceptions capture only a limited share of the objective climate signal.

Panel B further categorizes households into self-reporting accuracy classes: over-reporters are dominant, at about 25%, followed by under-reporters at 15% and a small fraction of accurate perceivers at 4%. This pattern indicates systematic asymmetry in subjective reporting, with households more likely to perceive drought in relatively normal years than to miss an actual event. Such bias may reflect psychological or informational factors: for instance, limited access to early-warning information, prior experiences, or expectations formed by past losses.

Panel C disaggregates drought by residence, revealing clear spatial heterogeneity. The majority of perceivers are rural households (about 80%), likely reflects stronger exposure to rain-fed agriculture. In contrast, urban households, about 20% of perceivers, report drought far less often. Results are consistent with the socio-economic heterogeneity reported in Table 5. Households with limited access to EWS, lower literacy rates, and weaker technology capacity may over- or underestimate rainfall variability as drought. However, wealthier or better-informed households more accurately assess drought shocks. Rural bias in perception could also result from limited communication channels (see figure A-2 in the Appendix). This pattern reinforces the notion that drought awareness and reporting accuracy are strongly conditioned by livelihood structure and timely information accessibility across regions.

Panel D refers to the correlation between number of previous objective drought episodes experienced by the household and adaptation strategy with subjective drought in Uganda. The results show a weak negative correlation between subjective drought and drought frequency, while subjective drought is positively correlated with adoption strategy. This implies that households perceive drought is more closely associated with behavioral adjustment than the frequency of previous physical drought exposure.

Table (6): Subjective versus objective drought, perception-accuracy categories, and urban-rural residence

Panel A: Cross-classification of subjective and objective drought (row percentages)

Subjective drought (Household perception)	Objective drought classification				
	0 (Neutral)	1 (Abnormal to Moderate)	2 (Severe to Extreme)	3 (Exceptional)	Total %
No (0)	77.29%	20.19%	2.49%	0.03%	100%
Yes (1)	84.20%	12.27%	3.33%	0.20%	100%
Total %	79.37%	17.80%	2.74%	0.08%	100%

Panel B: Perception-accuracy categories (aggregated shares)

Category	Definition	Share %
Over_report	Subjdrought=1 & Objdrought=0	25%
Under_report	Subjdrought=0 & Objdrought>0	15%

Matchdrought	Subjdrought=1 & Objdrought>0		4%
Neutral	Subjdrought=0 & Objdrought=0		56%
Total			100%
Panel C: Subjective drought by urban/rural residence (row percentage)			
Subjective drought	Rural 1	Urban 2	Total %
0	74.64%	25.36%	100%
1	81.38%	18.62%	100%
Total	76.67%	23.33%	100%
Panel D: Correlation with subjective drought			
Past drought frequency	-0.026^{***}		
Adaptation strategy	0.079^{***}		

Source: Authors elaborations based on UNPS data (2009/10–2013/14).

Table 7 and Figure 3 jointly examine differences in production outcomes across households with and without drought perception to assess whether drought perception is associated with differences in adaptive capacity. Panel A of Table 7 compares the mean differences in objective drought between households that perceived drought and those that did not across Uganda's four main regions. In all cases, perceivers display significantly higher means ($p < 0.01$), with the most pronounced differential in the North (0.10), while nationally the difference amounts to roughly 0.05 ($t = 5.30^{***}$). In other words, households that perceive drought tend to live in drier areas. Panel B further supports these findings by presenting a breakdown of the distribution of LnTVP according to subjective drought status. The negative sign reflects the difference between the perceiver and non-perceiver group mean. Perceivers exhibit higher mean production than non-perceivers, particularly in the North. In addition, the regional distributions of perception mismatch (see Figure 4) show that over-reporting is prevalent across the regions, particularly in the North, where average TVP is higher. This pattern suggests that households with strong drought perception tend to be associated with higher production outcomes.

Figure 4 reinforces this pattern by visualizing a rightward shift and a heavier upper tail in distribution for perceivers, which is consistent with the mean differences obtained in Table 7. The kernel-density curves for both drought-perceiving and objectively affected households shift to the right and indicate a larger share of high production. These systematic patterns of mean and distributional differences are consistent with the idea that households perceiving or expecting drought conditions may be more likely to adjust their behavior in fertilizer use, certified seeds, planting, timing, or crop diversification to mitigate the climatic stress on production outcomes.

Self-reported drought may therefore be associated with indicators of behavioral resilience and risk awareness. This interpretation is consistent with the perception accuracy pattern presented in Table 6, where over-reporting may reflect increased sensitivity to climate variability.

Table (7): Regional T-test of objective drought and household production by drought perception

Region	Difference in Mean (std. dev.)	T-test (Pr: T< t)
Panel A: Regional mean differences in objective drought by subjective drought		
Region	Difference in Mean (std. dev.)	T-test (Pr: T< t)
Country level	0.05 (0.010)	5.30*** (0.00)
Central	0.05 (0.018)	2.85*** (0.00)
Eastern	0.06 (0.019)	3.21*** (0.00)
Northern	0.10 (0.025)	4.32*** (0.00)
Western	0.05 (0.022)	2.27*** (0.00)
Panel B: Regional mean differences in log Total Value Production by subjective drought		
Region	Difference in Mean (std. dev.)	T-test (Pr: T< t)
Country level	-0.71 (0.07)	-10.11*** (0.00)
Central	-0.65 (0.12)	-5.42*** (0.00)
Eastern	-0.80 (0.11)	-7.27*** (0.00)
Northern	-0.60 (0.13)	-4.63*** (0.00)
Western	-0.70 (0.12)	-5.58*** (0.00)

*** refers to p > 0.01, ** p < 0.05, and * p < 0.1
Source: Authors findings

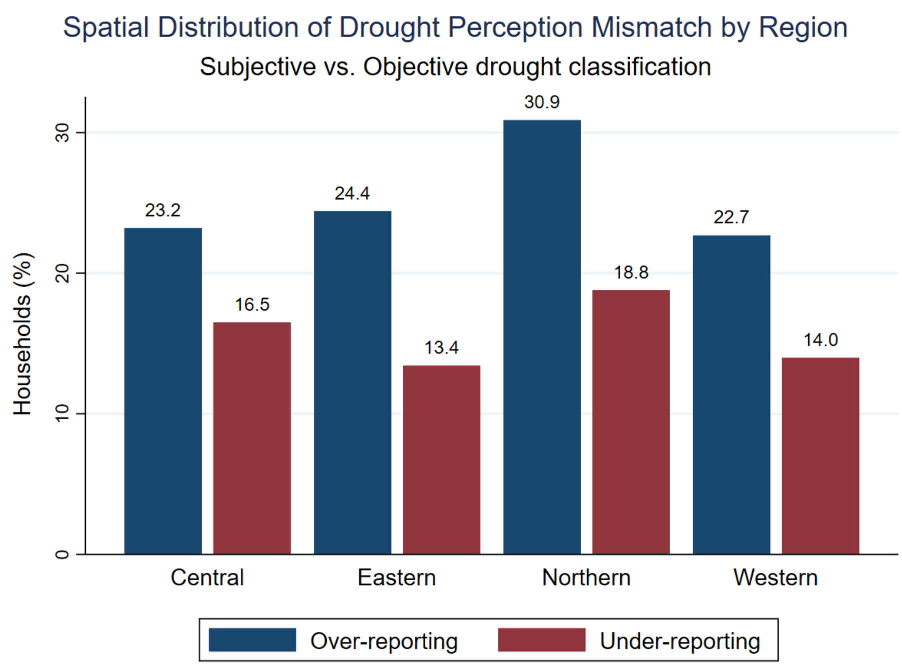

Figure 3: Regional distribution in mismatch between perceived and objective drought (%)

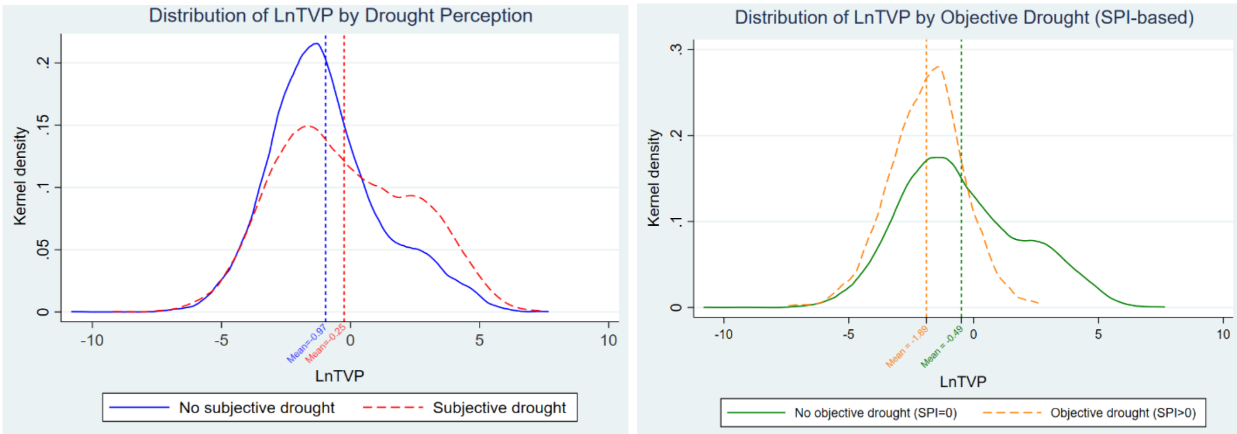

Figure 4: Kernel density of LnTVP by drought

Subjective versus Objective Drought: Which Matters More for Production?

Pairwise correlation and Variance Inflation Factor (VIF) diagnostic tests are conducted prior to main estimations. Results are reported in Tables B-1 and B-2 in the Appendix B section. According to Table B-1, there is a moderate positive correlation between self-reported drought and LnTVP, while objective drought is negatively associated with production outcomes, which is consistent with Becchetti et al. (2024) findings. VIF values, both single and mean, are below the threshold (=10), confirming that the variables are sufficiently independent.

Table (8) presents the Fixed-Effect estimation of how subjective and objective drought and perception accuracy proxies separately impact household production in Uganda, conditioned on other socio-economic and institutional characteristics and also climatic variables. A fixed-effect specification is employed to account for unobserved, time-invariant household characteristics that may influence results. In general, the analysis separates behavioral perception effects from physical exposure effects to compare the relative associations of perceived and objective drought with LnTVP. The results are conducted across nine model specifications (M1-M9), using a total of 3248 observations. The coefficient on subjective drought is positive and statistically significant at the 1% level across all model specifications, whereas objective drought exhibits a large negative and highly significant effect. These results are consistent with the pairwise correlation coefficients reported in Table B-1 and align with the findings of Twongyirwea et al. (2019), Kakeeto et al. (2019), Nguyen et al. (2020), and Ojara et al. (2024). The contrast in the sign of the drought coefficients suggests that households' behavioral response to perceived drought differs systematically from their reactions to objective drought stress. In more detail, when the perception-accuracy categories are included, Over_report exhibits a positive association with production level, whereas Under_report and Matchdrought have negative and significant coefficients. These results indicate that stronger drought perception is associated with higher outcomes, while failure to perceive drought and exposure to actual drought conditions are negatively associated to the production level.

In terms of control variables, temperature consistently shows a negative and significant association with yields, consistent with the adverse impact of heat stress on yields in FAO (2016). Drought Early Warning System and Technology are both positive and highly significant, which suggests that access to a warning system is associated with improved resilience. These findings are consistent with Akwango et al. (2017), Nguyen et al. (2020), and Orianji et al. (2020). Female labor share and female head regressors remain negative and significant across the models, which may reflect gender-related constraints in access to resources in Uganda. This outcome supports the conclusions of Nalwanga et al. (2025) who also report adverse gender effects, particularly the negative influence of female head households on welfare in the country. In addition, land ownership and wealth index both positively but weakly impact outputs, suggesting a modest role of having assets and land endowments. These results are consistent with Hübler et al. (2025).

Table (9) introduces coefficients transformed into elasticities and presents their intuitive measure of effect size. The estimated values show that subjective drought perception is associated with higher output levels by about [24.89-29.46] %, while exposure to physical drought conditions is negatively associated by roughly [48.60-49.45] %. This is consistent with the interpretation that perceived drought may act as a behavioral trigger for precautionary adoption, whereas objective drought represents an actual shock that constrains production capacity. Distinguishing perception accuracy explains these behavioral responses. Overestimators' production is higher by [23.45-40.89] %, suggesting that exaggerated climate risk perception may be associated with adoption strategies. Underestimators' production level is lower by [54.66-57.23] %, and that of matched drought households by about [38.45-44.11] %, indicating that recognizing drought only when it happens, or not recognizing it at all, is consistent with reactive responses or reduced levels of output. Additionally, control variables also have meaningful magnitudes. A one percent rise in temperature is associated with a decrease in production by about [71.16-81.72] %, whereas access to an early drought warning system is linked with higher production outcomes by [87.39-102.65] %, which highlights the potential importance of early warning system in Uganda. The adoption of technology is associated with higher production levels by about [10.97-11.91] %. These elasticities highlight the productivity-enhancing effects of timely information system and certified inputs. The gender variables also report unfavorable effects: female-headed households have lower outputs, and a higher female share of labor decreases production by [76.65-81.92] %, which underlines gender disparities in resource access and adaptive capacity.

Table (8): Fixed-Effects estimation Results: Effects of subjective and objective measures and perception accuracy categories on household production

Models	M(1)-Base	M(2)	M(3)	M(4)	M(5)	M(6)	M(7)	M(8)	M(9)
Dependent variables	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP
Temperature	-0.81***	-0.80***	-0.71***	-0.78***	-0.76***	-0.80***	-0.70***	-0.74***	-0.73***
EWS	1.02***	1.00***	0.89***	0.98***	0.94***	1.00***	0.87***	0.92***	0.90***
Technology	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***	0.10***
Malelaborshare	-0.28**	-0.28*	-0.28**	-0.28**	-0.29**	-0.28**	-0.28**	-0.29**	-0.29**
Femalelaborshare	-0.81***	-0.79***	-0.79***	-0.79***	-0.77***	-0.81***	-0.78***	-0.76***	-0.77***
Landownha	0.003	0.002	0.004	0.002	0.003	0.003	0.004	0.002	0.002
Ageeduhead	0.0003	0.00009	0.00002	0.0001	0.0001	0.00004	0.00007	0.00007	0.00007
Femhead	-0.82***	-0.78***	-0.82***	-0.79***	-0.78***	-0.83***	-0.79***	-0.76***	-0.79***
Poverty	-0.38***	-0.37***	-0.38***	-0.36***	-0.37***	-0.37***	-0.37***	-0.36***	-0.36***
Wealth_index	0.11*	0.11*	0.10*	0.11*	0.11*	0.11*	0.11*	0.11*	0.11*
year×region	-0.31***	-0.30***	-0.29***	-0.30***	-0.29***	-0.31***	-0.28***	-0.28***	-0.28***
Subjective drought		0.25***					0.22**		
Objective drought			-0.68***				-0.66***		
Over_report				0.34***				0.23**	0.21**
Under_report					-0.84***			-0.79***	-0.82***
Matchdrought						-0.48***			-0.58***
Control	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Estimation Tech.	*FE*	*FE*	*FE*	*FE*	*FE*	*FE*	*FE*	*FE*	*FE*

*** refers to $p > 0.01$, ** $p < 0.05$, and * $p < 0.1$
Source: Authors findings

Table (9): Marginal effects of subjective and objective measures and perception accuracy categories on household production

Models	M(1)-Base	M(2)	M(3)	M(4)	M(5)	M(6)	M(7)	M(8)	M(9)
Dependent variables	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP
Temperature	-81.72	-80.16	-71.16	-78.60	-76.75	-80.24	-70.08	-74.91	-73.17
EWS	102.65	100.12	89.24	98	94.96	100.83	87.39	92.25	90.12
Technology	11.79	11.91	11.08	11.75	11.33	11.51	11.20	11.33	10.97
Malelaborshare	-28.11	-28.11	-28.54	-28.07	-29.65	-28.06	-28.52	-29.51	-29.51
Femalelaborshare	-81.26	-79.59	-79.57	-79.51	-77.62	-81.92	-78.18	-76.65	-77.43

Landownha	-	-	-	-	-	-	-	-	-
Ageeduhead	-	-	-	-	-	-	-	-	-
Femhead	-55.98	-54.54	-56.03	-54.64	-54.50	-56.77	-54.80	-53.64	-54.68
Poverty	-31.71	-31.09	-31.66	-30.81	-31.49	-31.60	-31.12	-30.88	-30.81
Wealth_index	11.37	11.83	10.97	11.73	11.38	11.54	11.07	11.40	11.17
Subjective drought		29.46					24.89		
Objective drought			-49.45				-48.60		
Over_report				40.89				26.98	23.65
Under_report					-57.23			-54.66	-56.22
Matchdrought						-38.45			-44.11

*** refers to $p > 0.01$, ** $p < 0.05$, and * $p < 0.1$
Source: Authors findings

What Shapes Subjective Drought Perception and Accuracy?

Table 10 presents the fixed-effect logit estimates of three perception outcomes. Specifically, Model (10) examines determinants of subjective drought perception, Model (11) focuses on accurate perception (Match), and Model (12) captures the determinants of perception misalignment (Mismatch).

In Model (10), the coefficient on reduction in production is negative and statistically significant, indicating that households experiencing reduced agricultural output are less likely to report drought. In contrast, access to an Early Warning System (EWS) is positive and significant. This finding indicates that households receiving drought-related information are more likely to report drought conditions, which is consistent with the findings of Sunday et al. (2021). Female labor share and female head regressors show negative and significant signs. These signs reflect households with higher female participation in farm labor or those headed by women are less likely to subjectively perceive drought, which is consistent with Nalwanga et al. (2025) and Hübler et al. (2025) evidence that female-headed farmers in Uganda face greater constraints in responding to weather shocks. In Model (11), which assesses accurate perception, temperature is positive and highly significant. This suggest that higher heat stress is associated with more accurate drought recognition, which is consistent with FAO (2016) and Khan et al. (2021) conclusions that households in Uganda perceive higher temperature as a crucial factor in losing production. Early Warning System has a negative and significant effect in this model, suggesting that while warnings increase general awareness, they are not consistently associated with improved recognition accuracy when drought occurs, which supports the evidence of Akwango et al. (2017). The most experienced and educated household heads are more likely to recognize drought accurately. This fact is confirmed by Sevinc et al. (2021). In Model (12), which addresses mismatched drought perception, temperature remains positive and significant, indicating that high temperatures also raise the probability of reporting drought even when subjective indicators do not classify the period as drought. It is notable that temperature increases both match and mismatch drought, which may indicate that households rely more on felt heat stress than accumulated rainfall when forming drought perceptions. The coefficients for EWS and production reduction are statistically insignificant, suggesting that neither access to information nor output changes systematically affect perception errors. Importantly, land ownership and age/education of the household head are positive and statistically significant in this model, indicating that greater land endowment and higher experience/education are associated with higher levels of misperception. These findings support the conclusions of Karanja et al. (2017) and Sevinc et al. (2021) that land ownership and age shape farmers' perceptions.

The coefficients in Table (10) transformed into odds ratios in Table (11), allowing a direct interpretation of the proportional change in the likelihood of each perception outcome. In Model (10), the Exp(β) for EWS is greater than one, indicating that access to information increases the likelihood of reporting drought. The odds ratio for reduction in production is below one, suggesting experiencing production losses reduces subjective perception. Similarly, the odds ratios for gender regressors are less than one, suggesting that these households are less likely to perceive drought conditions. In Model (11), temperature shows an odds ratio greater than one, indicating a substantial increase in the likelihood of accurate drought recognition as temperature rises. The odds ratio for EWS remains significant and consistent with findings in Table (10). Greater access to drought information is associated with lower perception accuracy. The age and education of the household head also show an odds ratio above one, suggesting that greater experience and education improve perception accuracy. In Model (12), temperature continues to have an odds ratio greater than one, suggesting that high temperatures increase the likelihood of misperception-reporting drought when SPI index is normal. Land ownership and age/education of the head also show odds ratios greater than one, suggesting their positive and significant contributions to mismatched perception.

Table (10): Fixed-Effects Logit Estimates for the determinants of drought perception and perception-accuracy categories

Models	M(10)	M(11)	M(12)
Dependent variables	Subjective drought	Match drought	Mismatch drought
Reduction_tvp	-0.37***	0.21	-0.008
Temperature	0.009	1.94***	0.18**
EWS	0.12***	-1.45***	0.06
Malelaborshare	0.03	-0.08	-0.07
Femalelaborshare	-0.25***	0.18	-0.12
Landownha	0.002	-0.04	0.01*
Ageeduhead	-0.0002	0.0009*	-0.0003*
Femhead	-0.22**	0.01	-0.10
Poverty	-0.06	-0.11	-0.08
Wealth_index	0.002	-0.03	-0.01
year×region	-0.14***	0.14***	-0.07***
Control	*YES*	*YES*	*YES*
Estimation Tech.	*FE-LOGIT*	*FE-LOGIT*	*FE-LOGIT*

*** refers to $p > 0.01$, ** $p < 0.05$, and * $p < 0.1$

Source: Authors findings

Table (11): Odds Ratios corresponding to the Fixed-Effects Logit Models of drought perception and perception accuracy

Models	M(10)	M(11)	M(12)
Dependent variables	Subjective drought	Match drought	Mismatch drought
Reduction_tvp	0.68	-	-
Temperature	-	6.96	1.20
EWS	1.13	0.23	-
Malelaborshare	-	-	-
Femalelaborshare	0.77	-	-
Landownha	-	-	1.01
Ageeduhead	-	1	0.99
Femhead	0.79	-	-
Poverty	-	-	-
Wealth_index	-	-	-
year×region	0.86	-1.15	0.92

*** refers to $p > 0.01$, ** $p < 0.05$, and * $p < 0.1$

Source: Authors findings

Robustness Checks

To assess the robustness of the results, the production models are re-estimated by sequentially adding groups of control variables to the baseline specification, M(13). The baseline model includes climatic variables and production levels, while additional control variables are added sequentially across specifications. Table (12) and Figure (5) present robustness analysis in which the explanatory variables include the model panel by panel. In each column (M13 - M18) the sign and the statistical significance of the drought-related variables and temperature remain stable, indicating that the main relationships are not sensitive to the inclusion of control variables. The subjective drought consistently shows a positive association with agricultural output, the SPI-based drought index shows a negative link with outcomes, and temperature is associated negatively with outputs. The magnitude of the subjective drought and temperature effects are declining after the introduction of technology and information and further with gender and labor structure regressors. This pattern is consistent with the possibility that drought perception may be associated with access to drought information and household labor structure. In contrast, the objective drought effect size remains unchanged, which suggests a stable and persistent association of drought shocks with production losses. In terms of other control variables, poverty consistently reduces production, access to assets improves it, and EWS access and technology increase output levels. Gender-related variables show negative and significant effects in production, and land ownership remains weak and insignificant. Overall, the robustness analysis supports the stability of the key empirical findings.

Table (12): Robustness of drought model specifications (M13-M18)

Regressor Groups	Models	M(13)	M(14)	M(15)	M(16)	M(17)	M(18)
	Dependent variables	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP	LnTVP
Base Model	Subjective drought	0.37^{***}	0.45^{***}	0.36^{***}	0.27^{***}	0.22^{***}	0.22^{***}
	Objective drought	-0.63^{***}	-0.83^{***}	-0.62^{***}	-0.66^{***}	-0.66^{***}	-0.66^{***}
	Temperature	-0.95^{***}	-0.92^{***}	-0.92^{***}	-0.67^{***}	-0.69^{***}	-0.70^{***}
Economic Controls	Poverty	-	-0.40^{***}	-0.40^{***}	-0.42^{***}	-0.37^{***}	-0.37^{***}
	Wealth_index	-	0.17^{***}	0.17^{***}	0.11^{***}	0.11^{***}	0.11^{***}
Human Capital	Ageeduhead	-	-	0.0001	0.00005	0.00007	0.00007
Technology/Information	EWS	-	-	-	0.88^{***}	0.87^{***}	0.87^{***}
	Technology	-	-	-	0.11^{***}	0.11^{***}	0.11^{***}
Gender Labor Structure	Malelaborshare	-	-	-	-	-0.28^{***}	-0.28^{***}
	Femalelaborshare	-	-	-	-	-0.78^{***}	-0.78^{***}
	Femhead	-	-	-	-	-0.79^{***}	-0.79^{***}
Land Ownership	Landownha	-	-	-	-	-	0.004
	year×region	-0.38^{***}	-0.37^{***}	-0.37^{***}	-0.31^{***}	-0.29^{***}	-0.28^{***}
	Control	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	OBS	*3248*	*3248*	*3248*	*3248*	*3248*	*3248*
	Estimation Tech.	*FE*	*FE*	*FE*	*FE*	*FE*	*FE*

*** refers to $p > 0.01$, ** $p < 0.05$, and * $p < 0.1$

Source: Authors findings

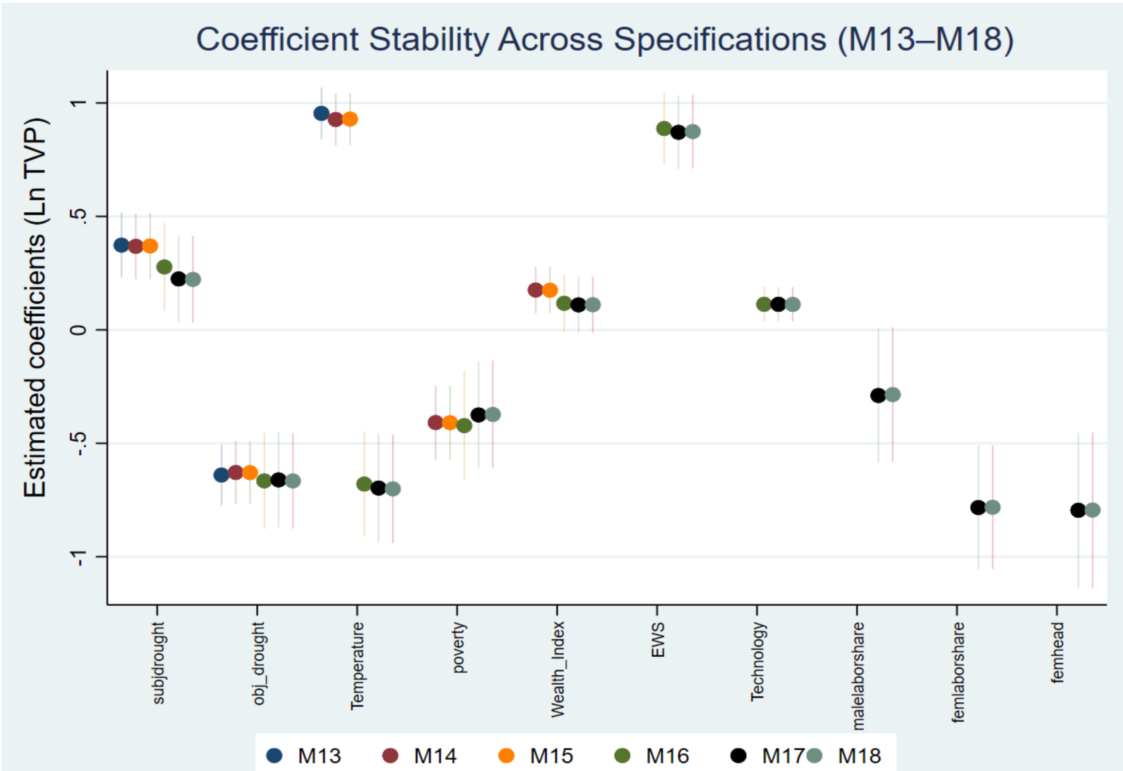

Figure 5: Robustness of estimated coefficients across specifications (M13–M18)

As shown in Table (13), there are alternative specifications for the lagged perceptions and accuracy indicators (see M19 to M22). Results exhibit that there is a positive association between subjective drought and production, and the lagged form is not statistically significant. This suggests that drought perception acts through immediate behavioral responses (short-term effect) rather than through persistent effects. The perception-accuracy indicators offer further insights into the impacts. Over-reporting of drought conditions is positively associated with production outcomes in the current period, while its lagged effect is not significant. This pattern may indicate that households anticipate drought conditions and adjust their inputs within the same season as precautionary behavior. However, the under-report indicator and its lagged effect are statistically significant, indicating that failure to recognize the drought conditions may delay adaptive responses and lead to negative effects on production outcomes (long-term effect). In addition, Matchdrought shows no statistically significant relationship with production, indicating that correct identification of drought conditions is not sufficient to affect production.

Table (13): Fixed-Effects estimation Results: Effects of lagged subjective and objective measures and perception accuracy categories on household production

Models	M(19)	M(20)	M(21)	M(22)
Dependent variables	LnTVP	LnTVP	LnTVP	LnTVP
Subjective drought	0.30**			
l.Subjective drought	0.04			
Over_report		0.31**		
l.Over_report		0.05		
Under_report			-0.48*	
l.Under_report			-0.76**	
Matchdrought				0.12
l.Matchdrought				0.01
Control Variables	*YES*	*YES*	*YES*	*YES*
Estimation Tech.	*FE*	*FE*	*FE*	*FE*

*** refers to $p > 0.01$, ** $p < 0.05$, and * $p < 0.1$
Source: Authors findings

Conclusive remarks and Policy Considerations

Subjective drought perception and objectively measured drought tend to impact household total value production. In Uganda we found a clear asymmetry between behavioral and physical dimensions of weather shocks. Subjective drought is consistently associated with higher production, while objective drought is associated with lower output. Households that anticipate drought risks may adopt actions that stabilize or enhance yield. The analysis of perception accuracy further emphasizes that households that overestimate drought perform better than those that underestimate it. This pattern highlights the crucial role of timely recognition and adopting resilience strategies. In addition, the results suggest that households may rely more on heat stress than on accumulated rainfall when shaping drought perceptions. Temperature also plays a significant role in forming households' perception, shaping both accurate and inaccurate drought recognition (mismatch and match drought). While this supports rapid awareness in some cases, it also contributes to misperception where heat stress does not correspond to meteorological drought. In terms of socioeconomic factors, poverty, technology, and gender structures significantly influence both production and perception outcomes and are consistently associated with both production and perception outcomes. Female-headed households and systems with high female labor share face structural barriers that limit their ability to respond to weather shocks. The robustness check confirms that these core connections remain stable across alternative specifications.

The findings have several policy implications. First, improving the Drought Early Warning System (EWS) to deliver timely information is essential. The current system increases awareness but does not improve perception; information should be disseminated on time and incorporate not only precipitation details but also temperature and other climatic indicators. Localizing warning systems to a sub-country scale can disseminate timely and effective climate information. Second, expanding households' access to climate-smart technologies, like drought-tolerant seed varieties or more sustainable irrigation systems, could help them translate perception into effective adaptive responses. Strengthening agricultural extension services, like rapid advisory visits, to link perception and action. These implications can translate into actionable plans to enhance household resilience to climate changes, and should be considered in development agendas, included the ongoing debate on Common African Position (Gebrihet et al., 2026).

Third, the results consistently show gender-based constraints in climate adaptation. Targeted support policies for female farmers are needed, particularly for female-headed households and systems with a higher female labor share that face asset, credit, and endowment barriers. Fourth, farmers' climate literacy should be enhanced to reduce the cost of misperceptions. As already recently pointed (Mbah and Liberty, 2025), promoting farmers' climate literacy at schools, churches, and trading centers helps them to react to weather shocks at the correct timing, in regions with frequent misperception of drought conditions.

The study has limitations. First, the objective drought index relies on rainfall, which does not fully account for temperature-driven evaporation and soil moisture condition. Integrating major climate indices would allow a more comprehensive measurement of climate shock. Second, subjective drought is measured as a binary indicator and therefore does not capture differences in the intensity of perceived drought. Future work could incorporate ordinal perception scales or qualitative interviews to better understand how households evaluate drought severity and duration. Finally, extending the analysis to additional case studies and neighboring countries would make it possible to compare how different agri-eco zones and cultural interpretations of weather shocks shape the relationship between farmers' perceptions and outcomes. Additionally, such comparative studies would assess the external validity of the findings.

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Declarations

Funding

This study was carried out within the Research Projects of Relevant National Interest (PRIN), 2022 PNRR Call, project "REcovering the agrifood system from Shocks Induced by Labour Inputs, ENergy, Climate Extremes (RESILIENCE)" (Prot. P2022JTSFB).

Competing interests

The authors declare that they have no competing interests.

Data availability

Data are available upon request.

Acknowledgements

The authors thank participants at the SITES-AICC Conference 2026, Development and Climate Mitigation/Adaptation, for their valuable comments and suggestions on earlier drafts.

APPENDIX

Appendix A: Conceptual Framework

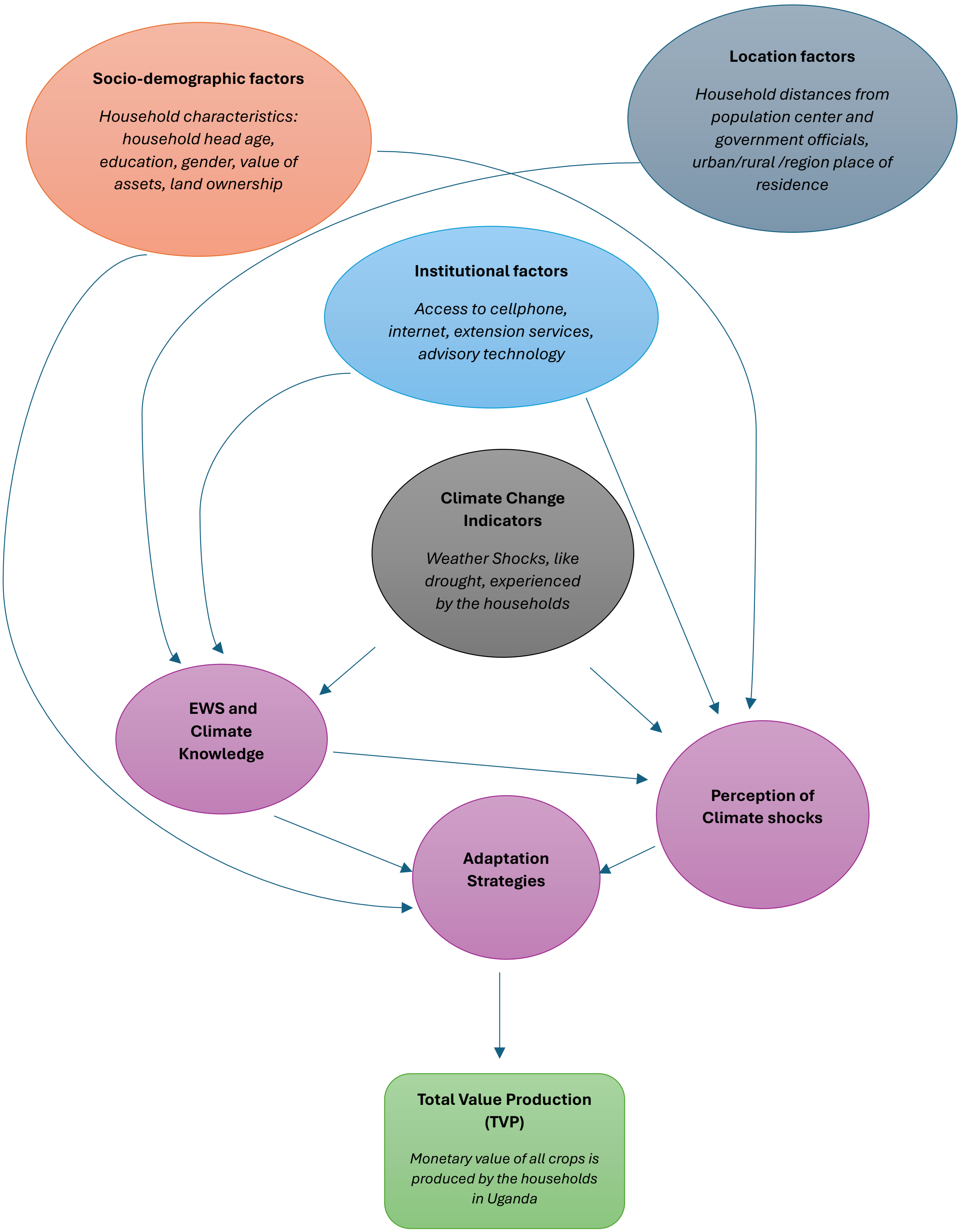

Figure A-1. Conceptual Framework of Household Response to Weather shocks in Uganda

Appendix B: Supplementary Descriptive Statistics

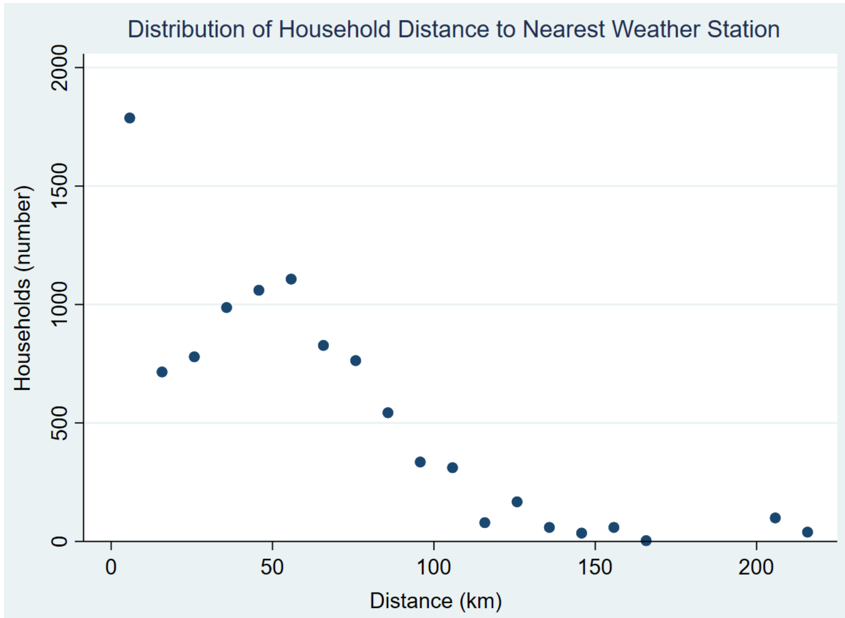

Figure B-1: Households distance distribution to nearest weather station in Uganda
Source: Authors calculations in QGIS based on Uganda_ARC2_CHIRPS shapefiles.

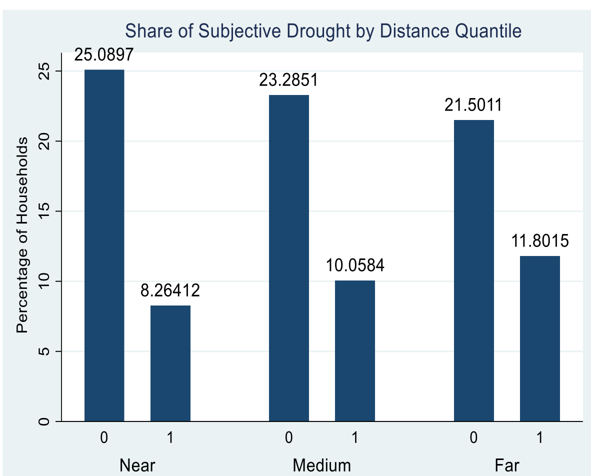

Figure (B-2:a): Share of subjective drought by distance from population center over 20000 persons

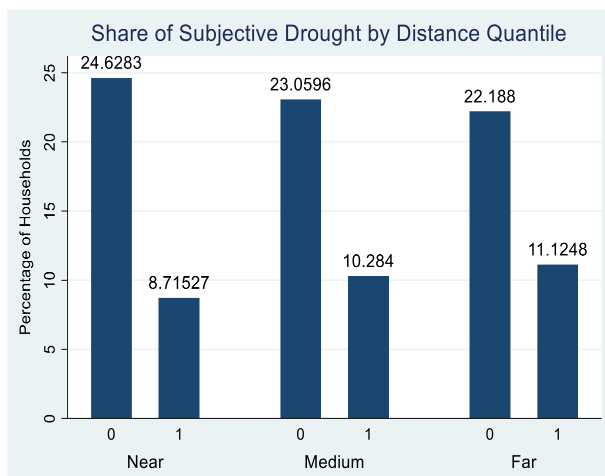

Figure (B-2:b): Share of subjective drought by distance from governmental officials

Figure B-2: Share of objective and subjective drought by distances from population center and governmental officials
Source: Authors findings based on UNPS data

Appendix C: Supplementary Econometric Modelling

Table (C-1): Pairwise correlations among core variables

	LnTVP	Subjective drought	Objective drought
LnTVP	1		
Subjective drought	0.14	1	
Objective drought	-0.21	-0.072	1

Source: Authors findings

Table (C-2): Multicollinearity diagnostics: VIF test results

	M(1)	M(2)	M(3)	M(4)	M(5)	M(6)	M(7)	M(8)	M(9)	M(10)	M(11)	M(12)
Single VIF<5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	1.13	1.12	1.13	1.12	1.12	1.12	1.12	1.13	1.12	1.15	1.15	1.15

Source: Authors findings

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