Drought Impacts on Income Composition and Diversification

Evidence from Households in Namibia's Zambezi Region

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Abstract

As climate variability intensifies across Sub-Saharan Africa, smallholder farmers increasingly face the challenge of sustaining their livelihoods under recurrent drought conditions. This thesis examines how drought affects income composition and diversification among rural households in Namibia's Zambezi region, using panel data collected in 2019 and 2023. It employs fixed-effects regression models to estimate the impacts of both objective drought indicators – such as precipitation and relative precipitation – and subjective measures based on self-reported drought exposure. Additional models explore interactions between precipitation and local soil conditions as well as longer-term income adjustments following the 2019 drought.

The findings reveal that precipitation shows limited explanatory power for changes in income structure, whereas self-reported drought is significantly associated with shifts in specific income sources. However, there is no evidence of increased income diversification, suggesting that households adjust within existing livelihood structures rather than expand into new ones. Moreover, the interaction model highlights that high sand content in the soil reduces the positive effects of rainfall on income.

These results underscore the importance of local perceptions and ecological conditions in shaping adaptive responses to climate shocks. They also point to structural barriers that limit transformation, such as poor market access and limited livelihood alternatives. These findings show the value of using farmer perceptions and environmental context – in this case soil quality – to better understand local drought impacts. Policy efforts should go beyond short-term relief and address the structural constraints that limit households' ability to adapt, such as limited access to markets, education, and income opportunities.

Keywords: Drought, Income Diversification, Smallholder Farmers, Namibia, Perceived Drought, Precipitation

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Abbreviations

CHIRPS	Climate Hazards Centre InfraRed Precipitation with Station Data
CRAVE	Climate Resilient Agriculture in three of the Vulnerable Extreme northern crop-growing regions
EIF	Environmental Investment Fund
FMD	Foot-and-Mouth Disease
NGO	Non-Governmental Organisation
OLS	Ordinary Least Squared
PES	Payments for Environmental Services
SDI	Simpson’s Diversity Index
SLU	Swedish University of Agricultural Sciences
TLU	Tropical Livestock Unit

1. Introduction

As climate change intensifies, droughts have become increasingly frequent, prolonged, and unpredictable across Sub-Saharan Africa (IPCC 2022). In Namibia, one of the driest countries on the continent, smallholder farmers depend heavily on rainfed agriculture and ecosystem services such as water, fertile soils, and grazing land to sustain their production and income. When rainfall patterns shift or fail entirely, the consequences extend beyond poor harvests, affecting household income, food security, and overall livelihood stability (Bahta & Myeki 2022). Even in Namibia's northeastern Zambezi region, which receives higher rainfall than most parts of the country, smallholder farmers face growing uncertainty due to erratic rainfall and shifting seasonal patterns (Mendelsohn 2006; Teweldemedhin et al. 2015). These environmental changes often force households to adapt, not just in how they farm, but in their overall strategies to earn a living. Many households combine crop and livestock production with other non-farm incomes. During droughts, they may reallocate their labour, adjust investment decisions, or shift toward alternative income sources. Yet it remains unclear how these changes unfold in practice, and whether they lead to more resilient livelihoods.

This raises the question of how smallholder households adapt their income composition in response to drought. Do they shift from farm-based to non-farm income? Do they diversify? And how do these responses differ depending on whether drought is measured through objective climate data or perceived at the household level? This thesis aims to examine these questions by analysing how drought, measured objectively through precipitation and relative precipitation data and subjectively through self-reported drought exposure, affects the composition and diversification of household income in Namibia's Zambezi region. The analysis uses panel data from 2019 and 2023 and applies fixed-effects regression models to estimate these effects. The findings show that perceived drought exposure is more strongly associated with changes in income composition than objective precipitation data. However, households tend to adjust within existing livelihood strategies, without evidence of increased income diversification.

While the growing body of research has explored how rural households adapt to climate shocks, much of this literature has focused on agricultural outcomes such as yield, consumption, and food security (Dercon 2004; Musungu et al. 2024). Fewer studies have investigated how drought influences the broader composition of household income, particularly the relative roles of farm, off-farm, and transfer based income streams (Chuang 2019; Matsuura-Kannari et al. 2023). Even less attention has been given to how different types of drought measures shape the responses, though it can be assumed that drought perception has an impact on the behavioural responses of smallholder farmers (Liu et al. 2016; Chuang 2019). This study addresses these gaps by analysing both the composition of household income and the influence of different drought measures on adaptive responses, thereby contributing to a more nuanced understanding of adaptation behaviour under environmental stress.

This study makes three key contributions. First, it provides a comparative analysis of objective and subjective drought indicators to assess which better explains household-level income responses. This is important because policy responses often rely on objective measures, yet subjective perceptions may better capture the realities that shape household decision making. Second, it examines not only changes in specific income sources but also in overall household diversity, using the Simpson's Diversity Index as a measure of income diversification. Third, it draws on panel data spanning over two years, allowing to capture both short-term and medium-term responses.

The remainder of this thesis unfolds as follows: Section 2 reviews the existing literature on household responses to drought, focusing on income composition, diversification, and the role of subjective versus objective drought measures. Section 3 provides background on the Zambezi region, while Section 4 introduces the conceptual framework linking drought exposure to changes in income composition and livelihood strategies. Section 5 describes the data sources and construction of key variables. Section 6 outlines the empirical strategy, including the fixed-effects regression models and identification approach. Section 7 presents the main results, and Section 8 explores potential mechanisms behind the observed patterns and reflects on their implications for rural adaptation and resilience. Section 9 discusses the study's limitations. Finally, Section 10 concludes by summarizing the key findings and offering reflections for policy and future research.

2. Literature Review

A consistent finding in the literature is that drought shocks lead rural households to adjust how they generate their income. These adjustments include reallocation of labour away from agriculture, shifts in the importance of different income streams, and in some cases, diversification. Chuang (2019) shows that Indian farmers respond to negative rainfall shocks by shifting into agricultural wage labour and off-farm employment, particularly in areas where agriculture remains sensitive to rainfall anomalies. Similarly, Musungu et al. (2024) find that in Ethiopia, droughts lead to a reallocation of labour toward off-farm self-employment, especially when productivity in agriculture declines and households can access alternative livelihood options. Evidence from Kenya further shows that households in low-rainfall regions are more likely to engage in off-farm work as a long-term strategy, though limited adjustment to short-term rainfall shocks was found (Mathenge & Tschirley 2015). These studies indicate that drought affects not only agricultural outcomes but also the composition of household income, depending on available opportunities and local conditions. This thesis builds on these insights by analysing how drought exposure influences income from specific sources – such as crops, livestock, environmental products, and off-farm work – in the Namibian context.

One potential income adjustment strategy is income diversification, often framed as reducing vulnerability by spreading risk across multiple income streams. However, the capacity to diversify is not equally distributed. Cunguara (2011) shows that in southern Mozambique, poorer households face more barriers in engaging with off-farm income sources during drought years, while wealthier households benefit from better market access, education, and productive assets. A similar pattern was found in rural Bangladesh, where diversification improves food security but disproportionately benefits better-off households (Matsuura-Kannari et al. 2023).

Structural and institutional factors shape households' capacity to reallocate income. Musumba et al. (2022) emphasize that diversification in rural Africa is strongly mediated by access to markets, extension services, credit, and functioning local institutions. Asfaw et al. (2019) further show, using panel data from Malawi, Niger, and Zambia, that exposure to climate shocks often pushes households into diversification, especially when other coping strategies are unavailable. However, they also find that diversification does not consistently improve welfare, suggesting that households may be limited to low-return activities due to restricted access to higher-value opportunities. This thesis seeks to contribute to this literature by examining the extent and structure of income shifts and diversification among smallholder households in Namibia's Zambezi region, where both socioeconomic and institutional limitations may shape how households respond to drought exposure.

In addition to these structural limitations, the persistence of past shocks can further delay or suppress changes in income composition. Using longitudinal data from rural Ethiopia, Dercon (2004) demonstrates that rainfall shocks have long-term effects on household welfare, including reduced consumption growth and limited recovery. Repeated exposure to drought can trap households in low-return livelihood activities and constrain their ability to respond to new shocks. This study considers these longer-term effects by examining how the income composition of affected households changed following the 2019 drought.

While meteorological data capture physical drought conditions, it is often households' perceptions that determine whether and how they adjust their income strategies. Research shows that past experiences with climate variability shape current behavioural responses. For example, households living in historically variable environments tend to exhibit weaker adjustments to new droughts (Chuang 2019). Moreover, perceived drought severity does not always align with rainfall data. Instead, it reflects local realities such as soil quality, crop sensitivity, and farming practices (Liu et al. 2016). In South Africa, Danso-Abbeam et al. (2024) identify three dimensions of perceived drought impact – economic, environmental, and social – and show that severity perceptions are influenced by household size, past drought exposure, non-farm employment, and access to extension services. Together, these studies suggest that subjective drought indicators capture context-specific vulnerability and coping behaviour that may not be fully reflected in meteorological indicators. This thesis contributes by comparing the explanatory power of perceived and objective drought measures in predicting changes in household income composition.

Finally, environmental conditions – particularly soil quality – play a crucial role in determining how precipitation affects income. Even in years with adequate annual precipitation, the capacity to benefit from rainfall depends on factors like soil texture, erosion, and water retention. Agricultural drought, as Liu et al. (2016) argue, cannot be understood through meteorological indicators alone, since local environmental factors moderate how precipitation affects crops and natural resources. Additionally, Dong and Ochsner (2018) demonstrate that soils with high sand content retain less moisture, thereby weakening the productivity of rainfall. In such areas, even relatively wet years may not support income recovery. This study integrates this perspective by analysing how soil sand content interacts with rainfall to shape household income composition, thus highlighting the ecological dimension of livelihood resilience.

3. Background

The Zambezi region is located in the northeastern part of Namibia[1], forming a narrow strip of land that borders Angola, Zambia, Zimbabwe, and Botswana. It has a hot and semi-arid climate and is distinguished by a landscape of floodplains, seasonal wetlands, and perennial rivers, such as Zambezi, Kwando, and Chobe. These features set it apart from the predominantly arid conditions found across the rest of the country (Mendelsohn 2006).

According to the 2023 census, the Zambezi region has a population of 142,373, accounting for 4.7% of Namibia's population (Namibia Statistics Agency 2024). It is home to approximately 12,000 smallholder farmers with a farming area ranging from 1 to 10 hectares each. Most of them engage in rainfed agriculture for both consumption and income generation. Farming systems vary by geography: dryland farmers typically begin planting with the onset of rains in October or November, while river field farmers – located along the riverbanks – start as early as August, using residual soil moisture after floodwaters recede. Most households practice mixed farming, growing maize, sorghum, pearl millet, beans, groundnuts, and melons, alongside raising cattle, goats, pigs, and poultry. Maize is the primary staple crop and is widely cultivated, but irrigation is very rare, with the Kalimbeza rice project being an exception. Livestock production is experiencing recurring outbreaks of foot-and-mouth disease, due to wildlife in the area, which reduces the production and marketing. In addition to agriculture, many households rely on woodland resources for fuel, construction materials, fodder, and traditional medicine. Forestry plays a key role in rural livelihoods, supported by ongoing projects focused on inventory, fire management, and sustainable utilization (Zambezi regional council 2024).

Zambezi is Namibia's region with the highest rainfall, receiving between 555 and 690 mm of rainfall annually, compared to less than 200 mm in the western and southern parts of the country (Kaseke et al. 2016). These precipitation differences are illustrated in Figure 1. Rainfall is concentrated in the November to April growing season but is highly variable across years. Temperatures average between 20 to 22°C and is predicted to increase by 2.0 to 3.5°C due to climate change with greater variability in rainfall (Teweldemedhin et al. 2015).

[1] In 2023, Namibia's GDP per capita was approximately $4,168 USD (World Bank 2024).

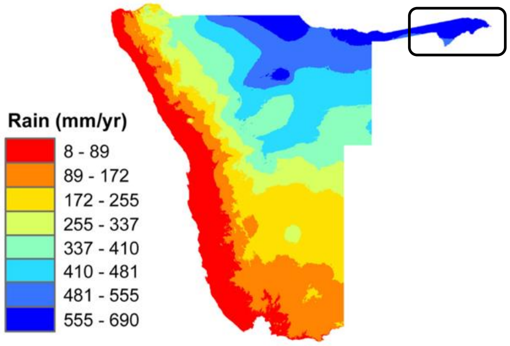

Figure 1. Average annual rainfall across Namibia, with the Zambezi Region outlined in black. The northeastern Zambezi Region receives the highest rainfall in the country, with annual totals raining from 555 to 690mm. Source: Kaseke et al. 2016.

Despite relatively high rainfall, water availability for crops remains limited due to droughts and soil conditions. In roughly one out of three years, seasonal totals fall below the 500mm threshold required for realizable maize yields (Gaughan & Waylen 2012; Dieppois et al. 2019). Soils in the Zambezi region are primarily Arenosols, and Cambisols, but also include Fluvisols along riverbanks (Kiesel et al. 2022). Arenosols are sandy soils with low organic matter and limited water holding capacity (FAO 2014). The soils pose constraints for rainfed agriculture, particularly in dryland areas. Fluvisols in floodplain zones have more favourable properties, but have mostly restricted access due to conservation zoning (Kiesel et al. 2022).

Institutional and community-based support structures play a key role in helping households navigate climatic and agricultural challenges. In the Zambezi region, the Environmental Investment Fund (EIF) has implemented targeted interventions to promote climate-resilient agriculture and strengthen rural livelihoods. One prominent example is the Climate Resilient Agriculture in three of the Vulnerable Extreme northern crop-growing regions (CRAVE) project, which introduced conservation agriculture practices, promoted the use of solar-powered technologies, and supported smallholder farmers with training, market access, and financial support. These efforts aim to reduce vulnerability to rainfall variability and improve the long-term viability of farming systems in areas with limited infrastructure and ecological constraints (EIF, 2024).

4. Conceptual Framework

Smallholder farmers in Sub-Saharan Africa, particularly in drought-prone countries such as Namibia, must consistently decide how to allocate limited resources – including land, labour, and capital – across available livelihood activities. These include rainfed crop production, livestock farming, wage labour, small-scale businesses, and remittances (Bryan et al. 2009). The goal of these decisions is to secure household income and food consumption while minimizing exposure to risk. Under typical condition, households allocate more resources to activities expected to yield the highest and most reliable returns. When agricultural production is anticipated to perform well, farmers may intensify their efforts on the farm. However, these decisions are made in the context of significant uncertainty, particularly due to climate variability.

A drought – or even the expectation of one – alters the decision environment by lowering the expected returns from agriculture. When farmers anticipate poor rainfall, they foresee lower crop yields and increased risks of loss, making agriculture a less attractive option compared to alternative livelihood activities (Chuang 2019). Declines in rainfall often lead to reduced crop yields, livestock stress or mortality, and input waste, which together compromise both food security and income (Thornton et al. 2014). As the returns from rain-dependent agriculture fall, households reassess how to allocate their time and labour. To stabilize income, farmers may reduce their reliance on the most climate-sensitive activities and shift toward alternative income sources that are either less affected by drought or entirely unrelated to climatic conditions. This reallocation of effort can be seen as a risk management strategy in response to changing environmental constraints.

The extend to which a household is able to adjust its livelihood strategy depends on several factors, including asset holdings, market access, institutional support, and household characteristics (Karlan et al. 2014). Notably, human capital – particularly education – plays a role in shaping a household's capacity to adapt to drought. Education enhances the ability to interpret climate information, pursue off-farm employment, and manage small-scale enterprises. More educated household members are also more likely to adopt risk-reducing strategies and diversify income sources (Di Falco & Veronesi 2013).

4.1 Immediate Responses to Shocks

Coping mechanisms are the short-term, immediate actions taken by the households to address the acute impacts of weather shocks, particularly in times of crisis. These mechanisms are reactive and aim to minimize the immediate harm from reduced agricultural output or food scarcity.

For example, smallholder farmers may sell livestock to generate quick cash for food or other essential needs. Additionally, farmers may engage in migration – either seasonal or permanent – seeking labour opportunities in urban centres or other regions that are less affected by the drought (Gray & Mueller 2012).

Farmers may also reduce agricultural costs, by reducing additional labour and seeds, or even plant fewer crops to preserve resources for future agricultural cycles. The sale of assets and livestock is another resort to address immediate cash flow needs. These assets are critical for households that depend on them for sustenance and income during crises, but their sale comes at the cost of reducing long-term resilience (Janzen & Carter 2013).

4.2 Long-term Adaptation Strategies

Adaptation strategies are long-term, proactive measures that households adopt to reduce vulnerability and adapt to future weather shocks. These strategies are aimed at building resilience by diversifying income sources, improving agricultural practices, and securing long-term resources (Barrett et al. 2001).

Livelihood diversification is one of the key coping strategies for smallholder farmers. In response to the uncertainty of agricultural production, farmers often seek to diversify their income sources by engaging in non-agricultural activities such as employment, wage labour, or small businesses. This reduces their dependence on agriculture and spreads risk across multiple income streams, helping them better withstand future shocks (Matsuura-Kannari et al. 2023). Moreover, remittances from family members working in urban areas or abroad can provide crucial financial support during times of drought, further reducing household reliance on agriculture alone.

Another key long-term strategy is improving agricultural resilience through the adoption of climate-smart agricultural practices. These include the use of drought-resistant crops, rainwater harvesting, and improved soil management techniques that increase the ability of smallholder farmers to cope with changing climatic conditions (Ebeke & Combes 2013; Lipper et al. 2018). However, access to these adaptive practices can be limited for many smallholders due to constraints such as lack of resources and insufficient market access.

Strengthening social safety nets is also an essential strategy. Access to formal safety nets, such as government programs, NGO assistance, and community-based support systems, can help households to recover from the immediate effects of weather shocks (Stoeffler & Premand 2020).

Drawing from the literature, the following testable hypotheses outline expected household responses to drought conditions:

1. Households with greater livestock holdings will use livestock sales as a short-term buffer against reduced agricultural productivity.
2. External income sources, particularly remittances and government or NGO transfers, will gain importance during drought periods, providing stability and partially substituting lost agricultural income.
3. Households are likely to increase their income diversification in response to drought, as expanding their range of income sources helps them to better absorb agricultural shocks.
4. Households experiencing drought conditions are likely to reallocate labour from agricultural activities to non-farm activities, such as wage labour or self-employment, to sustain household income.

These hypotheses serve as a guide for the empirical analysis and help structure the interpretation of the results.

5. Data

Panel data The primary panel data was collected in two waves by the Collaborative Research Centre 228: Future Rural Africa in collaboration with the University of Namibia. The dataset consists of 652 households from 45 enumeration areas in the Zambezi region, all of which were surveyed in both 2019 and 2023. Households were selected through a two-stage stratified random sampling process: first, enumeration areas were randomly chosen. Second, households were randomly selected within those areas. The sample is therefore regionally representative. The dataset captures information on demographic characteristics, land use, livestock ownership, asset wealth, income composition, and self-reported droughts. Data collection was timed according to the agricultural calendar and took place between June and August in both waves.

Table 1 summarizes the sample for 2019 and 2023. Households in the dataset are moderate in size, averaging around five members. Household heads are middle-aged, with an average age of 49.4 years in 2019 and 53.3 years in 2023. The proportion of male-headed households is slightly above 50 percent, and most household heads are married.

Education levels vary across households. The dataset records education in categorical form, which is transformed into a numerical scale for analysis. The scale ranges from 0 for no formal education to 17 for postgraduate university education. On average, household heads have 8.6 years of schooling in 2019 and 8.25 years in 2023, indicating that most individuals have completed at least primary education, but relatively few attain higher education[2].

Agriculture plays a key role in household livelihoods, with both crop farming and livestock keeping contributing to income generation. The dataset includes information on cropland size, representing the total land available for farming, and cultivated land, referring to the portion actively used for planting. There is significant variation in landholdings, reflecting differences in agricultural engagement across households.

Livestock ownership, measured in Tropical Livestock Units (TLU), reflects both the number and type of animals owned. Beyond serving as a financial asset, livestock is an important source of income, with households generating earnings from direct sales of animals and livestock products such as milk and meat. However, reliance on agricultural income – both from crop and livestock sales – is

[2] Poverty remains widespread, particularly in rural regions like Zambezi, where rates exceed the national average of 28.7%. National statistics show that 80% of the poor have only primary education or none, while fewer than 1% of university graduates are poor (Ashipala 2023). This suggests that the sample in this study – where households average over 8 years of schooling – is somewhat more educated than the typical rural population.

relatively low compared to other sources, suggesting that many households depend on additional income streams to sustain their livelihoods.

Table 1. Household characteristics

	2019	2023
Characteristics of the household head		
Age	49.43	53.29
	(16.73)	(16.07)
Male (0/1)	0.53	0.56
	(0.50)	(0.50)
Married (0/1)	0.70	0.71
	(0.46)	(0.46)
Years of schooling	8.60	8.25
	(4.57)	(4.34)
Characteristics of the household		
Household size	5.02	5.06
	(2.45)	(2.37)
Cropland (in ha)	9.23	5.00
	(15.31)	(33.75)
Cultivated land (in ha)	5.21	5.87
	(24.83)	(34.49)
Total TLU	8.26	5.6
	(20.25)	(12.83)
Asset index (sum)	8.89	9.19
	(4.35)	(4.42)
Observations	652	652

Note: This table presents means and standard deviations in parentheses for the full sample by the year surveyed. Male and married are binary indicators for whether the household head is male and married, respectively. Years of schooling refers to the completed years of formal education by the household head. Household size is the average number of individuals living in one household. Cropland and cultivated land refer to the total area owned and cultivated (in hectares), respectively. Total TLU represents total livestock holdings. The asset index is the sum of owned household assets, with higher values indicating greater asset ownership.

Table 2 provides a detailed breakdown of household income source shares, allowing for an assessment of livelihood diversification. Households earn income from a mix of agricultural and non-agricultural activities, with some sources playing a more dominant role. Transfers from NGOs and the government represent a major component of household income, suggesting a significant reliance on external support mechanisms. Employment and business sales are also important sources of earnings. Remittances contribute to household income, with some households increasingly depending on financial support from family members or networks outside the region. Agricultural income from livestock and crop sales, while present, is not the primary source of earnings for most households, even though many engage in subsistence farming, cultivating crops for their own consumption. Income from environmental products[3] and payments for environmental services (PES) are minimal, suggesting that direct financial gains from natural resource use are limited.

The degree of income diversification is measured using the Simpson's Diversity Index[4], which ranges from 0 to 1. An index value close to 1 indicates high diversification, reflecting a balanced reliance on multiple income sources, while a value closer to 0 suggests dependance on fewer sources. The calculated index is relatively low at 0.15 in 2019 and 0.14 in 2023, indicating limited diversification within households' income portfolios.

[3] Income from environmental products refers to income generated in the natural environment, such as the collection and sale of firewood, wild fruits, medical plants, thatch grass, or other non-timber forest products.

[4] The Simpson's Diversity Index is calculated as $SDI = 1 - \Sigma_j s_{ijt}^2$,, where s_ijt, is the share of income from source j for household i in year t. The index ranges from 0 (complete specialization) to 1 (maximum diversification).

Table 2. Share of monetary income sources form total monetary income and Simpson's Diversity Index

	2019	2023
Share of income sources		
Crops	0.02	0.03
	(0.11)	(0.14)
Livestock products	0.01	0.02
	(0.08)	(0.09)
Livestock	0.08	0.07
	(0.22)	(0.21)
Business sales	0.1	0.09
	(0.25)	(0.26)
Employment	0.16	0.11
	(0.32)	(0.28)
Environmental products	0.03	0.02
	(0.16)	(0.11)
Remittances	0.03	0.2
	(0.15)	(0.37)
Transfers form NGOs and the Government	0.43	0.28
	(0.45)	(0.41)
Payments for environmental services (PES)	0	0
	(0)	(0.06)
Rent	0	0.01
	(0.01)	(0.08)
Other	0.03	0.02
	(0.16)	(0.11)
Diversity index		
Simpson's Diversity Index	0.16	0.14
	(0.22)	(0.21)
Observations	652	652

Notes: This table presents means and standard deviations (in parentheses) for the share of each income source in total household monetary income, based on the balanced sample. Income sources include crops, livestock products, livestock sales, business activities, employment, environmental products, livestock sales, business activities, employment, environmental products, remittances, transfers from NGOs and the government, payments for environmental services (PES), rent, and other sources. The Simpson's Diversity index (SDI) is included as a measure of income diversification, where higher values indicate greater diversity in income sources.

The household survey also collected information on drought experiences over the 12 months prior to the survey, allowing for a subjective assessment of drought exposure. Table 3 presents the proportion of households that reported experiencing a drought in each year, along with how they rated the severity of its impact. In 2019, 76.5% of households reported a drought, with the majority rating it as severe or very severe. In 2023, drought experiences were far less common, with only 28.5% reporting any impact.

Table 3. Perceived drought in the last 12 months in percent

	2019	2023
Experienced a drought in the last 12 months	76.50	28.50
Severity of Drought		
No Effect	23.50	71.50
Very mild	0.10	0.46
Mild	2.30	1.23
Severe	14.10	10.10
Very Severe	60.00	16.70

Note: This table presents the percentage of households that reported experiencing drought in the 12 months prior to the survey, as well as the perceived severity of the drought. Severity categories are based on self-reported assessments ranging from 'no effect' to 'very severe'.

Precipitation data This study utilizes precipitation data from the Climate Hazards Centre InfraRed Precipitation with Station Data (CHIRPS v3.0), a high-resolution, quasi-global rainfall dataset. CHIRPS provides precipitation estimates at a 0.05° spatial resolution, integrating satellite-derived infrared data with in-situ station observations to enhance accuracy.

For this study, CHIRPS v3.0 data is used specifically for the Zambezi region of Namibia. Household locations from the survey data are spatially matched to the precipitation dataset, allowing for the extraction of annual rainfall estimates at the household level. This process is conducted for the two years covered in the panel data, 2019 and 2023, to analyze variations in precipitation and their relationship with self-reported drought. Table 4 shows the average rainfall totals in the 12 months preceding each survey wave.

Table 4. Precipitation at the household locations

	2019	2023	30-year average
Annual Precipitation	418	347	609
	(38.7)	(35.3)	(27.3)

Note: This table presents means and standard deviations in parentheses for the annual precipitation (mm) preceding each survey and the 30-year average (1988-2018).

Figure 2 shows the monthly distribution of precipitation over the 12-month period preceding each survey round. The data reveals seasonal variation, with most rainfall concentrated between November and February in both years, and very low rainfall during the middle of the year, particularly from July to September. Notably, the 2022/2023 period experiences considerably less rainfall in October and April compared to 2018/2019, while March 2023 has substantially more rainfall.

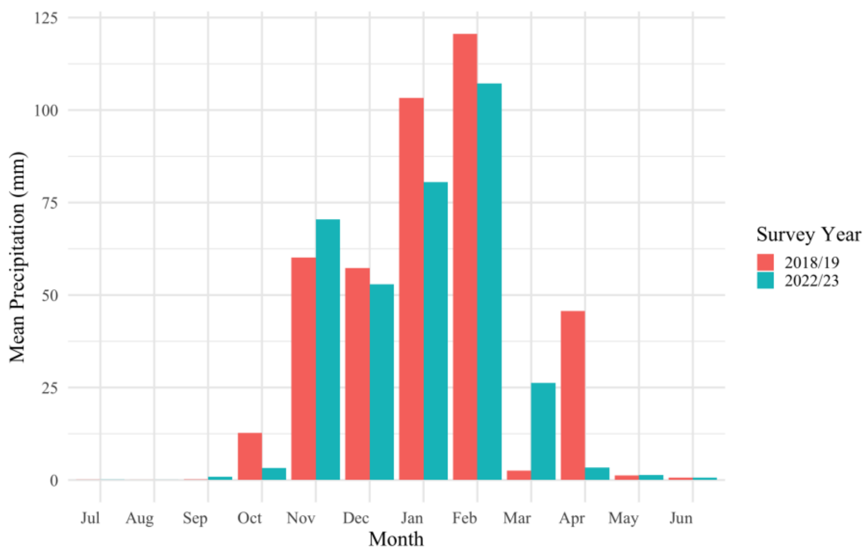

Figure 2. Monthly precipitation (mm) in order with the 12 months before the survey

Figure 3 displays the household-level annual precipitation across the Zambezi region for 2019 and 2023 in the 12 months preceding the survey. Each point represents a surveyed household, which is matched to the amount of precipitation recorded at its location. The map shows spatial differences in rainfall across the region, as well as temporal variations between the two years.

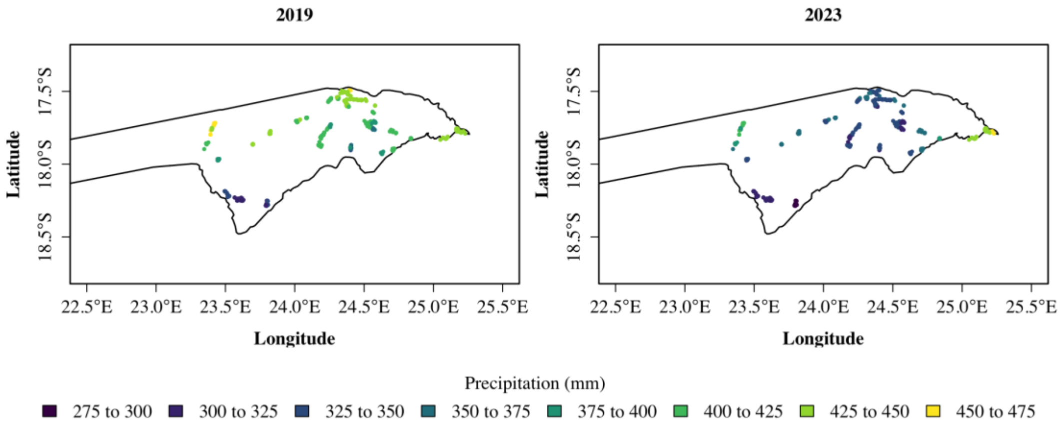

Figure 3. Precipitation levels at household locations in the Zambezi region for 2019 and 2023. The maps display annual rainfall values (in mm) matched to the household coordinates.

To examine the relationship between measured rainfall and drought perception, a logistic regression model is estimated using self-reported drought experience as the dependent variable and household level annual precipitation as the explanatory variable, with year fixed effects included[5]. The results show a significantly negative relationship: higher annual precipitation is associated with a lower likelihood of households reporting a drought ($p = 0.0018$), but only when year fixed effects are included. This shows that self-reported drought perceptions align with rainfall levels when controlling for year-specific factors, such as differences in rainfall distribution during the growing season, the timing of the rainy season onset, or public discourse around drought and food security. Without these controls, the relationship disappears, indicating that perceptions are not solely driven by household-level rainfall but are also shaped by broader contextual conditions. The model also shows that, holding precipitation constant, households surveyed in 2023 are significantly less likely to report drought than those surveyed in 2019 ($p < 0.001$), consistent with the descriptive statistics.

[5] The relationship was estimated using a logistic regression model of the form

$$logit(Drought_{it}) = \alpha + \beta_1 \cdot Precipitation_{it} + \beta_2 \cdot Year2023 + \varepsilon_{it}$$

where $Drought_{it}$ is a binary variable for perceived drought, and $Precipitation_{it}$ is the annual rainfall in millimetres for the household i in year t. The result table is presented in Table A1 in the appendix.

6. Empirical Framework

6.1 Identification strategy

This thesis estimates the causal effect of drought on household income composition and income diversification. The identification strategy leverages variation of precipitation across space and time, combined with household and year fixed effects, to isolate exogenous drought exposure.

Households' income-generating behavior may be influenced by characteristics such as soil quality, risk preferences, or land access, which are either unobserved or time-invariant in the data. To control for this, a household fixed-effects model is applied, accounting for all time-invariant, unobserved heterogeneity. In addition, year fixed effects are included to capture macro-level shocks that may simultaneously affect all households

6.1.1 Drought measures

Four different drought indicators are used to capture both objective and subjective experiences:

1. Precipitation: Total rainfall over the 12 months preceding the survey (reference month: July).
2. Relative precipitation: Annual precipitation expressed as a percentage of the 30-year long-run average of the household location. This allows for identifying drought conditions to what is historically "normal" in each area.
3. Perceived drought binary: Whether the household reported experiencing a drought during the 12 months preceding the survey.
4. Perceived drought severity: A categorical variable capturing severity of self-reported drought (e.g., mild, severe).

While perceived drought variables reflect important behavioral and psychological aspects of drought exposure, they may be influenced by recall bias, expectation shifts, or media narratives – and are therefore not necessarily exogenous. In contrast, objective precipitation is not shaped by household behavior or perceptions. Although it may correlate with income as an outcome of weather variability, it is not influenced by income-related characteristics such as wealth, education, or expectations, making it more appropriate for causal analysis.

6.1.2 Why precipitation is used for causal interference

The central identification strategy relies on objective precipitation measures. These vary within households over time and are assumed to be exogenous to household decisions, conditional on household and year fixed effects. This approach isolates the variation in rainfall that is not driven by household-level factors or common shocks across years.

As shown at the end of Section 4, the correlation between perceived drought and actual precipitation is positive when year fixed effects are omitted but becomes significantly negative once they are included. This reversal suggests that subjective drought measures are shaped by influences beyond local rainfall variation, including year-specific conditions that may affect how drought is perceived or recalled. These influences can confound the relationship between drought exposure and outcomes if not properly accounted for. In contrast, objective precipitation is not affected by such perception-driven dynamics and provides variation that is more plausibly independent of household behavior. The fixed effects approach further strengthens this identification strategy by accounting for time-invariant household traits and shared temporal shocks, reinforcing the use of precipitation as the primary variable for causal analysis.

This strategy is consistent with work such as Musungu et al. (2024) who use rainfall variation in fixed-effects models to identify the impact of weather shocks. In this thesis, precipitation serves as the primary explanatory variable for causal analysis, while perceived drought measures are included as supplementary variables for understanding behavioral responses and validating patterns of exposure.

6.2 Main model specification

To estimate the effect of drought on household income composition and income diversification, a two-way fixed-effects panel regression model is employed. This approach controls for time-invariant unobserved heterogeneity at the household level, as well as for year-specific shocks that may affect all households simultaneously.

The baseline model is specified as follows:

$$Y_{it} = \beta Drought_{it} + \delta' X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes the outcome variable for household *i* in year *t*. It represents a range of household income outcomes. Specifically, the outcome variables include the share of income derived from various sources, including crop production, livestock products, livestock sales, own-business activities, wage employment, environmental products, remittances, transfers from NGOs or government, payments for ecosystem services or nature conservation, rental income, and other sources. In addition to these source-specific shares, the Simpson's Diversity Index is used to measure the degree of income diversification across income streams (Asfaw et al. 2019). Higher values indicate a more balanced distribution of income across sources. The main explanatory variable of interest, $Drought_{it}$, is defined in four ways: as total annual precipitation (in millimeters), relative precipitation (defined as the annual rainfall to the 30-year historical average of that location), a binary indicator of whether the household reported experiencing a drought, and a categorical measure of self-reported drought severity. The drought variables refer to the 12 months preceding the survey date. The vector X_{it} includes time-varying household-level control variables such as household size, age and education of the household head, livestock ownership, and other socioeconomic factors. The term α_i represents household fixed effects, which control for all time-invariant unobserved household characteristics, while γ_t denotes year fixed effects that capture time-specific shocks common to all households. To ensure conservative inference, each model is estimated using both heteroskedasticity-robust and household-clustered standard errors, with the larger of the two reported. This accounts for potential issues related to both non-constant variance and within household correlation over time.

6.2.1 Incorporating soil conditions

To examine whether the relationship between precipitation and income composition is influenced by local drought vulnerability[6], an interaction term between precipitation and soil sand content is introduced. Sand content serves as a proxy for soil texture, with higher values indicating lower water retention and greater sensitivity to rainfall variability. This interaction term enables testing whether precipitation effects vary depending on underlying soil conditions. In areas with sandier soils, weaker effects of precipitation are expected, since lower water retention limits the benefits of additional rainfall.

Since soil texture is time-invariant at the household level, incorporating it into a fixed-effects model would lead to its full absorption. To address this, the interaction model is estimated without household fixed effects but retain the full set of control variables. The model is estimated using heteroskedasticity-robust standard errors. This approach allows for the exploration of heterogeneity in the relationship between precipitation and income outcomes across different soil conditions.

[6] Local drought vulnerability refers to how soil properties – specifically sand content – affect the capacity to retain water, thereby influencing the severity of drought impacts under low rainfall conditions.

6.2.2 Additional Analysis: Regression on income share changes conditional on prior drought exposure

To complement the panel-fixed effects analysis, an additional analysis examines whether households that experience drought in 2019 adjust their income composition and income diversification differently between 2019 and 2023. This approach allows for the identification of longer-term patterns in household income adjustments following a climate shock. Affected households may be expected to shift away from climate-sensitive income sources and increase reliance on more stable income streams or diversify to new income sources between 2019 and 2023.

The change in income share, as well as the Simpson's Diversity Index between 2019 and 2023, is calculated for each household. These change variables serve as the dependent variables in a series of regressions, where the explanatory variable is the binary perceived drought variable that indicates whether a household experienced a drought in 2019. The model also includes a set of control variables measured in 2019. The empirical model is specified as:

$$\Delta Y_i = \beta Drought_i + \delta' X_i + \varepsilon_i \tag{2}$$

where ΔY_i denotes the change in the income share or diversification index of household i between 2019 and 2023. $Drought_i$ is a binary variable equal to reporting a drought in 2019. X_i is a vector of household characteristics measured in 2019, including household size, age and marital status of the household head, education, cultivated land area, land tenure type, total livestock units (TLU), asset index, and sand content of the soil. Robust standard errors are used in all regressions to account for heteroskedasticity.

7. Results

This section presents the main empirical findings on how drought affects income composition in Namibia.

7.1 Effects of precipitation and relative precipitation

The regression results using precipitation and relative precipitation (Table 5) do not show statistically significant effects on any income category or on income diversification. These results suggest that, within this specification, rainfall variation does not exhibit a robust relationship with household income composition or diversification. While none of the effects are statistically significant, the coefficients for relative precipitation tend to be larger in magnitude than those for absolute precipitation, indicating that relative rainfall measures may be more sensitive to changes in income structure – though the evidence remains insignificant.

Table 5. Fixed-effects regression results for the effects of precipitation and relative precipitation on income shares and diversification

	Precipitation	Relative Precipitation
Crop production	-0.0004	-0.2152
	(0.0002)	(0.1409)
Livestock products	0.0000	0.0061
	(0.0001)	(0.0643)
Livestock sales	0.0000	0.0148
	(0.0004)	(0.2559)
Own-business activities	-0.0005	-0.3370
	(0.0005)	(0.2987)
Wage employment	0.0008	0.4900
	(0.0007)	(0.4224)
Environmental products	-0.0001	-0.0900
	(0.0003)	(0.1886)
Remittances	-0.0001	-0.1147
	(0.0005)	(0.3196)
Transfers from NGOs and Government	0.0003	0.2320
	(0.0008)	(0.4773)
PES and nature conservation	0.0001	0.0507
	(0.0000)	(0.0312)
Rental income	0.0001	0.0461
	(0.0001)	(0.0590)
Other sources	-0.0003	-0.1637
	(0.0003)	(0.1819)
Simpson's Diversity Index	-0.0007	-0.4299
	(0.0004)	(0.2651)
Observations for each regression	1,154	1,154

*Note: Coefficients marked with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors, reported in parentheses, are used. All models include household and year fixed effects. The dependent variables are listed in the first column; the independent variables are shown at the top of each column. Each regression includes 1,154 observations after excluding 150 observations with missing values in at least one explanatory variable. Of these, 68 were dropped due to missing precipitation data resulting from unavailable household GPS coordinates. The remaining 82 were excluded due to missing values in control variables. Missingness appears to be random and not systematically related to the dependent variable. Results are robust to clustering at household level; see Appendix Table A2.*

To assess whether soil characteristics influence household responses to rainfall variability, an interaction model was estimated using a pooled OLS with robust standard errors. This approach allows for the inclusion of time-invariant variables such as sand content, which cannot be estimated in fixed-effects models due to their lack if within variation.

The results in Table 6 indicate that the interaction between relative precipitation and sand content significantly affects specific income sources, particularly livestock sales and other income. For livestock sales, both the relative precipitation and sand content show positive associations with income share. However, the interaction term is negative and statistically significant, showing that the association between precipitation and livestock income share is weaker in areas with higher sand content. A similar pattern emerges for income from other sources, where both precipitation and sand content are positively associated with income share, while the interaction term is significantly negative, again showing that the benefits of rainfall are attenuated in sandy regions.

For rental income, both precipitation and sand content are negatively associated with income, while the interaction term is positive and marginally significant. No significant effects are observed for other income categories or for the Simpson's Diversity Index. These results are based on relative precipitation. An alternative specification using absolute precipitation is provided in Appendix Table A3, with similar patterns but with smaller effect sizes.

Since household fixed effects are not included in this specification, the estimates may also reflect unobserved, time-invariant household characteristics that correlate with both soil conditions and income composition. As a result, the interaction effects should be interpreted with caution, as they may capture not only heterogeneity in precipitation response but also other unobserved household traits.

Table 6. Pooled OLS regression results: Interaction effects of relative precipitation and sand content on income shares and diversification

	Relative Precipitation	Sand Content	Interaction term
Crop production	0.0249	0.0035	-0.0034
	(0.4338)	(0.0068)	(0.0103)
Livestock products	-0.0774	-0.0002	0.0006
	(0.2674)	(0.0040)	(0.0060)
Livestock sales	2.0282**	0.0256**	-0.0439**
	(0.8406)	(0.0107)	(0.0182)
Own-business activities	-0.1570	-0.0034	0.0053
	(1.1174)	(0.0157)	(0.0250)
Wage employment	0.1030	-0.0035	0.0069
	(1.3445)	(0.0181)	(0.0299)
Environmental products	-0.3155	-0.0040	0.0058
	(0.5794)	(0.0080)	(0.0128)
Remittances	-0.5280	0.0012	-0.0037
	(1.3593)	(0.0191)	(0.0298)
Transfers (NGOs/Government)	-1.2352	-0.0259	0.0427
	(1.6843)	(0.0233)	(0.0373)
PES and nature conservation	-0.0535	-0.0006	0.0010
	(0.0399)	(0.0005)	(0.0009)
Rental income	-0.5515*	0.0082*	0.0110*
	(0.2987)	(0.0046)	(0.0065)
Other sources	1.6109**	0.0206**	-0.0335**
	(0.7376)	(0.0095)	(0.0162)
Simpson's Diversity Index	0.0882	0.0008	0.0009
	(0.8483)	(0.0117)	(0.0189)
Observations for each regression	1,120		

*Note: Coefficients marked with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors, reported in the parentheses, are used. Relative precipitation is calculated as the deviation from the long-term mean (1988–2018) for the respective household location. The dependent variables are listed in the first column; the independent variables are shown at the top of each column. Interaction term tests whether the effect of precipitation varies by sand content. Each regression includes 1,120 observations after excluding 184 observations with missing values in at least one explanatory variable. Of these, 68 were dropped due to missing precipitation data resulting from unavailable household GPS coordinates. The remaining 116 were excluded due to missing values in control variables. Missingness appears to be random and not systematically related to the dependent variable. Results from the model using absolute precipitation instead of relative precipitation are presented in the appendix; see Appendix Table A3. The direction of effects is consistent, though effect sizes are smaller.*

7.2 Effects of self-reported drought measures

The analysis using self-reported drought indicators (Table 8) show more significant effects compared to the precipitation measures. Income from "other sources" shows a significant decline both under the binary drought measure and under severe drought conditions. Livestock sales significantly increase in the context of mild droughts, while environmental products significantly decrease.

The Simpson's Diversity Index of income diversification shows a negative and statistically insignificant coefficient under mild drought, whereas the coefficients for the other drought categories are close to zero. The effects vary across income sources and level of drought severity, indicating heterogenous responses.

Table 7. Fixed-effects regression results using self-reported drought indicators

	Drought binary	Drought mild	Drought severe
Crop production	-0.0000	0.0080	-0.0005
	(0.0100)	(0.0089)	(0.0103)
Livestock products	0.0025	-0.0047	0.0030
	(0.0052)	(0.0075)	(0.0054)
Livestock sales	0.0100	0.1081*	0.0040
	(0.0205)	(0.0615)	(0.0202)
Own-business activities	0.0163	-0.0520	0.0207
	(0.0264)	(0.0880)	(0.0272)
Wage employment	0.0090	0.0421	0.0069
	(0.0295)	(0.0615)	(0.0300)
Environmental products	-0.0173	-0.1185**	-0.0109
	(0.0140)	(0.0602)	(0.0136)
Remittances	-0.0090	-0.0875	-0.0038
	(0.0254)	(0.0641)	(0.0259)
Transfers (NGOs/Government)	0.0362	-0.0845	0.0439
	(0.0393)	(0.1016)	(0.0400)
PES and nature conservation	0.0007	0.0002	0.0008
	(0.0020)	(0.0024)	(0.0020)
Rental income	-0.0038	0.0060	-0.0045
	(0.0043)	(0.0053)	(0.0044)
Other sources	-0.0578***	0.0444	-0.0643***
	(0.0171)	(0.0545)	(0.0171)
Simpson's Diversity Index	0.0047	-0.0560	0.0085
	(0.0178)	(0.0447)	(0.0181)
Observations for each regression	1,218	1,218	1,218

*Note: Coefficients marked with *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors, reported in the parentheses, are used. The dependent variables are listed in the first column; the independent variables are shown at the top of each column. Each regression includes 1,218 observations after excluding 86 observations with missing values in the control variables. Missingness appears to be random and not systematically related to the dependent variable. Results are robust to clustering at household level; see Appendix Table A4.*

7.3 Changes in Income Shares and Diversification Following the 2019 Drought

This section shows the results from the regression analysis on income share changes and income diversification between 2019 and 2023, conditional on whether households experienced drought in 2019 (Table 9).

The results indicate that households affected by drought in 2019 experienced a statistically significant increase in crop income and other income, compared to those not affected. This pattern is consistent with a shift in income composition among drought-affected households between 2019 and 2023.

In contrast, the share of income from transfers (including from NGOs and government) shows a significant decline among households that reported a drought. No statistically significant effects were found for the remaining income categories or for the Simpson's Diversity Index index.

Table 8. First-difference regression results: Effect of 2019 drought exposure on changes in income composition between 2019 and 2023

	Drought binary
Crop production	0.0348**
	(0.0155)
Livestock products	-0.0019
	(0.0077)
Livestock sales	0.0097
	(0.0261)
Own-business activities	-0.0028
	(0.0388)
Wage employment	-0.0671
	(0.0411)
Environmental products	0.0208
	(0.0185)
Remittances	0.0280
	(0.0373)
Transfers (NGOs/Government)	-0.1225**
	(0.0500)
PES and nature conservation	0.0032
	(0.0023)
Rental income	-0.0045
	(0.0089)
Other sources	0.1234***
	(0.0300)
Simpson's Diversity Index	0.0101
	(0.0256)
Observations	596

*Note: Coefficients marked with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors, reported in the parentheses, are used. The dependent variables are listed in the first column; the independent variables are shown at the top of each column. Each regression includes 596 observations after excluding 56 with missing values in the control variables. Missingness appears to be random and not systematically related to the dependent variable. The dependent variables are calculated as changes in income shares between 2019 and 2023; therefore, only one observation per household is used.*

8. Mechanisms and discussion

This section explores the mechanisms behind the observed relationships between drought and household income composition, as well as the broader implications of these findings. It is structured into four subsections. Section 8.1 focuses on the contrasting results between precipitation and self-reported drought measures in the main model. Section 8.2 investigates the role of environmental vulnerability, focusing on how soil conditions moderate the effect of rainfall. Section 8.3 examines longer-term changes in income composition following the 2019 drought, identifying signs of partial recovery but limited transformation. Finally, section 8.4 discusses structural constraints that limit adaptation, drawing implications for drought resilience and policy recommendations.

8.1 Objective and perceived measures

Although total precipitation was similarly low in 2019 and 2023 (Table 4), perceived drought exposure differed markedly, with 76.5% of households reporting drought in 2019 versus only 28.5% in 2023 (Table 3).

The lack of statistically significant effects from precipitation measures likely reflects limited variation between the years. Moreover, annual precipitation totals do not capture key factors such as rainfall timing or alignment with agricultural needs, which limits their usefulness for identifying behavioral responses. Torres et al. (2019) show that the timing of rainfall is an important economic variable, and that models based only on annual totals tend to underestimate the economic impacts of water scarcity. Furthermore, it is also possible that households have limited time to adjust income-generating strategies within the 12-month reference period, meaning that coping or adaptation responses may not yet be fully reflected in observable income changes.

The model using self-reported drought does show responses in income composition in contrast to the models based on precipitation. Drought exposure seems to have a negative effect on environmental products such as wild foods and firewood under mild drought conditions, likely due to reduced availability or access to natural resources. In the original survey of the panel data, many households report that too many people were collecting these resources, making them increasingly scarce during dry periods.

Income from “other sources”, though this variable is undefined in the dataset, likely includes irregular earnings such as occasional labor or single payments. Their sensitivity to drought suggests that these sources are particularly vulnerable during environmental shocks.

Livestock sales increase significantly under mild drought, supporting Hypothesis 1, which suggests that livestock can act as a short-term buffer. This pattern aligns with previous findings showing that farmers often sell livestock to cope with drought-induced shortages (Danso-Abbeam et al. 2024). However, this effect does not hold under severe drought conditions, which could reflect constraints such as depleted herds, poor market access, or animal health issues. This aligns with prior findings that livestock productivity, fertility and health decreases as drought impacts livestock (Bahta & Myeki 2022). The time required for the heard to recover is determined by the severity of the drought and might also affect livestock income after a drought accrued (Angassa & Oba 2013). A further constraint is the presence of Foot-and-Mouth Disease (FMD), which is endemic in the Zambezi region and partly driven by wildlife-livestock interactions, especially with large buffalo populations (Ashipala 2023). Low annual precipitation increases the risk of FMD outbreaks, as livestock movements in search of pasture and water raise transmission likelihood (Ayebazibwe et al. 2010). These conditions reduce animal health and limit access to regional beef markets, further constraining livestock sales as a coping strategy during severe droughts (Ashipala 2023).

The Simpson's Diversity Index does not show significant changes under any drought category. This suggests that while households adjust the composition of their income in response to drought, these changes are either to small in scale or represent shifts between existing sources rather than the addition of new ones. Since the Simpson's Diversity Index reflects both the number of income sources and the evenness of their distribution, such reallocation does not necessarily increase diversification (Asfaw et al. 2019).

8.2 Environmental vulnerability

Even when households receive similar amounts of rainfall, their ability to benefit from it depends on local environmental conditions, such as soil quality, water access, and crop choices (Kurukulasuriya & Mendelsohn 2007). Soil quality mediates how effectively households can convert rainfall into income. The interaction between precipitation and sand content reveals that rainfall benefits are weaker in areas with sandy soils – due to poor water retention capacity – particularly for income from livestock and "other sources". This suggests that even when rainfall increases, households in ecologically fragile zones are less able to use it due to the soil's inability to retain moisture. This is consistent with findings that soil texture can dominate moisture availability and reduce the productivity of rainfall (Dong & Ochsner 2018).

For rental income, the interaction term suggests a different pattern: while rainfall is negatively associated with rental income in low sand areas, this effect becomes more positive as sand content increases. This may reflect temporary or opportunistic land use when rainfall makes otherwise marginal land more usable, although the mechanism is less clear and may warrant further investigation.

These findings highlight that environmental conditions shape not only exposure to drought, but also the extent to which households can benefit from favorable rainfall. In areas with sandy soils, even improved precipitation may offer limited income gains due to poor water retention and reduced productive potential. Adaptation strategies must therefore consider not just rainfall variability but also underlying environmental constraints that limit the productive response to precipitation.

8.3 Longer-term patterns: Recovery without transformation

The model examining changes in income shares between 2019 and 2023 shows that households affected by drought in 2019 made modest but statistically significant adjustments in their income composition over time. The households affected show an increase in income from crops and “other sources”, alongside a decline in transfers form NGOs and government.

The observed increase in crop income may reflect better rainfall timing in 2023, particularly during crop maturation. March 2023 experienced substantially more rainfall than March 2019 (26.3 mm vs. 2.6 mm, Figure 2), which may have supported kernel development and improved yields. As Zhang et al. (2019) show, water availability during the late reproductive stage – specifically grain filling and maturation – is critical for determining final yield, with water stress during this stage having a direct and significant impact on grain weight.

At the same time, this increase is more likely to reflect a partial recovery from the more severe drought conditions in 2019 than a broader improvement in agricultural performance. This interpretation is consistent with the findings from the fixed-effects models using both objective and self-reported drought indicators (Tables 5 and 7), which show no statistically significant effect of drought on crop income across the sample.

While this increase in crop income may appear to reflect a positive trend, it is somewhat counterintuitive, as one might expect households to reduce their reliance on farming under ongoing drought conditions. However, for many in the region, crop production remains a core livelihood activity. As largely subsistence-oriented farmers, they may continue cultivating even under unfavorable conditions, because they have few viable alternatives.

In this context, even modest improvements in harvest outcomes – despite dry conditions – can shape how drought severity is perceived. Many households who reported a drought in 2019 did not report one in 2023, even though overall rainfall levels were similar. This may suggest that farmers perceived 2023 as less severe because the rainfall, while still limited, better aligned with crop needs and supported production.

The increase in "other sources" may reflect a continued or renewed reliance on flexible and irregular sources of earnings over time. As discussed in Section 8.1, these income sources are assumed to be informal or seasonal and may indicate limited access to more stable livelihood options. While such income can help households bridge short-term gaps, it offers little protection against prolonged or repeated shocks.

The decline in NGO and government transfers stands out, especially given that 2023 was also a dry year. One possible explanation is that the 2019 drought was more widely recognized as a national crisis. It was officially declared a state of emergency and received significant media and government attention, with around one-third of the Namibian population reportedly requiring drought relief at the time (Shikangalah 2020). In contrast, although conditions in 2023 were also dry, they may have drawn less public and institutional response. This difference in visibility and urgency could explain the reduction in external support, as attention and resources in 2023 may have been directed toward other pressing challenges, such as pandemic recovery and economic instability. This pattern offers only partial support for Hypothesis 2, which expected external transfers to compensate for lost agricultural income during droughts. While such support was indeed more prevalent in 2019, its decline in 2023 – despite similarly dry conditions – suggests that these safety nets are not consistently available. This interpretation is consistent with findings that NGO interventions are commonly used as drought-risk management strategies among smallholder farmers. For example, Danso-Abbeam et al. (2024) report that over 50% of farmers in their study relied on NGO or government assistance, although the availability and consistency of such support can vary significantly over time.

Despite the observed changes in specific income shares, there is also in this model no evidence of increased income diversification. While some adjustment has occurred, it appears to be relatively contained and may reflect coping rather than adaptation.

8.4 Structural limits to adjustment and implications for adaption

Across the models, households adjust their income shares in response to drought, but withing existing strategies rather than through structural transformation. This result stands in contrast to Hypothesis 3, which anticipated greater diversification in response to drought as a strategy to reduce vulnerability. In this case, households appear to rely on adjusting existing sources rather than expanding their income base.

One possible explanation for the relatively modest changes observed between 2019 and 2023 could be that many households had already adjusted their income strategies in response to earlier shocks. Chuang (2019) shows that farmers living in historically more variable climates were more likely to have diversified ex-ante and therefore exhibited weaker behavioral responses to subsequent events. In Namibia, a series of severe droughts over the past decade – including in 2013, 2015–2016, and 2019 (Liu & Zhou 2021) – may have exhausted many adaptation options, leaving little room for further shifts by 2023.

This interpretation is further supported by the absence of increased income diversification, following the drought exposure. While previous studies suggest that households may diversify as a risk management strategy (Salazar-Espinoza et al. 2015; Arslan et al. 2017; Asfaw et al. 2019), this thesis finds no significant effect on the Simpson's Diversity Index. The index remains stable across all drought categories, suggesting that households adjusted income shares within an existing set of sources rather that expanding to new ones.

Beyond prior exposure, structural barriers likely prevent larger changes. As Eriksen and Silva (2009) note, poorer households often face substantial barriers to entering higher-return non-farm activities, particularly during drought years. Factors such as lack of capital, limited education or skills, and poor access to markets or infrastructure likely restrict the range of viable coping strategies. These structural constraints also help explain the limited evidence for Hypothesis 4, which anticipated that households would shift labor from agriculture to non-farm activities such as wage labor or self-employment.

These findings relate to a broader discussion in the literature about the nature of livelihood diversification in rural contexts. While diversification is often cited as an adaptation strategy, its persistence and effectiveness vary depending on access to assets, vulnerability to shocks, and local economic opportunities. Musumba et al. (2022) similarly emphasize that in low-resource environments, livelihood responses are often bounded by pre-existing vulnerabilities and limited adaptive capacity.

Objective drought indicators, such as annual or relative precipitation, do not consistently explain income changes in this study. This contrasts with findings from other contexts (e.g. Chuang 2019) were rainfall shocks lead to diversification. In this case, precipitation alone appears to be a weak predictor of behavioral responses. Once the sand content of the soil is considered, a more differential pattern can be seen. Precipitation interacts with soil conditions to influence outcomes, showing that adaptation is partly determined by environmental factors. This aligns with Liu et al. (2016), who emphasize that agricultural drought cannot be understood through meteorological indicators alone, as it results from the complex interplay between weather patterns, soil properties, crop needs, and farm management practices.

Moreover, in this study self-reported drought exposure seems to be a better predictor of income shifts. While it does not describe the physical conditions more accurately, it indicates that how drought is experienced and perceived also plays a key role in shaping behavior.

These insights have clear implications for policy. First, drought monitoring and early warning systems should include not just total precipitation, but also rainfall timing and local environmental factors such as soil characteristics. While current systems often focus on meteorological and hydrological data (Liu et al. 2016), the inclusion of household-level perceptions and ecological context could enhance the accuracy and relevance of drought assessments. Second, support strategies must go beyond short-term relief to address the structural barriers that limit household flexibility. Investments in infrastructure, market access, credit, and skill development are crucial to enabling broader adaptation. Finally, targeted interventions in ecologically vulnerable areas – such as sandy soil zones – could help households better absorb and respond to drought shocks over time.

In short, strengthening resilience to drought requires recognizing that vulnerability is shaped not only by climate events, but also by the social, economic, and environmental conditions under which those events are experienced. Effective adaptation policy must engage with all aspects.

9. Limitations

While the study gives insights into how rural households in Namibia's Zambezi region adjust their income composition in response to drought, several limitations should be acknowledged. These limitations relate to the data, measurement and modeling strategies, as well as the scope and generalizability of the findings.

9.1 Data and temporal limitations

The analysis is based on two survey rounds conducted in 2019 and 2023. Both years where comparably dry, meaning that the data does not include observations from a favorable year. This restricts the ability to fully capture the effects of climatic variation on income composition.

The precipitation data used in the analysis comes from the CHIRPS dataset, a widely used satellite-based product combining remote sensing and station data. While CHIRPS is valuable in regions with sparse weather station coverage, its estimates represent rainfall averages over grid cells of roughly 5 km * 5 km. This spatial averaging may fail to capture small scale variability in rainfall which can be relevant for household level agricultural and livelihood outcomes. Although the Zambezi Region is relatively flat and does not present terrain-related challenges for satellite measurement, the scale may still introduce measurement error and weaken the estimated relationship between rainfall and income outcomes.

Furthermore, soil sand content, used in the interaction model as a proxy for environmental vulnerability, is time-invariant. This means that any changes in soil quality or land degradation over the period studied are not reflected in the analysis.

9.2 Measurement and Survey Limitations

Several variables in the study, including drought exposure and income sources, are self-reported by households. While this provides valuable insight into perceived vulnerability and lived experience, such response might be subject to recall bias, differences in interpretation, or social desirability effects.

The Simpson's Diversity Index is used to measure income diversification, but it may not fully reflect temporary, seasonal, or informal shifts in household income activities. Small within-category adjustments or intermittent income sources might not be captured, potentially underestimating the extent of short-term adaptation.

9.3 Scope and generalizability

The analysis focuses on a single region in northeastern Namibia. While this provides detailed, context specific insights, the findings cannot be generalized to the entire country, which includes diverse agro-ecological zones, livelihood systems, and institutional environments. Generalizing to other drought-prone countries must also be done with caution, as drought experiences, coping mechanisms, and support structures differ widely across contexts. However, the mechanisms identified here – such as the role of livestock as a buffer or the limits to diversification – may still offer some useful insights into how smallholder farmers adapt to drought in other settings with similar environmental and institutional characteristics.

10. Concluding Remarks

This thesis examines how drought affects the composition and diversification of smallholder household income in Namibia's Zambezi region. By combining objective measures of precipitation with self-reported drought experiences, it offers a nuanced perspective on how droughts shape rural livelihoods. Drawing on panel data from 2019 and 2023, the analysis reveals that while precipitation levels alone do not significantly alter income structures, subjective drought exposure is associated with changes in income sources, such as reduced income from environmental products and other income, and an increased reliance on livestock sales as coping mechanisms.

One of the central contributions of this study is its comparative analysis of objective and perceived drought indicators. The findings suggest that self-reported droughts better predict behavioral responses than precipitation-based measures, underlining the importance of local perception in shaping adaptive strategies. In this thesis, this pattern may be partly driven by the fact that both survey years are comparably dry, limiting the variation in objective rainfall indicators and highlighting the added value of the subjective assessment. This highlights a gap in conventional climate risk assessments, which often overlook subjective experiences that directly inform household decision-making.

Despite the changes in income composition, the thesis finds little evidence of increases in income diversification. The Simpson's Diversity Index remains relatively stable, suggesting that most households adjust within existing livelihood structures rather than expanding into new income-generating activities. This pattern reflects both prior exposure to repeated droughts and structural barriers such as limited market access, capital constraints, and low levels of education or skills. The interaction analysis further demonstrates that environmental vulnerability – particularly sandy soils with low water retention – can weaken the positive effects of rainfall, reinforcing the idea that adaptation capacity is deeply context-dependent.

These findings point to several important implications. While drought relief programs from the government and NGOs play a critical role in helping households cope with immediate shocks, they are not sufficient on their own. To support more resilient and forward-looking adaptation, policy efforts must complement short-term assistance with long-term structural investments. These include improving access to education, infrastructure, financial services, and off-farm employment opportunities. In ecologically vulnerable areas such as Namibia's Zambezi region, targeted support is especially needed to ensure that rural households are not only better protected during droughts but also better equipped to pursue sustainable and diversified livelihoods over time.

Future research could build on this study by incorporating more detailed temporal data, particularly on intra-annual rainfall patterns, to better capture the timing of drought impacts. Including data from a year with more favorable rainfall conditions would offer a clearer contrast to dry years and allow for a deeper understanding of coping, adaptation and recovery processes. Moreover, integrating qualitative data on household perceptions, coping narratives, and institutional support could deepen our understanding of how drought experiences translate into livelihood decisions. As climate change continues to reshape rural environments, research and policy alike must move beyond emergency relief and address the deeper, structural barriers that limit adaptive capacity. Doing so will be essential to support smallholder households no just in coping with drought, but in building more stable and resilient livelihoods.

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Popular science summary

In Namibia's Zambezi region, smallholder farmers rely heavily on rainfed agriculture and natural resources to sustain their livelihoods. However, droughts – now more frequent and unpredictable due to climate change – pose a serious threat to these rural households. This thesis investigates how drought affects the way families earn their income, specifically whether they diversify their livelihoods to become more resilient. Using detailed data from the same households in 2019 and 2023, the analysis considers both objective measures (like rainfall data) and subjective ones (how people themselves reported experiencing drought). Interestingly, it is the perceived drought that better explained how households adjust their income. Families are more likely to sell livestock or lose income from environmental products like firewood when they felt the impact of drought, even if rainfall levels were similar across years. However, there is little evidence that households took up new income-generating activities or become more diversified over time. Instead, most adapt within existing strategies, likely due to structural constraints such as limited market access, lack of education, and poor infrastructure. The analysis also shows that ecological conditions matter: households on sandy soils, which retain less water, are less able to benefit from rainfall when it occurs. These findings suggest that strengthening rural resilience requires more than just weather monitoring – it calls for policies that address both the environmental and socioeconomic barriers that limit household adaptation. Supporting long-term livelihood security in the face of climate change means investing in education, infrastructure, and local capacity – not just responding to the next drought.

Appendix 1

Table A1. Logistic regression results: Effects of precipitation on self-reported drought

	(1) No Year FE	(2) Year FE
Precipitation	0.0108***	-0.0056***
	(0.0014)	(0.0020)
Observations	1,120	1,120

*Note: Coefficients marked with ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors, reported in parentheses, are used. Both models control for household head's age, marital status, years of education, land size, social capital, and sand content. The independent variable is listed in the first column; columns (1) and (2) show two model specifications using the same binary dependent variable for self-reported drought. Model (2) includes year fixed effects. The final sample includes 1,120 observations after excluding 184 observations with missing values in at least one explanatory variable. Of these, 68 were dropped due to missing precipitation data resulting from unavailable household GPS coordinates. The remaining 116 were excluded due to missing values in control variables. Missingness appears to be random and not systematically related to the dependent variable.*

Appendix 2

Table A2. Fixed-effects regression results using clustered standard errors at the household level

	Precipitation	Relative Precipitation
Crop production	-0.0004	-0.2152
	(0.0002)	(0.135)
Livestock products	0.0000	0.0061
	(0.0001)	(0.0617)
Livestock sales	0.0000	0.0148
	(0.0004)	(0.2456)
Own-business activities	-0.0005	-0.3370
	(0.0005)	(0.2867)
Wage employment	0.0008	0.4900
	(0.0007)	(0.4053)
Environmental products	-0.0001	-0.0900
	(0.0003)	(0.1809)
Remittances	-0.0001	-0.1147
	(0.0005)	(0.3067)
Transfers from NGOs and Government	0.0003	0.2320
	(0.0008)	(0.4580)
PES and nature conservation	0.0001	0.0507
	(0.0000)	(0.0299)
Rental income	0.0001	0.0461
	(0.0001)	(0.0567)
Other sources	-0.0003	-0.1637
	(0.0003)	(0.1745)
Simpson's Diversity Index	-0.0007	-0.4299
	(0.0004)	(0.2543)
Observations	1,154	1,154

*Note: Coefficients marked with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the household level. The dependent variables are listed in the first column; the independent variables are shown at the top of each column. Coefficients are identical to those in Table 6, confirming that results are robust to clustering. For conservative inference, the larger standard errors were reported in the main text.*

Appendix 3

Table A3. Pooled OLS regression results: Interaction effects of precipitation and sand content on income shares and diversification

	Precipitation	Sand Content	Interaction term
Crop production	0.0002	0.0042	-0.0000
	(0.0007)	(0.0064)	(0.0000)
Livestock products	-0.0002	-0.0006	0.0000
	(0.0005)	(0.0047)	(0.0000)
Livestock sales	0.0027**	0.0208*	-0.0001**
	(0.0014)	(0.0107)	(0.0000)
Own-business activities	-0.0005	-0.0056	0.0000
	(0.0019)	(0.0160)	(0.0000)
Wage employment	0.0005	-0.0011	0.0000
	(0.0021)	(0.0171)	(0.0000)
Environmental products	-0.0008	-0.0068	0.0000
	(0.0009)	(0.0078)	(0.0000)
Remittances	-0.0008	0.0020	-0.0000
	(0.0023)	(0.0200)	(0.0001)
Transfers from NGOs and	-0.0021	-0.0251	0.0001
Government	(0.0027)	(0.0229)	(0.0001)
PES and nature conservation	-0.0001	-0.0007	0.0000
	(0.0001)	(0.0005)	(0.0000)
Rental income	-0.0008*	-0.0073*	0.0000
	(0.0004)	(0.0042)	(0.0000)
Other sources	0.0024**	0.0188**	-0.0001*
	(0.0012)	(0.0092)	(0.0000)
Simpson's Diversity Index	0.0003	0.0012	-0.0000
	(0.0014)	(0.0117)	(0.0000)
Observations	1,120		

*Note: Coefficients marked with *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors used. Precipitation is measured as total annual rainfall at the household level. The dependent variable is listed in the first column; the independent variables are shown at the top of each column. The interaction term tests whether the effect of precipitation varies by sand content.*

Appendix 4

Table A4. Fixed-effects regression results using clustered standard errors at the household level

	Drought binary	Drought mild	Drought severe
Crop production	-0.0000	0.0080	-0.0005
	(0.0096)	(0.0086)	(0.0099)
Livestock products	0.0025	-0.0047	0.0030
	(0.0050)	(0.0072)	(0.0051)
Livestock sales	0.0100	0.1081*	0.0040
	(0.0197)	(0.0590)	(0.0194)
Own-business activities	0.0163	-0.0520	0.0207
	(0.0254)	(0.0844)	(0.0261)
Wage employment	0.0090	0.0421	0.0069
	(0.0283)	(0.0590)	(0.0288)
Environmental products	-0.0173	-0.1185**	-0.0109
	(0.0135)	(0.0577)	(0.0130)
Remittances	-0.0090	-0.0875	-0.0038
	(0.0244)	(0.0615)	(0.0249)
Transfers (NGOs/Government)	0.0362	-0.0845	0.0439
	(0.0378)	(0.0976)	(0.0384)
PES and nature conservation	0.0007	0.0002	0.0008
	(0.0019)	(0.0023)	(0.0020)
Rental income	-0.0038	0.0060	-0.0045
	(0.0041)	(0.0051)	(0.0042)
Other sources	-0.0578***	0.0444	-0.0643***
	(0.0164)	(0.0523)	(0.0164)
Simpson's Diversity Index	0.0047	-0.0560	0.0085
	(0.0171)	(0.0429)	(0.0174)
Observations for each regression	1,218	1,218	1,218

*Note: Coefficients marked with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is listed in the first column; the independent variables are shown at the top of each column. Coefficients are identical to those in Table 8, confirming that results are robust to clustering. For conservative inference, the larger standard errors were reported in the main text.*

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