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þÿDrought Patterns and Househo Resilience to Shocks in Sehala Seyemt District of Wag Hemra Administrative Zone, Amhara Region, Ethiopia

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DROUGHT PATTERNS AND HOUSEHOLDS' RESILIENCE TO SHOCKS IN SEHALA SEYEMT DISTRICT OF WAG HEMRA ADMINISTRATIVE ZONE, AMHARA REGION, ETHIOPIA

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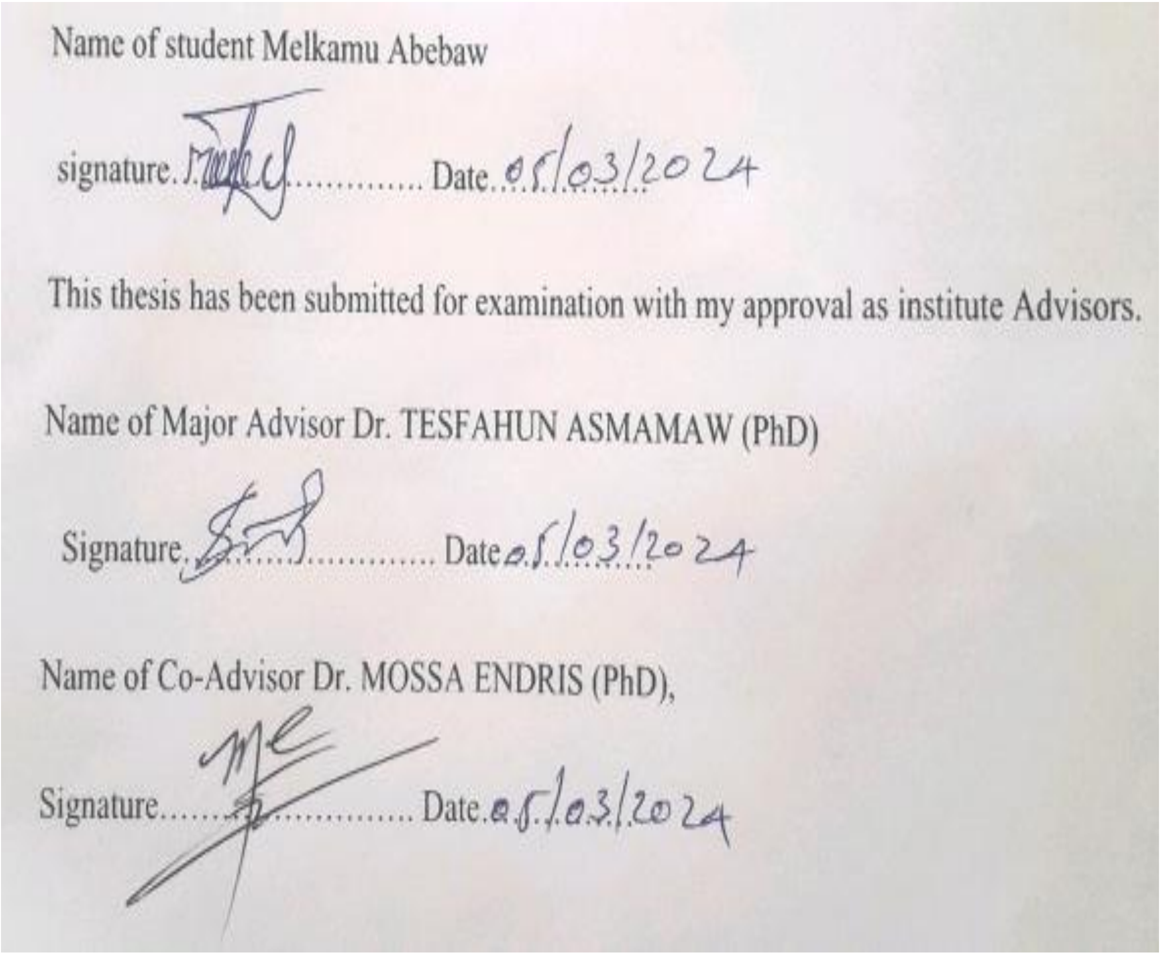
Declaration on originality

I, Melkamu Abebaw, Registration Number/I. D BDU1403142, do hereby declare that this thesis is my original work and that it has not been submitted partially; or in full, by any other person for an award of a degree in any other university/institute.



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APPROVAL SHEET

The undersigned certify that they have read and hereby recommend to the Institute of Disaster Risk Management and Food Security Studies, Bahir Dar University, to accept the Thesis submitted by Melkamu Abebaw entitled “Drought Patterns and Households’ Resilience to Shock in *Sehala Seyemt district* of *Wag Hemra* administrative zone, Amhara region, Ethiopia”, in partial fulfillment of the requirements for the award of a Joint Master’s Degree in Disaster Risk Management and Food System Resilience.

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ABSTRACT

Any attempt to increase the capacities of people who experience shocks from drought and food insecurity regularly must start with a basic comprehension of resilience's roots. The study focuses on households' resilience to drought and shocks in Sehala Seyemt Woreda in Wag Hemra Zone, Amhara region. The study also investigated households' food security status and their interaction with resilience and shocks. The research employed a cross-sectional design with a mixed research approach. The study area was selected purposefully. The woreda embraced thirteen Kebeles. However, the study selected three Kebeles randomly, and a total of 326 respondents were selected using a simple random sampling technique and allocated in proportion to the population size of the Kebeles. Two focus group discussions were also held in each Kebele. The Standard Precipitation Index, multivariate stage confirmatory factor analysis, household multidimensional food insecurity index, and ordinal logistic regression model were employed to analyze the data. The Standard Precipitation Index assessment indicated that drought in the study area had significantly risen between 1992 and 2022. From the confirmatory factor analysis, the household asset index was the most critical positive factor with a factor loading of 0.831 for households being resilient or not, followed by households' access to basic services with a positive factor loading of 0.819 and households' adaptive capacity with a positive factor loading of 0.75. A significant portion (73.31%) of the household lies under moderate resilience and non-resilient status, and a sizeable portion (61%) of the household has moderately and severely food insecure status. The interactive effect of households' resilience pillar and shock exposure on households' food security status indicated that assets, access to basic services, and adaptive capacity possess a negative and highly significant effect on households' food insecurity status, and shock exposure has a significant and positive effect on households' food insecurity status. This study revealed drought concerns affecting households' resilience and food security. Urgent interventions are needed to enhance resilience and address evolving food security dynamics, emphasizing sustainable initiatives to build household coping strategies to shock and bounce back better aftershock occurrence. The findings contribute to the discourse on creating secure, sustainable initiatives and a resilient future.

***Keywords**: Resilience, Drought, Food insecurity, Households, Sehala Seyemt District,*

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ABBREVIATIONS AND ACRONYMS

ABS	Access to basic service
AC	Adaptive capacity
ASAL	Arid and semi-arid lands
AST	Asset
CFA	Confirmatory factor analysis
CSI	Coping strategy index
DD	Dietary Diversity
DFID	Department for International Development
EFA	Exploratory factor analysis
EU	European Union
FAO	Food and agricultural organization
FCS	Food Consumption Score
FDG	Focus Group Discussion
GDP	Growth domestic product
GIS	Geographical Information System
GWP	Global water partnership
HDDS	Household Dietary Diversity score
HFIAP	Household Food Insecurity Access Prevalence
HFIAS	Household food insecurity access scale
HH	Household Head
HHS	Household Hunger Scale
KII	Key Informant Interview
MCLZ	Mixed Cereal Livelihood Zone
MFI	Multidimensional food insecurity index
MHFS	Multidimensional Household food security

MIMIC	Multiple Indicator Multiple Cause
MMR	Mixed Method Research
NAPA	National Adaptation Programme of Action
OECD	Organization For Economic Cooperation and Development
PCA	Principal component analysis
PO	Proportional odds
RCI	Resilience Capacity Index
rCSI	Reduced Coping Strategies Index
RI	Resilience index
RIMA	Resilience Index Measurement Analysis
RSM	Resilience structural matrix
SAFS	Self-Assessed Food Security
SEM	Structural equation model
SPI	Standardized Precipitation Index
SPSS	Statistical Package for the Social Sciences
SSN	Social Safety Net
TANGO	Technical Assistance to Nongovernmental Organizations
TLGLZ	Tekeze Lowland Sorghum and Goat Livelihood Zone
TLU	Tropical livestock index
UNICEF	United Nations Children’s Fund
USAID	United States Agency for International Development
WFP	World Food Program
WHO	World Health Organization
WMO	World meteorological organization

CHAPTER ONE: INTRODUCTION

1.1 Background of the study

Drought is a major problem worldwide, especially for poorer countries and vulnerable communities (Abebe et al., 2020). It's difficult to define exactly what drought is, but basically, it means a long time without rain, which can cause water shortages and crop failures and it is the result of the combination of both natural and anthropogenic causes; however, according to Gebremedhin et al. (2020), the anthropogenic cause has increased in the first 21-century and one of the most common natural induced disasters that have a significant influence on the environment, economic, and social situations. Some experts are confident that climate change has already resulted in meteorological droughts that are longer and more intense in some parts of the world, particularly in southern Europe and West Africa.

Drought has many direct and indirect impacts on various sectors, and it is a normal recurring event that affects the livelihoods of millions of people around the world (Getachew, 2018, Juana et al., 2014, Kala, 2017). Over the years, drought has been a growing concern globally due to its debilitating direct and indirect effects on livelihoods (Bekele et al., 2014) and it is a covariate or widespread phenomenon that can cross international borders, rendering informal risk management arrangements ineffective. The most difficult climate hazard and threat to food security is drought (Twongyirwe et al., 2019). There are three times as many people affected by drought in Africa as there are by all other natural-induced disasters combined (Dinkelman, 2017).

Ethiopia experiences drought regularly with adverse effects on various sectors, including agriculture (Bayissa et al., 2019. In Ethiopia, where our study is focused, drought happens often, especially in places like Wag Hemra Zone. These areas depend a lot on rain for agriculture, so when there's a drought, it can lead to not having enough food and needing help from outside (Haftu et al., 2022). Despite this fact, the consequences of shocks resulting from climate variability and the rate of recovery across households are not consistent depending on their resilience capacity (Mengistu et al., 2018). More and more, the idea of resilience is utilized to guide research and programs that focus on households and communities in ecologically unstable environments (Thiede, 2016) and it has quickly become a priority for development (Jones et al., 2018, Jones and Tanner, 2015, 2017).

In Sub-Saharan Africa, food insecurity is a serious issue that exacerbates hunger, malnutrition, and poverty (Yitbarek and Huseyin, 2020, Zone, 2005). The National Adaptation Programme of Action (NAPA) prioritizes agriculture and food security as the most vulnerable sectors to the negative effects of climate change and variability. Food security is one of the most climate-sensitive sectors in the nation (Krishnamurthy et al., 2013). Due to the effects of food insecurity can touch almost every aspect of society, policymakers, practitioners, and academics around the world are extremely interested in the subject (Andrew et al., 2013).

Following the 2015 drought, the Ethiopian government and international donor organizations have stepped up their efforts to strengthen resilience to climate extremes. This has included establishing new government organizations to concentrate on disaster risk reduction and making sure that pertinent parties collaborate closely with the National Meteorological Agency to get accurate forecasts of probable flooding or drought that might prompt early action (Jjemba et al., 2017), but still, it is legendarily known that Wag Hemra zone in general and the study area, in particular, are drought prone due to erratic rain and most households in the society are societies aid dependent livelihoods due to different reasons from those and the main reason is recurrent drought (Tofu et al., 2022).

Most of the people in North Wollo and Wag Hemera depend on food aid. Farmers' reliance on rain-fed agriculture is one of the major causes of the community's extreme food insecurity and poverty in the area (Danie and Firafis, 2021, Daniel et al., 2022). Even if some authors studied the issues of drought, its consequences, and household resilience the issues need updated information since these issues are dynamic characteristics especially since the issue of drought is highly dynamic and results in cascading negative effects on most sectors. Addressing these issues was the motivation to conduct this study and explore the patterns and effects of drought over time and also to understand the household resilience capacity and food security status.

1.2 Problem statement of the study

Ethiopia, situated as one of Africa's nation’s most susceptible to the impacts of recurring droughts, confronts substantial challenges in household resilience, resulting in widespread socio-economic hardships (Danie and Firafis, 2021). Despite a wealth of researchers such as; Asmamaw et al., 2019, Abebe et al. (2020), Kourouma et al. (2022), Beyene et al. (2023), and others examining drought patterns, household resilience, and food insecurity across Ethiopia, crucial research gap exists, hindering a holistic understanding of the interconnected dynamics within the unique context of the Sehala Seyemt District in the Wag Hemra Administrative Zone of the Amhara region.

The multifaceted impacts of drought on household resilience, as evidenced by the studies of FAO (2013) and Viste et al. (2013), necessitate a more nuanced and region-specific exploration. In Ethiopia's predominantly agrarian economy, where rain-fed agriculture is integral to livelihoods, recurrent droughts pose significant challenges to agricultural productivity, food security, and overall household well-being (Bachewe, 2009; Morton, 2007; Sibhatu and Qaim, 2017). These challenges contribute to food deficits, leading to hunger, malnutrition, and undernourishment.

While various studies have investigated climate-related concerns impacting household livelihoods, such as drought a comprehensive understanding of their interconnected effects on resilience and food security in Sehala Seyemt District is lacking. Existing research has focused on specific aspects of these issues (Alinovi et al., 2010; Vaitla et al., 2012, Bayissa et al., 2015; Getachew, 2018; Asmamaw et al., 2019; Liou and Mulualem, 2019; Tefera et al., 2019; Abebe et al., 2020, Kassaye et al., 2021; Senamaw et al., 2021; Haftu et al., 2022, Kourouma et al., 2022; Lelamo et al., 2022; Beyene et al., 2023;), but a holistic approach to unravel the intricate relationships and empirical evidence on the patterns of drought over time yet to be undertaken.

Furthermore, existing studies on household resilience to food insecurity have predominantly utilized limited indicators, creating a methodological gap. While some researchers have employed measures like HFIAS, DD, FCS, and daily calorie intake, there is a lack of international coordination and agreement on methodologies, hindering a comprehensive understanding of how these developments impact household food security uniformly. This necessitates research efforts to bridge this gap by applying a multidimensional food security index, as recommended by Maxwell et al. (2013) and Koyachew and Bamlaku (2021), to gain a nuanced understanding of household food security status. This study aims to fill these critical gaps by undertaking a comprehensive investigation into the interdependence of drought patterns, household resilience, and food insecurity in the Sehala Seyemt District.

1.3 Research Objectives

1.3.1 General Objective

The main objective of this study was to comprehensively explore the dynamics of drought, household resilience, and food security in the Sehala Seyemt District, Ethiopia, and provide insights that can inform policy-making, guide development initiatives, and stimulate further research to address the broader challenges associated with these issues.

1.3.2 Specific Objectives

The specific objectives of the study were:

1. To examine the patterns of drought over time
2. To evaluate households' resilience capacity to shock and food security status
3. To explore the interactive effect of shocks and households' resilience capacity on household food security status

1.4 Research Questions/Hypotheses

The study gathered enough information through data collection and analysis to respond to the following key research questions

1. What is the trend of drought in the study area? Has it increased or decreased?
2. How is the status of households' resilience capacity and their food security status in the study area revealed by the shock?
3. How does the relationship manifest between household resilience capacities, exposure to shock, and the state of food security?

1.5. Significance of the Study

This study was carried out mainly for academic purposes and literature development that adds to the existing body of knowledge by providing insights into drought patterns and the consequences of drought-induced disasters in the study area. This contributes to academic research by offering new data and perspectives on the subject. This can guide future academic studies in developing and refining techniques and this research came up with some important findings/results, which identified the drought patterns and consequences of drought-induced disasters in the study area, adding supportive pieces of literature on the best measurement methods of household food security status, and also show the relationship among household resilience capacity, drought exposure, and food security outcomes and also the findings are expected to contribute to a broader understanding of these complex dynamics, offering insights that can inform to policymakers, decision-makers, and interventions not only in the Sehala Seyemt District but also potentially serve as a model for addressing similar challenges in other regions of Ethiopia and beyond. The findings contribute to a broader understanding of the complex dynamics between household resilience capacity, drought exposure, and food security outcomes. This adds depth to academic discussions and theories related to these topics.

1.6. Scope and Limitations of the study

1.6.1. Scopes of the study

Spatially the study has covered one *District*, which is *Sehala Seyemt District Wag Hemra* administrative zone *Amhara* region Ethiopia specifically three randomly selected *Kebeles*, and the study targeted 326 resident households with key informant interviews and focus group discussion support. Thematically this study comprehended four counted issues:

First, the study explored the patterns of drought over time by employing Standard precipitation index (SPI) drought analysis with 30 years of precipitation input parameter only, which is mostly used to identify meteorological drought. Focus Group Discussion (FGD) and Key Informant Interview (KII) were employed to identify the overall patterns of drought especially the socioeconomic parts of drought. Second, the households' resilience status was analyzed using FAO RIMA II. Depending on the community's context and FAO RIMA IIs recommendation to analyze households’ resilience to shock intermediate outcome variables like Access to basic services, Asset, Adaptive capacity, and social safety net were employed. To uncover latent variables Access to basic services observed variables such as Access to improved water, Access to telecom, Access to irrigation, Access to savings and credit institute, Access to extension service, Access to a paved road, Distance to a health center, Distance to nearest public transport and Distance to the nearest market was employed, to uncover the latent variable Asset, observed variables such as Livestock size in TLU, Cultivable land size, and Non-agricultural and Agricultural wealth index were employed, to uncover the latent variable Adaptive capacity observed variables such as households head Literacy status, households Dependency ratio, Crop diversification index, Livestock diversification index, and Income diversification index were employed, and to uncover the latent variable Social safety net formal and informal transfer in ETB were employed. Third, the household’s food security status was measured using multidimensional food security proxy indicators such as Coping Strategies Index (CSI), Reduced Coping Strategies Index (rCSI), Household Food Insecurity and Access Scale (HFIAS), Household Hunger Scale (HHS), Food Consumption Score (FCS), Household Dietary Diversity Scale (HDDS), and a self-assessed measure of food security (SAFS) were considered and at last but not list to examined the interactive effects of households' resilience capacity and shocks on households’ food security status employed ordinal logistic regression model. Packages of software used for the above four objectives were ArcGIS version 10.8, STATA version 17, SPSS version 27, and SPI. This research was conducted from December/2022 up to February/2024.

1.6.2. Limitations of the Study

Due to the limitation of time, the research employed a cross-sectional research design to study households’ resilience and food security. However, these issues are complex and can change over time. This approach may not fully capture causality or changes over time. Using cross-sectional panel data or a longitudinal design might provide more accurate insights into these multidimensional issues. For the first objective of the research, which focused on drought analysis, reliable station-based precipitation data was desired. However, due to the absence of national meteorological stations in the study district, the research had to rely on remote sensing data instead. This reliance on remote sensing data may introduce limitations in accurately capturing drought patterns. Additionally, utilizing only one method (standard precipitation index) and one input parameter (precipitation) may not be enough to clearly show the drought pattern and comprehensiveness of the analysis. The study's applicability could have been enhanced by including multiple districts with diverse agro-ecological conditions. However, due to time and budget limitations, the research was confined to a single district which has homogeneous agroecology. Consequently, the insights derived may not fully represent the variability present in regions with different agroecological characteristics. The last challenge but not least is unstable peace and inaccessibility of the internet makes it take more than enough time and effort.

1.7. Conceptual framework of the study

The examination of existing literature guides the formulation of a conceptual framework, aiding in the definition of observed variables, latent variables, and both dependent and independent variables. This conceptual framework serves as the groundwork for the data collection process, outlining the necessary information to be gathered, processed, and analyzed. Importantly, this conceptual framework not only supports but also vividly and clearly elucidates the research activity. Consequently, a conceptual framework is established to offer analytical support in understanding household resilience over time, specifically in the face of shocks like drought, and the multidimensional status of household food security in the study area, including their interactions. The conceptual framework for this study builds based on the context of the study area. According to authors like (Alinovi et al., 2010, FAO, 2018, D’Errico and Smith, 2019) households' resilience capacity index (RCI) status is analyzed through four latent variables called resilience pillars such as access to basic service (ABS), asset (AST), adaptive capacity (AC) and social safety net (SSN). Those latent variables are explained by different observed variables selected based on the context of the study community’s lifestyle. So, the observed variables that explain access to basic service are access to improved water, access to telecom, access to irrigation, access to savings and credit institute, access to extension service, access to a paved road, distance to a health center, distance to nearest public transport and distance to the nearest market was employed; the observed variables those used to uncover the latent variable asset Livestock size in TLU, Cultivable land size, Non-agricultural asset index (mobile jewelry (gold, silver) mobile phone Television/Radio and bed (timbre made or “shibo”) and Agricultural wealth index(water pump, plow, workable Moferkenber, sickle, and an ax) were employed. For latent variable adaptive capacity household head literacy status, household dependency ratio, crop diversification index (Millet, Sesame, Teff and Mung bean (local name Masho)), livestock diversification index (ox, milking cow, other Cattel like (Bull and heifer), Donkey and small ruminants) and income diversification index (from crop income from animal production, income from trade, income from rents, income from vegetables and fruits and income from Apicultural products) and observed variables that used to uncovered latent variable social safety net are formal and informal transfer of ETB. Those four resilience pillars are continuous variables and those are intermediate variables that were used as explanatory variables in this study. Another explanatory variable was shock, which is a counted variable that the households experience of different shocks like Severe flooding, Severe drought, Livestock/crop disease, Desert locusts damaged crop/grazing land, Land inaccessible due to conflict, Loss of crops/livestock/tree plantation due to conflict, Sharp food price increase, Unavailability of agricultural or livestock inputs, Sharp increase in the price of agricultural or livestock inputs, Sharp drop in the price of agricultural, livestock or tree plantation products and Death/severe illness of head of household/caregiver in the past five years were employed based on a literature review of Knippenberg and Hoddinott (2019) article. The outcome variable for this study is the Household’s multidimensional food security index (MFI) which was measured through 24 questionnaires developed by Maxwell et al. (2013) and those questionnaires considered seven food security indicators. As mentioned in the article of Tesfahun et al. (2017) Food security is positively affected by household resilience, whereas negatively affected by shocks, and households’ resilience is affected by shocks oppositely.

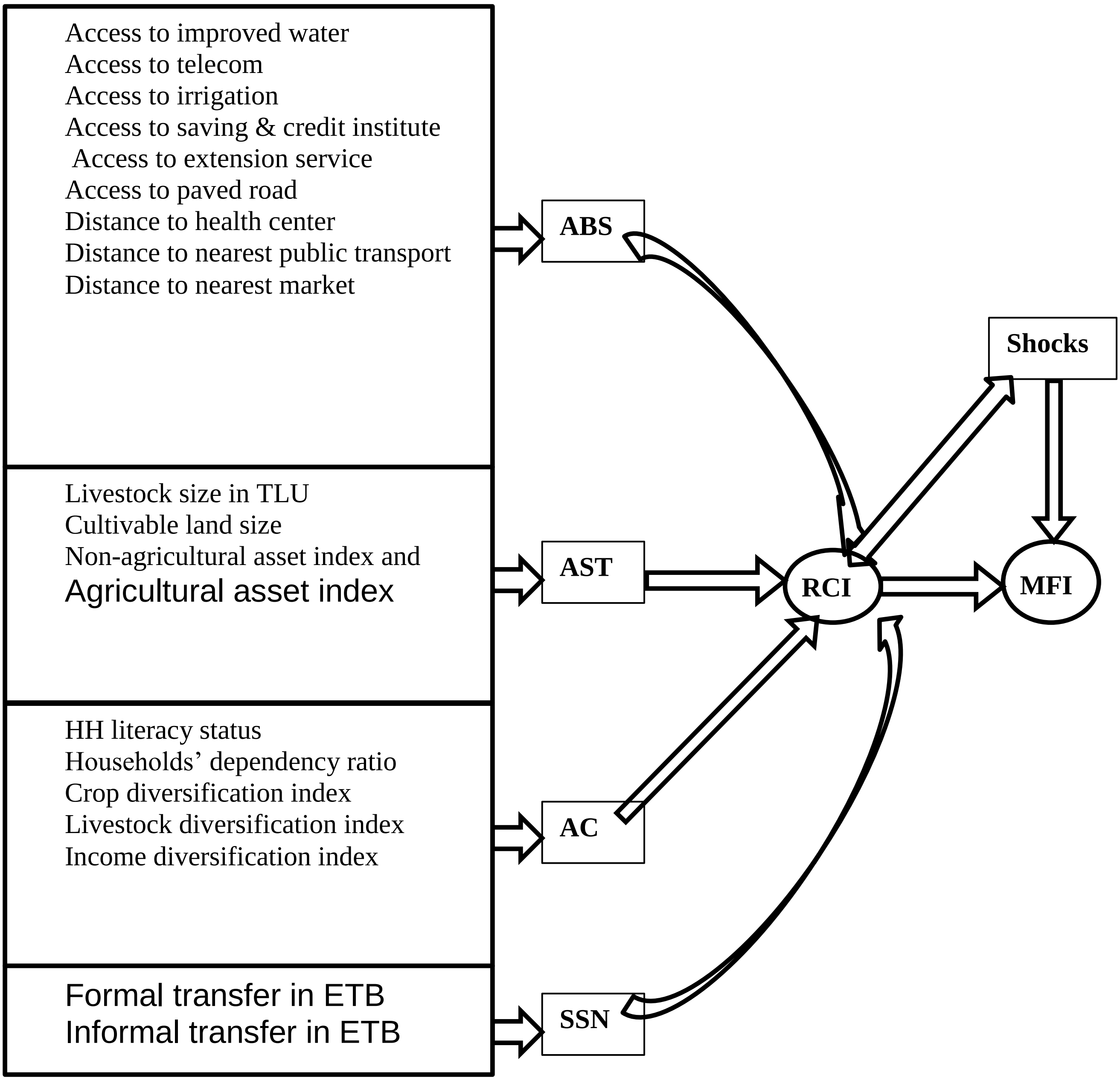

Figure 1:1 Conceptual Framework of the study

Source: Constructed based on the literature reviewed (2023)

CHAPTER TWO: REVIEW OF RELATED LITERATURE

This chapter embarks on the concepts, theories, and robust definitions of the issues raised that are relevant to this study, those related to key terms such as drought, household resilience, and food security. It is obvious that different disciplines provide varied definitions of the terms raised above, but the concepts and definitions included in this research were selected based on their suitability for this study, their inclusiveness, ease of understanding, and their popular use by academicians and practitioners.

2.1. Definition and concepts

Drought: A lack of precipitation over an extended period, typically a season or more, that causes water scarcity for a particular activity, group, or environmental sector is the general definition of a drought (Mekonnen and Gokcekus, 2020). There are two different ways to define a drought: conceptually and operationally. Understanding the concept of drought is essential for a comprehensive grasp of its nature and the implications it carries. The operational definition of drought serves to determine the beginning, end, and severity of the drought (Yitbarek and Huseyin, 2020).

Lloyd-Hughes (2014) noted that drought, according to the Oxford English Dictionary of 2011, is caused by dryness, aridity, or a lack of moisture and the state or quality of dry aridity of the climate or weather; absence of precipitation. Unfortunately, confusing dryness with aridity and weather with climate complicates the situation more than clarifies it.

In advance, a better definition of drought is provided by the World Meteorological Organization's lexicon (1992), which reads as follows: “extended absence or a marked lack of precipitation and period of parched weather that lasted long enough to prevent precipitation and result in a major hydrological imbalance. “The four basic categories of drought are social, agricultural, hydrological, and meteorological (Kim et al., 2015, Meza et al., 2020, Yitbarek and Huseyin, 2020).

Resilience: According to the United States Agency for International Development (USAID), resilience is the capacity of individuals, families, communities, nations, and systems to prepare for, respond to, and recover from shocks and stresses in a way that minimizes long-term vulnerability and promotes equitable progress (Frankenberger et al., 2012). “The capacity to predict, absorb, accommodate, or recover and adapt from crises and disasters in a timely, effective and sustainable manner is referred to as resilience to shocks” (FAO., 2013). According to the European Union (EU), “Resilience is the ability of an individual, a household, a community, a country or a region to withstand, to adapt, and to quickly recover from stresses and shocks (sSassi, 2018).

The UN's Food and Agriculture Organization (FAO) has put up a definition of resilience that emphasizes its applicability to the food and agricultural industry: "Resilience is the capacity to anticipate, absorb, accommodate, or recover from crises and disasters in a timely, effective, and sustainable manner (Dufour et al., 2014).

This study used the FAOs definition B/c it is inclusive, clearly stated and widely used in ample literature, which reads, “Resilience is the capacity to anticipate, absorb, accommodate, or recover from crises and disaster in a timely, effective and sustainable manner”. As a result, it suggests the capacity to overcome the difficulty by changing, learning new skills, and adapting. In countries around the globe that are food insecure or chronically vulnerable, resilience has emerged as a key operational concept (Vaitla et al., 2012).

Food security: “a situation that exists when all people, at All times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life” (Pollard and Booth, 2019).

Food insecurity: “food insecurity is limited or uncertain availability of nutritionally adequate and safe food or limited or uncertain ability to acquire acceptable foods in socially acceptable ways” (Schroeder and Smaldone, 2015).

Exposure: Exposure is the amount of population, livelihoods, assets, resources, services and/or systems that could be affected directly and/or indirectly by a drought event. People frequently discuss how the population has been impacted directly or indirectly. Injuries, illnesses, various health repercussions, evacuation and displacement, as well as economic, social, cultural, and environmental loss, are examples of direct effects. Indirect impacts are additional long-term effects that result in unsafe or unhealthy conditions as a result of disruptions and changes in the economy, infrastructure, society, or people's physical or mental health (Saulnier et al., 2020).

Shock: A disruption in the living conditions that has an adverse impact on the household can be characterized as a shock, as noted by Chiwaula and Waibel (2009).

The standard precipitation index is a powerful, flexible index that is simple to calculate. Precipitation is the only required input parameter (Svoboda et al., 2012).

Asset (AST): Assets are the resources that people have access to in terms of money, technology, and services (such as health care, school etc.) (Cinner et al., 2018).

Access to basic services (ABS): It considers the household's ability to utilize supportive institutional and public service settings (Uexkull et al., 2020).

Adaptive capacity (AC): "Adaptive capacity comprises the properties of a system that enable it to modify itself to maintain or achieve a desired state in the face of perceived or actual stress" (Jakku and Lynam, 2010).

Social safety nets (SSN): It denotes the support system that a household can depend on in times of a crisis (Uexkull et al., 2020).

2.2. Empirical review

2.2.1. Patterns of drought

Both spatial and temporal patterns of drought frequently change, as different authors noted. For example, the report of Cammalleri (2021), indicates that projections show that over many regions of the world, droughts will become more frequent and severe (even more severe than the worst droughts in the period 1981–2010), and also Nooni et al. (2022), Mohammed and Yimam (2021), quoted that under all scenarios, the spatial-temporal pattern and trends indicate that Africa is expected to see changes in drought characteristics.

As reported, risks related to drought are complicated, systemic, and escalating. Such systemic threats are emerging and not immediately obvious. Drought has caused widespread malnutrition, famine, migration, and social conflict in African countries (Hakuza and Waita, 2008). When a year's total amount of rainfall is below average, it can happen during a time when moisture is especially needed for plant growth, like in the early summer. However, in northern Ethiopia, there is not enough moisture and rainfall to grow various sorts of crops throughout the year (Yitbarek and Huseyin, 2020).

The meteorological subsystem (SPEI) initiates drought propagation, which then moves through the agricultural subsystem (SVI) and the hydrologic subsystem (SRI) (Fuentes et al., 2022).

2.2.2. Types of droughts and its characteristic indicators

Different types of droughts have their specific spatiotemporal characteristics (Wang et al., 2016). A drought becomes hazardous when water demands are no longer met (Cammalleri, 2021).

Vast of literature classified droughts into four major types such as meteorological drought, hydrological drought, agricultural drought and socio-economic drought, but some of them were classified into five including ecological drought.

Meteorological Drought: A shortage in precipitation during a specific period and location compared to climatologically average values is known as a meteorological drought. Using meteorological data products on precipitation that are available from national and international weather agencies, meteorological drought can be defined. A typical definition of meteorological drought involves comparing the rainfall in a certain location and period. This occurs when actual rainfall in a region is far lower than the region's climatological mean. Weather-related drought decreases soil moisture, which always has an impact on crop yield (Cammalleri, 2021, Wang et al., 2016, Yitbarek and Huseyin, 2020).

Hydrological drought: is defined as a significant decrease in the availability of water in all its forms appearing in the land phase of the hydrological cycle (Ceglar, 2008, Wang et al., 2016).

The impacts of dry spells on surface or subsurface hydrology are the subject of hydrologic drought rather than the meteorological cause of the incident. The impact of hydrologic drought on river basins is frequently used to determine its frequency and severity. Agricultural and meteorological droughts frequently occur out of phase with hydrologic droughts (Panagoulia and Dimou, 1998).

Agricultural drought: A drought in agriculture happens when the moisture content of the soil is so low that it significantly decreases crop and pasture output. Agricultural drought definitions relate different aspects of meteorological drought to effects on agriculture, emphasizing, for instance, a lack of precipitation, deviations from the norm, or a variety of meteorological parameters like evapotranspiration and by examining the properties of soil moisture and the morphology of plants during growth, agricultural drought reveals the amount to which soil moisture is below the minimum need of plants (Liu et al., 2016, Wang et al., 2016).

Socio-economic drought: Production and consumption are impacted by the shortage of water in both the natural system and the human socio-economic system, which is known as the socio-economic drought phenomenon (Liu et al., 2016). The characteristics of meteorological, agricultural, and hydrological drought may also be included in the socioeconomic consequences of drought (Panagoulia and Dimou, 1998). Socioeconomic drought is characterized as combining features of agricultural, hydrological, and meteorological drought with the supply and demand of some economic good. It is distinct from other types of droughts in that its incidence is influenced by supply and demand dynamics. Numerous economic commodities, including water, fodder, food grains, fish, and hydroelectric power, are weather-dependent. Water supply is abundant in certain years but insufficient to meet human and environmental needs in other years due to the natural unpredictability of the climate. A rising population and a surge in demand for such goods and services can sometimes make this situation worse, resulting in a scramble for the limited amount of water that is available (Gokcekus, 2020)

Ecological drought: Recently has ecological drought been acknowledged. It has been described as a water deficit that stresses ecosystems and negatively impacts the existence of both plants and animals. However, there are currently no defined indices to measure ecological drought, in contrast to agricultural drought (Gokcekus, 2020).

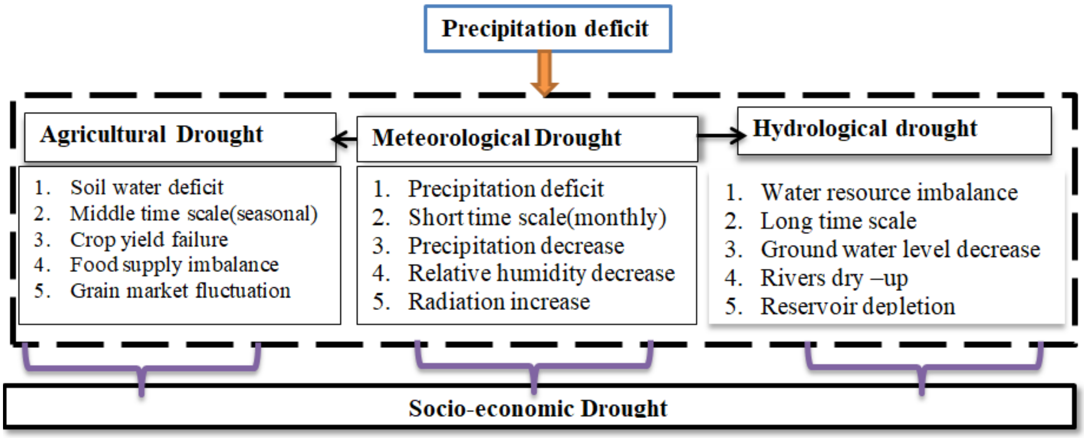

Figure 2. 1: Drought transfer processes and interactions

Source: Adapted from Liu et al. (2016)

2.2.3. Drought causes and consequences

As discussed by the special reports of drought, increased population, inadequate government policies and programs, environmental deterioration, and dispersed authority in the management of natural resources all contribute to the consequences of drought (Cammalleri, 2021). The world's poorest and most vulnerable people face the most acute dangers from shocks and pressures (Beyene et al., 2023). Natural systems are impacted by the effects of climatic variability and change, which is a dynamic entity. Frequent drought is a significant feature of climate variability and the recent climate change that humanity has been experiencing (Nazareth, 2014).

Ethiopia's susceptibility to climate change is determined by its geography, climate, and natural resources. Substantial portion of Ethiopia is found in the horn of Africa and it has many physiographic characteristics (Mera, 2018). As stated by this author the temperature in the highland areas (40%) ranges from 6 °C (43 °F) to 26 °C (79 °F) and includes regions with elevations greater than 2500 m and reaching 4500 m.a.s.l. (Alpine). The central plateau has a moderate climate with little seasonal temperature variance, falling in the intermediate range between 1800 and 2500 m.a.s.l. The lowlands are less than 1500 meters above sea level and have substantially higher temperature changes between 25 and 30 °C.

The majority of Ethiopia's population lives in rural areas and relies on rain-fed agriculture and pastoral activities and there has been limited development of surface water and groundwater resources for irrigation and other uses. Due to this Ethiopia has unfortunately experienced droughts regularly, which is a significant climatic risk that affects the long-term viability of this quickly developing African country (Azeb and van Laerhoven, 2018, Temam et al., 2019).

As mentioned by Temam et al. (2019) when compared to the baga season, the belg season had the most pronounced drying patterns across the country. The south-east and north-west of Ethiopia have seen a trend towards decreases in rainfall (increasing meteorological droughts), and some parts of the east have seen increases in rainfall or decreases in the intensity of meteorological droughts and also in terms of agriculture, the Belg season is crucial for the growth of tef (Eragrostis tef), a mainstay of the Ethiopian diet, and the Belg season is important for long-cycle crops, whereas the Meher season is the main rainy season across most of the nation and the majority of crops are grown, yet it shows there is a 1%–6% increase in dryness on average when compared to the Belg season.

Authors stated that throughout the past century, both meteorological and agricultural droughts have increased as tested by SPI and SPEI drought indicators.

In terms of the drought's geographical variance over the research period, the center and northern regions of the zone were the most severely affected, and its severity increased from south to north (Amba et al., 2022). The belg rains (February to May), which were deemed to have failed, and the Kiremt rains (June to September), which were late and irregular, caused drought conditions and failed harvests in Ethiopia's central-northeast areas in 2015 (Philip et al., 2018). Central-north, central, and central-south regions have the highest shock intensity (Solomon et al., 2018).

The overall Upper Awash basin of Ethiopia’s future seasonal drought projection indicates a greater reduction from 2050 onwards as compared to the present or past time, but there was critical increased seasonal and annual drought from 1983 to 2016

(Haftu et al., 2022) and this study find that Compared to SPEI, which more accurately captured both severe and intense droughts, in the analysis, SPI largely underrepresented drought. According to Mekonnen and Woldeamlak (2015), investigation of all periods (3, 6, 12 and 24 months), the frequency and magnitude of drought events revealed complicated and specific spatial patterns, but the cumulative frequency of droughts for the three intensity classifications (moderate, severe, and extreme) revealed that the southern river basin had the highest persistent drought risks during the course of the investigation and the occurrence of drought during wet season have significant socio-economic impact. Ethiopia experienced contemporary documented droughts in 1988, 1991 to 1992, 1993 to 1994, 2001, 2002 to 2003, 2009, 2011, and 2015 to 2016, all of which were accompanied by significant El Nino events.

Ashenafi et al. (2021), said that this implies that long-lasting and severe droughts accompany El Nino episodes in Ethiopia. When compared to the rest of the study region, most districts in the southern and eastern zones had more severe droughts (Tefera et al., 2019). At three-month (summer) timescales, all stations experienced extreme drought with magnitudes ranging from -2.18 to -3.44, and at twelve-month (year) timescales, from -1.9 to -3.03 (Mohammed et al., 2018).

As authors Tefera et al. (2019), mentioned that the severity of the drought increased the likelihood of it occurring decreased. As a result, mild droughts were more common or frequently occurred, while intense droughts were less common or delayed to occur across all time scales. When drought occurs in more than 50%, 30 to 50%, and less than 30% of the years, respectively, a given area's drought probability can be divided into high, moderate, and low drought probability zones (Senamaw et al., 2021).

In the northern regions of Ethiopia natural and anthropogenic-induced disasters are the main causes of drought. The most frequent causes are lack of rainfall or precipitation, human activities, drying out of surface water flow easily, climate changes or global warming, lack of food reserves, high food prices in markets, cattle purchased at a low price, and a lack of knowledge about adaptive farming techniques (Yitbarek and Huseyin, 2020). Moisture transported from Gulf of Guinea is another cause, as Souverijns et al. (2016), mentioned that during the rainy season, if there is less moisture transported from the Gulf of Guinea it results in less precipitation across Sudan and the Ethiopian Highlands.

According to Abenet et al. (2016) finding the socioeconomic effects of the drought in the Horn of Africa, and specifically in eastern Ethiopia, are exacerbated by a number of issues that are linked to wasting, underweight, and stunting. As detailed by Yimer et al. (2017), since the summer is the primary wet season in north eastern Ethiopia and accounts for more than 70% of the yearly rainfall, the overall number of drought occurrences was higher in the summer than in the spring. If it doesn't rain during this season, 85% to 95% of Ethiopia's food crop that is grown during this season will fail. Hirvonen et al. (2020), approved that chronic undernutrition rates increased in areas with a weak road network in 2015 due to the drought.

As found by Alemayehu and Bewket, (2016), and Bewket (2009) Amhara region fluctuation of crop production is mostly caused by inter-annual and seasonal rainfall variability. Drought brings about a substantial effect on the Ethiopian economy, for instance, during the drought in 1984–1985, the gross domestic savings decreased by 58.6% while the GDP decreased by 9.7% and agricultural output decreased by 21%. This study found that Ethiopia's inability to control hydrological variability raised the level of poverty there by 25% and decreased the country's economic growth potential by roughly 40% (Mera, 2018).

According to Hermans and Garbe (2019) between 2008 (the year that the last significant drought in northern highlands of Ethiopia occurred) and 2016, 43 percent of the households questioned participated in some type of temporary or permanent migration, either within Ethiopia or outside. This has a strong link to the rural Ethiopian highlands' pervasive poverty. With severe food shortages in three out of four households and declining wealth in roughly every third household during the drought, this poverty is exacerbated. Consequently, the drought increases strain on people's ability to make a living and key informants and specialists claim that the frequency and severity of droughts have doubled in recent years.

As mentioned by Tassew (2022), in his article on the effects of flooding and drought on clean water accessibility in Ethiopia, by mid-March 2022, 6.8 million people will require urgent humanitarian assistance, according to UNICEF, because of a lack of water. Over 100,000 pregnant and nursing mothers in Oromia and Somalia, as well as almost 225,000 malnourished children, require immediate nutrition support. Children and women are particularly affected by the lack of access to safe water and the lack of water has forced nearly 155,000 kids in the lowlands of Somalia and Oromia to quit school.

2.2.4. Households' resilience to shock (Drought)

Resilience has rapidly risen to the top of the development agenda (Jones et al., 2018). According to DfID (2011), the analysis of resilience can be divided into three categories: exposure to hazards, sensitivity to their consequences, and the capacity to adjust to shocks. Thus, to analyze resilience, it is necessary to examine the risks present in a specific setting, determine which groups are most exposed, and comprehend the nature of those groups' vulnerabilities.

As indicated by Beyene et al. (2023), households are classified based on derived resilience scores into non-resilient ($RI \leq 0.00$), moderately resilient ($0.00 < RI \leq 0.50$), resilient ($0.50 < RI \leq 1.00$), and highly resilient ($1.00 < RI$) categories concerning food insecurity. The survey results reveal that 42.8% of the household's demonstrated resilience at various levels (18.2% moderately, 15% resilient and the remaining highly resilient), while 57.2% of the households were deemed non-resilient. Household resilience to drought (shock) is anticipated to be positively associated with the share of expenditures during the drought relative to the "normal" scenario (Farahani and Jahansoozi, 2022). Another author Uexkull et al. (2020) stated that Resilience is significant because it extends beyond straightforward poverty indicators. Resilience and wellbeing are not always positively associated. Some researches that investigate the link between resilience and poverty reduction even mention a potential trade-off between resilience and wellbeing.

One of the elements influencing the decline in the sustainability of rural communities is drought. The increasing emphasis on resilience, which encourages adaptability and flexibility in these circumstances, is a crucial component of managing and coping with this risk and improving the living conditions of rural households. Resilience, in fact, aims to lessen the negative effects of drought and enhance rural households' ability (Bathaiy et al., 2021). According to Akbari and Begdeli (2018), Bathaiy et al.

(2021) Social networks and information and communication technologies have an impact on a number of areas of rural living. As a result, social media influences public opinion and so plays a modern function in society. One of the most important modern forms of communication that has an impact on every part of human life is the Internet. A new category of interpersonal contact known as "Virtual Communication" has emerged as a result of the development of contemporary technology, particularly the Internet and the introduction of social media. Based on public participation, these interpersonal virtual connections create unique opportunities (like facilitators) to support significant improvements in a variety of societal domains and expand their scope.

There are various determinants of household; Haile et al. (2021) proved that gender of the household head is one factor for whether or not being resilient. Researchers found that male-headed households have a greater degree of resilience than female-headed households do. The resilience structure matrix demonstrates that access to income, food, and the social safety net are the most important pillars for resilience capability of both Male-headed households, and to that Access to basic services is the most important contributor for boosting resilience, followed by possession of assets and adaptive capacity in general.

2.2.5 Food security

Food security is a complex and multidimensional concept that encompasses the availability, access, utilization, and stability of food resources to ensure that all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life.

According to Mechlem (2004), Food security is a complex and multidimensional concept that encompasses the availability, access, utilization, and stability of food resources to ensure that all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life.

According to FAO et al. (2022) cited in Gadiso et al. (2023) stated as food security persists as a developmental hurdle, with an ongoing and concerning prevalence of food-insecure individuals. Current figures for Africa reveal that in 2021, chronic hunger impacted 278 million people, marking a twofold increase compared to the global population experiencing chronic hunger. Food insecurity correlates with adverse effects on dietary quality, as well as physical and mental health outcomes (Calloway et al., 2022).

The food security status of households in this study is assessed using a multidimensional method, employing seven food security indicators: Coping Strategies Index (CSI), Reduced Coping Strategies Index (rCSI), Household Food Insecurity and Access Scale (HFIAS), Household Hunger Scale (HHS), Food Consumption Score (FCS), Household Dietary Diversity Scale (HDDS), and a self-assessed measure of food security (SAFS). These indicators are addressed through 24 questionnaires) developed by Maxwell et al. (2013). Maxwell et al. categorize the household's food security status as food-secured, rarely food-insecure, moderately food-insecure, or severely food-insecure.

The responses to the Multidimensional Food Security Indicators (MFI) questions (Q1 – Q24) are recorded as follows: Often = 1 recoded as 1', Sometimes = 2 recoded as 2' Rarely = 3 recoded as 3' Never = 4 recoded as 4'. The score derived from these responses is a continuous measure over a recall period of one month (30 days), ranging from a minimum of 24 (if all 24 questions are answered with "Never"), to a maximum of 96 (if all 24 questions are answered with "Often"). This scoring system aligns with the HFIAS scoring system, which is derived from 9 questions and scores a minimum of 0 and a maximum of 27. However, as noted by Koyachew and Bamlaku (2021), unlike HFIAS scores, the MFIs higher or lower score does not necessarily indicate the food (in) security experience of a household. This is because among the 24 MFI questions, there are both negatively and positively worded questions that are answered "Often" (4) and are related to food security status.

2.2.6. The interactive effect of household resilience and shocks on households' multidimensional food insecurity status

The repercussions of climate change and other disruptive events are expected to negatively impact the food security of individuals, particularly those residing in developing nations whose livelihoods are closely tied to agriculture. Implementing changes in planting dates as a strategy to address climate change has proven to enhance the probability of households having an adequate food supply (Goshme, 2019).

In the modified RIMA-II model, food security and shocks are treated as independent variables separate from resilience capacity. The model conceptualizes resilience as a capability (RIMA-II, 2016). In contrast to its role as an indicator of resilience in RIMA-I, food security is now characterized as the "achievement of resilience" in the RIMA-II model. This model comprises both direct (descriptive) and indirect (inferential) analytical components. In the direct analysis, which involves factor analysis, the resilience capacity index (RCI) and a resilience structure matrix (RSM) are computed from four variables (ABS, AST, SSN, and AC). The indirect analysis employs a multiple indicator multiple causes (MIMIC) framework to explore potential determinants of food security, with RCI serving as a key variable.

Despite acknowledging resilience as a capacity, the RIMA-II model has some limitations. It provides a single composite index to summarize the diverse aspects of household livelihood capacities. The model divides these multidimensional factors into four domains or pillars, each with corresponding indicators for measurement (FAO, 2018)

A foundational principle of the concept of resilience is that households characterized as more resilient possess an enhanced ability to either prevent shocks or, in the event of a shock, employ effective coping mechanisms that do not permanently diminish their productivity capacity (Bahta, 2022). Given the escalating nature of food insecurity and its underlying causes observed over the past three decades, there is a pressing need to transition from solely measuring food insecurity and malnutrition to evaluating the resilience of populations during challenging times (Lokosang et al., 2016).

Resilience serves as a variable capable of predicting or elucidating food security. Its measurement encompasses the capacity of households, individuals, communities, and nations, and it is also employed to gauge the capacity of the overall system (Ansah et al., 2019)

The study reveals that the causes of food insecurity in Ethiopia encompass environmental deterioration, population growth, diminishing land holdings, disease outbreaks, shortages in cash income, insufficient social and infrastructure support, instability, and drought.

CHPTER THREE: RESEARCH METHODOLOGY

This chapter provides a brief overview of the study area, research design, sampling methods, sample size determination, data gathering methods, and data analysis methods.

3.1 Description of the Study Area

3.1.1 Location

This study was carried out in *Sehala Seyemt* District *Wag Hemra* zone east part of Amhara national regional state, Ethiopia. It is geographically located at $38^{0}20'$ 0” to 38^{0} 40’ 0” E longitudes to 12^{0} 50’ 0” to 13^{0} 0‘0" N latitudes and far from 799 km north of *Addis Ababa*, *Ethiopia* and 285 km northeast of *Bahir Dar,* capital of the *Amhara* regional state (Kebede et al., 2022). The study area is separated from *Ziquala* district by the Tekeze river on its east and southeast, the Semen (North) *Gondar zone* on its west, and *Abergelie* district on its northwest is the geographical boundary of the study area (see in Fig 1:2).

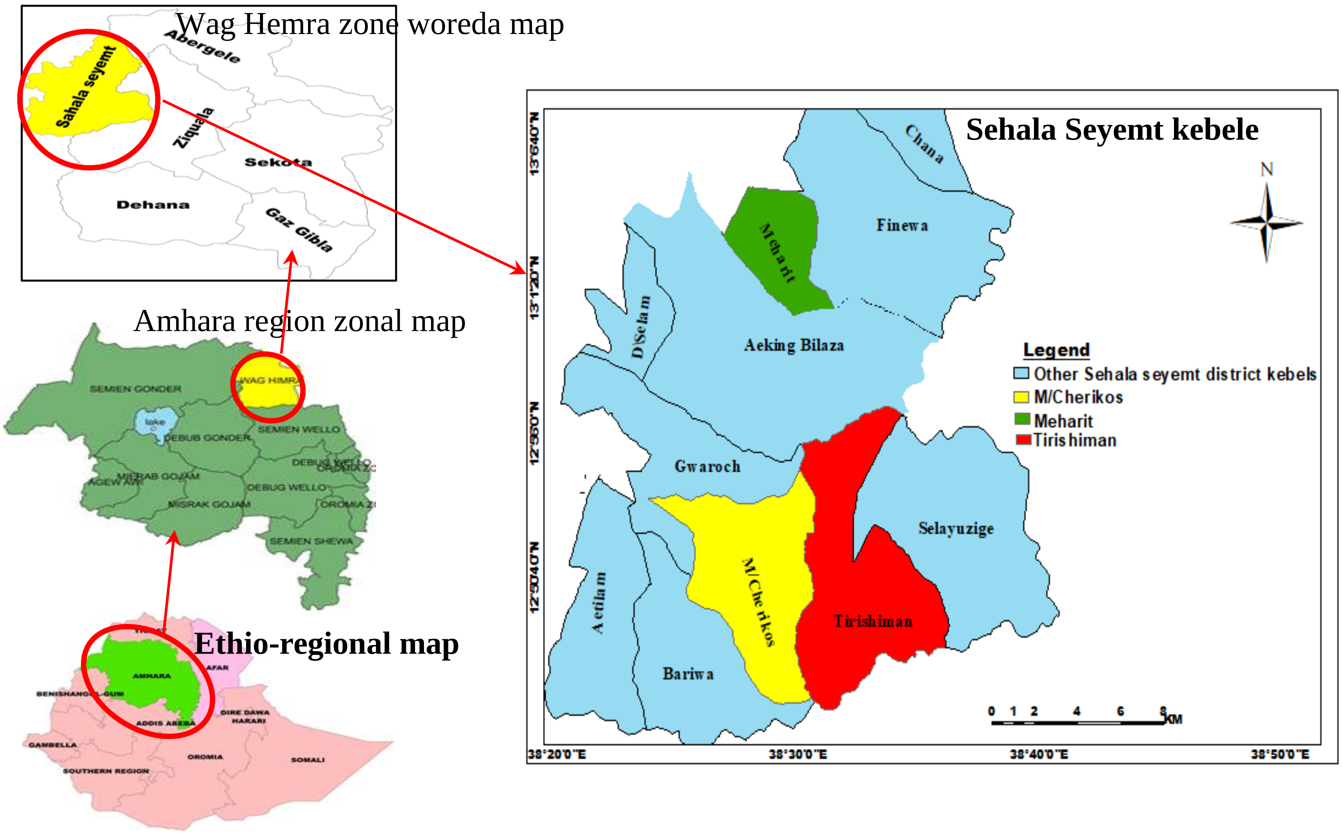

Figure 3:1 Map of the study area

Source: Author extraction from Ethiopia-shape file (2018)

3.1.2. Topography and Climate

According to Senamaw et al. (2021) quoted Berhanu`s (2012) Wag Hemra zone that included the study area is characterized by its rugged landscape, which includes mountains, high escarpments, deeply incised valleys, and arid and sumi-arid lands are its most prominent characteristics. The study area is characterized by monomodal rainfall, because according to (Abegaz and Kebede, 2022), about 86% of the rainfall is intense in Kiremt season (June to September) Kiremt rainfall had accounted 72 to 94 % to the total annual rainfall while that of belg rainfall also has had accounted 5 to 21% in the study area. As described by the study area Sehala Seyemt woreda has minimum of 0 mm, maximum of 126 mm and mean 26 belg season rainfall while minimum of 314 mm, maximum of 807 mm and mean of 538 Kiremt season rainfall and also it has 513 mean annual rainfall. The annual mean temperature of the study area ranges from 13.6 ^{O}C to 28.6 ^{O}C.

3.1.3. Major Soil Type

Ethiopian soil digital data reveal that the principal soils of the zone including the study area are distinguished by Cambisols, Luvisols, and Leptosols, which constitute 19.89, 16.6, and 63.51%, respectively, according to FAO (1997) cited in Senamaw et al. (2021).

3.1.4. Demography and socio-economic activities

Sehala Seyemt district is detached from *Ziquala* and the district has 13 *Kebeles* of which12 rural and 1 urban. The district has 39,435 total population size and over 90% of the population are farmers. The majority of the inhabitants practiced Ethiopian Orthodox Christianity, with 99.94% reporting that as their religion (Kebede et al., 2022).

Wag-Hemra zone is known for its considerable resources in the agriculture, mining, and tourism industries. Among many resources in the agricultural sector; small ruminants, apiculture, and high coverage of gum and resin trees are the major ones, and there are plenty of resources in the mining sector in the area. The other endowed resource of the entire zone is the presence of many rivers flowing throughout the year as water sources for irrigation agriculture (Abebe et al., 2019).

The livelihood of rural people in the study area depends on crop-livestock mixed farming systems. Crop production is dominant in the mid and high-land parts of the zone, and livestock rearing is the predominant livelihood source in lowland areas, especially the study district. The lowland areas of the zone dominantly depend on small ruminants (Yared and Sale, 2022).

3.2. Research Design

A research design acts as an idealized road map that directs investigators from the point of data collection to the composition of the research findings report. It is the theoretical framework that guides research, delineating the processes from developing hypotheses to analyzing evidence. study design, according to Kothari (2004), is the setting up of circumstances for data collection and analysis in a way that aims to combine relevance to the research purpose with economy in procedure. This architecture serves as the foundation for data gathering, measurement, and analysis. Similar to building a birdhouse, the visualization of a study plan frequently follows a linear series of steps. This design is not entirely flexible, though; certain parts are more set-in stone than others. Certain research may not have predetermined analytic techniques, assumptions, or data collection tools like the well-defined designs of some studies.

In a way, our study had no design at all, as De Munck (2009) highlights this variation in design. That is to say, we lacked a well-considered set of hypotheses to test, a set of data-gathering tools intended to gather information pertinent to these hypotheses, and a predetermined set of analytical techniques. But even studies without extensive preparation can be considered to have a design if we take a broader view of design, recognizing components of consistency, order, and system.

To provide a comprehensive assessment of the study problem, a cross-sectional survey research design was employed. A cross-sectional research design is a way to conduct research when both qualitative and quantitative data are collected and analyzed at the time or concurrently (Pawar, 2021). The research employed a combination of qualitative and quantitative mixed research approaches. Given its potential to provide valuable insights into the research phenomenon, insights that cannot be fully captured by solely relying on qualitative or quantitative approaches, the preference may lean towards using a combination of both methods rather than opting for just one (Njoroge and Wambugu, 2021). Integrating and combining multiple data sources is feasible within a mixed-methods research (MMR) approach, aiding in the investigation of complex topics (Dawadi et al., 2021). As noted by JOHN (2014) using a mixed research approach entails gathering and combining qualitative and quantitative data. In recent years, its popularity has increased. The audience for the study, the research challenge, and the researchers' backgrounds all influence the choice of research approach. This method integrates quantitative and qualitative data, frequently utilizing particular designs in conjunction with theoretical and philosophical frameworks. The essential premise is that, in comparison to employing either approach alone, this combination provides a more thorough grasp of the research problem.

3.3. Sampling methods and sample size determination

3.3.1. Sampling techniques

The study area, *Wag Hemra* zone and *Sehala Seyemt district*, were selected purposively based on erratic climate variability, high seasonal drought severity, duration and frequency depending on the evidence mentioned by Getamesay et al. (2021) and Senamaw et al. (2021), which stated that the number of severe drought years, notably in SPI-03 and SPI-12, more than rainy years. This data shows the *Wag Hemra zone* is prone to drought episodes. Next to that, three Kebeles among thirteen Kebele of Sehala Seyemit district and respondent households were selected by using a simple random selection method. Simple random selection is the most commonly used method of selecting a probability sample and is in line with the definition of randomization, whereby each element in the population is given an equal and independent chance of selection (Kothari, 2004). One method to achieve this is the lottery system, and this system was applied in this study by having the having the Kebele name from the sample frame written on a slip of paper or card. These slips are then drawn from a container one by one. To maintain an unbiased selection, it's important to shuffle the cards or slips of paper before each draw. All Kebeles of Sehala Seyemt district exist in similar agro-ecology and are homogenous in socioeconomic activities. Furthermore, to demonstrate the suitable sample selection procedures of the research without bias, the whole sampling procedure and structure of this study are shown in the accompanying figure 3.2.

3.3.2. Sample size determination

The target population of this study was household heads living in the desired sample of three *Kebeles* (*Mendere-Cherkos*, *Tirshiman,* and *Mehari*). Based on the initial visit of the *Kebele*, the household number was selected as the follow table:3.1

Table: 3:1 Number of households in the study area

No.	Selected kebeles	Number of households		
		Male	Female	Total
1	Menderecherkos	528	174	702
2	Tirshiman	441	99	540
3	Meharit	394	115	509
Total				1751

Source: Kebele Administration (2023)

The number of households within *Kebeles* is not equal due to this taking proportion was important. Since the population size of each *Kebeles* is different, the study has used sampling with proportional sample size allocation. Because selecting the proper sample size is not a matter of personal opinion; rather, it is an essential step in the research process without which you can find yourself spending months trying to answer a question or solve a problem with a tool that is either totally ineffective or excessively costly in terms of resources like time **(**Fox et al., 2009**)**.

The sample size can be determined using a variety of methods. Among these are employing a survey for small populations, replicating the sample size of related studies, using published tables, and using formulas to figure out the sample size. This study used a simplified Yamane (1967) formula with a 95% confidence level and a 5% standard error. The degree to which an assumption or number is likely to be accurate is known as the confidence or risk level. That is the likelihood that a random variable falls within the range of an estimate. The central limit theorem provides the basis for this confidence level. When a sample is frequently taken from the population, the central limit theorem states that the average of an attribute, like the mean obtained from that sample, is equal to the actual population value. Additionally, the attributes derived from those samples have a normal distribution around the true value (Nanjundeswaraswamy and Divakar, 2021).

So, Confidence interval = sample mean ± margin of error

$n = \frac{N}{1+N(e)2}$--- equation (1)

Where:

n = the sample size

N = the finite population

e = the level of significance or limit of tolerable error

1 = unit or a constant

So, n=1751/1+1751(0.05)2

n≈326

Last but not least, the sample households were chosen using the probability proportional to sample size because the number of households in each *Kebele* is different in number and applying proportional sampling for such a cause is advisable.

To determine the sample size at each *Kebele* Kothari (2004) proportional sample size determination formula was used as follow:

$ni = Ni \times \frac{n}{N}$ -- equation (2)

Where ni = sample size at i^{th} Kebele

Ni = number of households at i^{th} Kebele

n = total sample size of the three *Kebele*

N = total household in the three *Kebele.*

Accordingly, in the above statement the sample size selected as follows: *Menderecherkos*, *Tirshiman* and *Meharit is* 130, 101 and 95 consecutively

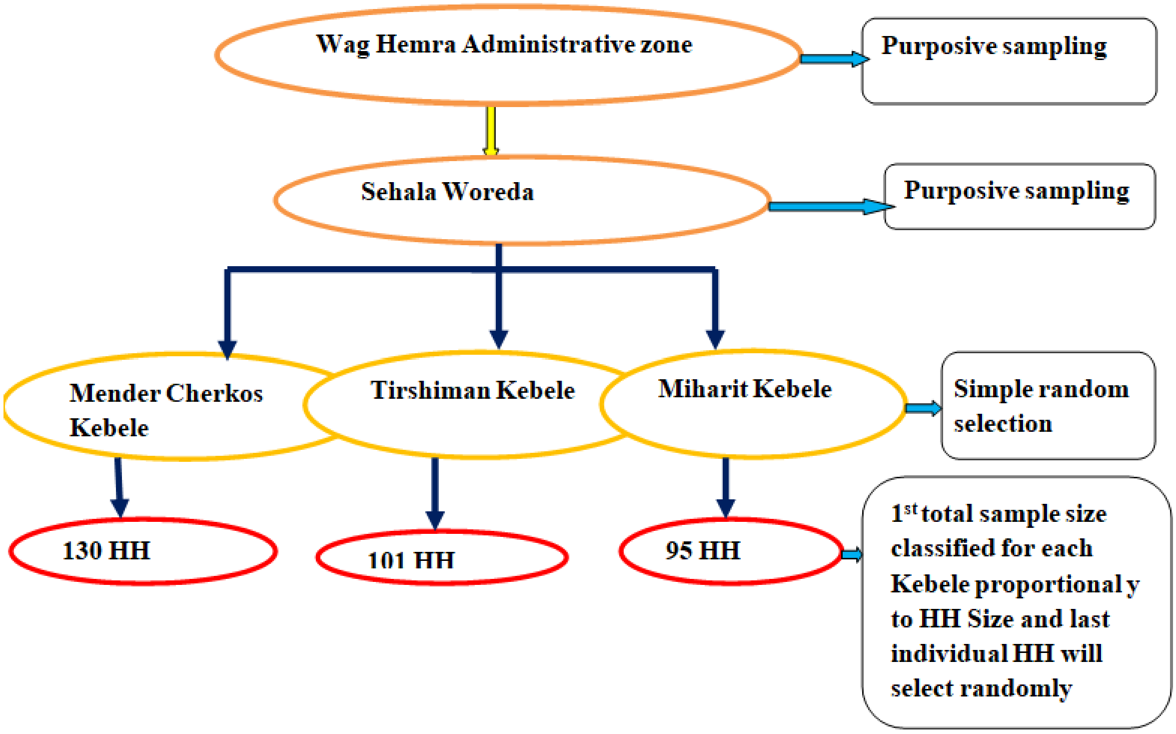

Figure 3:2 Sampling Procedure and Structure

Source: Authors computation, 2022

3.4. Types of data, source and data collection methods

In order to get the information needed for this study, it has been agreed upon the various categories of data that must be collected and the sources from which the data are to be gathered, and both primary and secondary data have been collected. In order to gather comprehensive and reliable information for this study, a structured approach to data collection was essential. This involved a detailed planning phase where various categories of data were identified as crucial for addressing the research questions and objectives. The categories of data were carefully selected to insure a multifaceted understanding of the research topic. This includes quantitative data about households' resilience, food security and precipitation data and qualitative data like interviews about drought condition of the study area. Secondary data, on the other hand, refers to data that has already been collected and published by others. This can include academic journals, books, reports, and online databases. Secondary data can provide valuable context, background information, or comparative data for the study.

3.4.1. Primary Data Sources

Household survey: This is the commonly used approach in various data collection activities. Data collection methods such as focus group discussions, key informant interviews, and questionnaires are all part of the survey process (Dillman et al., 2014). This research employed survey data collection method using data collection tools of FGD, KII and questionnaire as depicted below.

Household Questionnaires: Structured questionnaire has been prepared in English and translated into *Amharic*[1]. Then researchers construct the *Kobo* data collection toolbox[2], and write all the questionnaires on this data collection platform. The questionnaire was applied to 20 households as a pre-test before conducting data collection, and this helped assess the questionnaires whether or not enable them to achieve the research objectives and after that took some corrections, then distributed and gathered relevant data from the households.

Focus Group Discussion: As a qualitative data gathering technique, focus groups bring together multiple participants and one or two researchers to talk about a certain research issue. When gathering data about societal norms and the range of viewpoints present in a population, focus groups are particularly useful. Focus groups are usually just one technique among many that are employed to provide a full picture of the impact a certain issue has on a community. (FGD) one FGD was held in each sample *Kebele*. Each FGD comprised 8–10 participants who had been selected on the basis of their knowledge, age, and experience with drought shock to gather drought patterns, causes and consequences-related data such as food insecurity prevalence and household's resilience to drought and food insecurity.

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[1] Amharic Language serves as the indigenous language in the research locale

[2] A set of tools available for free, created for collecting field data in demanding conditions. Researchers, humanitarian aid workers, and development experts commonly use it to gather, organize, and analyze data in the field. The toolkit comprises a mobile application for data collection on smartphones or tablets, along with a web-based interface for managing the data.

Key informant interview (KII)

In-depth interviews are one of the most common qualitative methods. One reason for their popularity is that they are very effective at giving a human face to research problems. In-depth interviews are usually conducted face-to-face and involve one interviewer and one participant. Four KII was held with some governmental sector leaders and experts such as, *Sehala Seyemt District* Agricultural Office head, Food Security group leader of *Sehala Seyemt District*, animal resource expert in *Sehala Seyemt District* and early warning expert at the *district* level were interviewed to generate sufficient technical information related to drought patterns, causes, effects of drought, household's resilience status and interactive effects of these issues on prevalence of food insecurity in the study area.

3.4.2. Secondary Data Sources

Secondary data for the study were used which is 30 years (1993–2022) precipitation data with a spatial resolution of 0.050 or 5km was obtained from remote sensing products. This data used to assess drought patterns were extracted from the CHIRPS website at *https://climexp.knmi/CHIRPS-2.0/v*. the research used this precipitation dataset The evaluation of four gridded precipitation products, namely CFSR, PERSIANN-CDR, CHIRPS, and TRMM-3B42V7, revealed that CHIRPS stands out as the most suitable alternative not only for data-sparse regions of Ethiopia but also for areas with limited spatial coverage of gauging stations (Musie et al., 2019). According to Musie et al. (2019), the CHIRPS dataset provides high-resolution 0.05° precipitation data from 1981 to the present, covering daily, pentadal, and monthly time scales (Funk et al., 2015). Constructed using Version 2 of the atmospheric model rainfall field from the NOAA Climate Forecast System (CFS), TRMM-3B42V7 data, monthly precipitation climatology data (CHPclim), and rain gauge station data, the CHIRPS product represents a significant advancement (Duan et al., 2016).

The CHIRPS product has been found to closely align with rain gauge data across all observed stations, as reported by Nawaz et al. (2021). Its development has been instrumental in supporting the monitoring of droughts, particularly through initiatives such as the USAID Famine Early Warning Systems Network (FEWS NET). CHIRPS integrates various data sources, including the Climate Hazards group Precipitation

Climatology (CHPclim), 0.05° resolution satellite imagery, the satellite-only Climate Hazards Group Infrared Precipitation (CHIRP), and rain gauge data from national and regional meteorological services. This comprehensive approach allows CHIRPS to generate gridded rainfall time series suitable for trend analysis and seasonal drought monitoring, as outlined by Funk et al. (2015) and Nawaz et al. (2021).

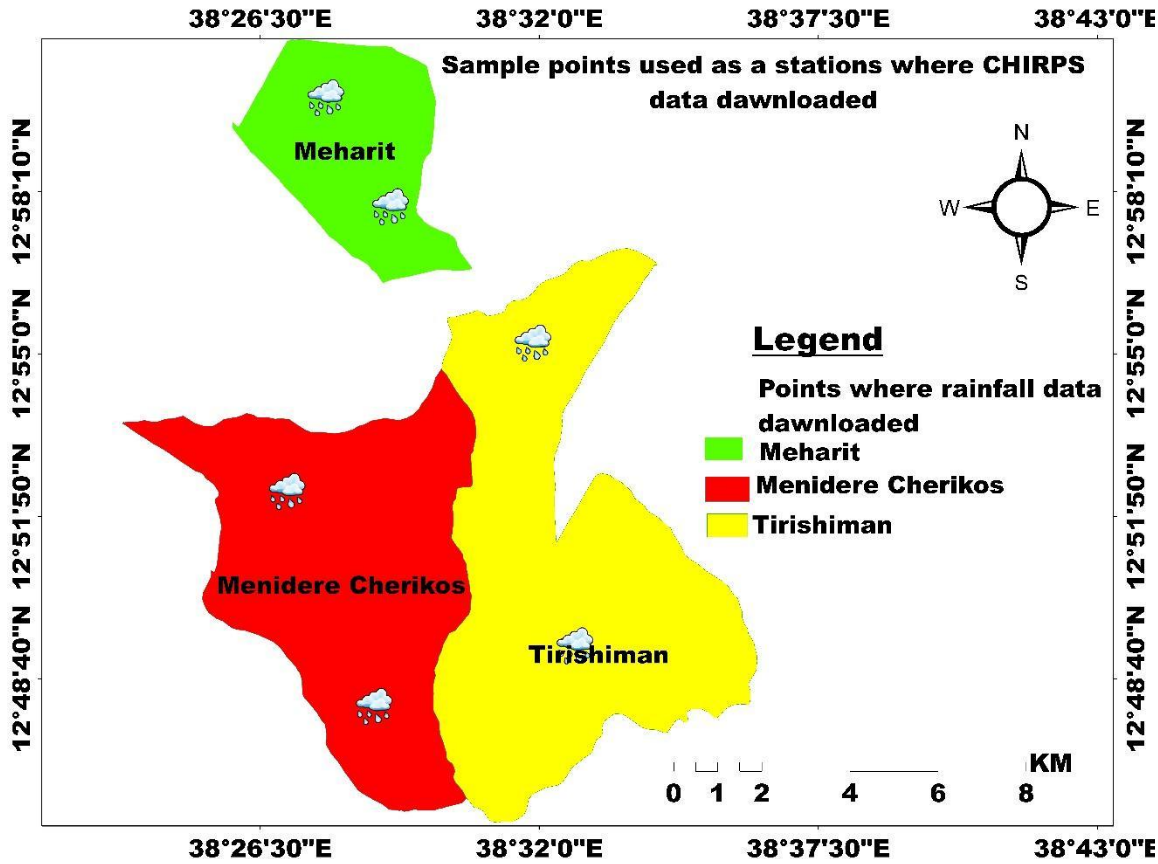

Figure 3:3 Maps that indicate the site in the study area where CHIRPS precipitation data downloaded

Source: Own extraction from Ethiopia-shape file (2018)

Standard precipitation Index

Numerous drought indicators have been created and utilized by meteorologists and climatologists worldwide over time. There were many different types, from straightforward indices like the percent of average precipitation and precipitation percentiles to complex indices like the Palmer Drought Severity Index. However, Svoboda et al. (2012) noted that American scientists understood the necessity for such an index to be clear, easy to compute, and statistically significant. Furthermore, American scientists McKee, Doesken, and Kleist developed the Standardized Precipitation Index (SPI) in 1993 after realizing that a shortage of precipitation has a variety of consequences on groundwater, reservoir storage, soil moisture, snowfall, and streamflow.

Positive SPI values indicate greater than median precipitation and negative values indicate less than median precipitation. Because the SPI is normalized, wetter and drier weather can be represented in the same way; thus, wet periods can also be monitored using the SPI and according to Svoboda et al. (2012) the index classified in to seven partition depends on the SPI score value (see table:4:2).

A common metric used to evaluate meteorological drought over a range of time periods is the standardized precipitation index (SPI). Specifically, the SPI is highly correlated with soil moisture levels over shorter durations, but it can also represent changes in reservoir storage dynamics and groundwater dynamics over longer timescales (Salimi et al., 2021). According to Cancelliere et al. (2007), the standardization of the data allows for meaningful comparisons of drought severity across climatic regions and historical periods, while its adaptation to various temporal scales allows for a thorough understanding of drought occurrences. Because of this characteristic, the SPI is incredibly useful for identifying patterns of drought, assessing threats specific to a given area, and developing plans for adaptation to changes in the environment. The study applied this drought condition assessment method.

Table 4:2 SPI value

2.0+	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

Source: Svoboda et al., (2012)

$SPI = \{(Xij - Xim) / \sigma\}$ -------equation (3)
Where, (Xij= is the seasonal precipitation and, Xim is its long-term seasonal mean and σ is its standard deviation).

3.5. Data Analysis and Interpretation

Analytical Approach: Quantitative and qualitative methods of data analysis were used to analyze the data gathered from fieldwork. The primary data collected from household respondents through structured questionnaire was first checked for accuracy. Most data analysis was done using quantitative methods, with qualitative analysis provided as necessary. For every study issue and goal, a particular, appropriate model is used and the study used a combination of qualitative and quantitative (mixed) research methods; the qualitative data were analyzed through narrative analytical approach, according to JOHN (2014), humanities-based narrative research collects personal narratives from subjects in order to examine their lives. After that, the researcher could recount the tales or arrange them in a narrative chronology.

the remote sensing data which is downloaded from CHIRPS web site and cleared and analyzed using Microsoft Excel 20 analytical tool, whereas the survey data which just collected on *KOBO* toolbox platform was downloaded into excel format from Kobo toolbox temporary cloud stored server which saved during the survey time and the questionnaires import, coded, entered into the computer, made cleared using Statistical Package for Social Science(SPSS) version 23 and analyzed using StataMP version 17(64-bit) analytical tools. Because of their complementing skills in data administration and statistical analysis, SPSS and Stata were used in this study. Because of its wide range of statistical methods and data visualization capabilities, SPSS which is well known for its user-friendly interface is used for preliminary data exploration and basic analyses. In contrast, Stata's comprehensive features for managing sizable datasets and carrying out intricate statistical modeling, in addition to its command-driven interface offering exact control over studies, are required for more intricate analyses and data manipulation assignments. This study guarantees thorough data analysis, strong outcomes, and increased trustworthiness of findings by utilizing the special qualities of both software packages.

To finalize this study four steps have been followed according to the specific objectives: First, determined the study areas over-time drought exposure patterns; second, examined household resilience to recurring drought; third, it looked at how household resilience and shock affected multiple aspects of food security status in households' level; and finally, assessed the interactive effect of household resilience capacity, drought exposure on food security outcomes in the household level.

3.5.1. Tools for Drought analysis

The patterns, severity, and frequency over time in the study area are assessed with standard precipitation index (SPI) analytical tools. The SPI is a potent, adaptable index that is easy to calculate. In actuality, the only necessary input parameter is precipitation. Furthermore, it is equally effective in examining both periods of rainfall and associated cycles, just as it is for scrutinizing dry periods (Svoboda and Fuchs, 2022, WMO and GWP, 2016). In addition to SPI, Key Informant Interviews (KII) and narratives obtained from Focus Group Discussions (FGD) were utilized to elaborate on the historical issues of drought in the study area.

3.5.2. Household resilience method of analysis

This study uses a composite indicator to determine how resilient a household is to food insecurity and shock. This is due to resilience's multifaceted nature, which makes it impossible to measure directly. Because of its very nature, measuring resilience is extremely difficult. Two distinct approaches have been used by earlier research on this subject to get around this obstacle.

To measure the resilience capacity two methods popularly applicable are those developed by the two esteemed organizations such as FAO and TANGO. However, FAO RIMA is more informative in terms of quantification (D'Errico and Smith, 2019). The TANGO and FAO indices are premised on the collection of data at a singular temporal point, irrespective of the fact that households may be subjected to exposure to shocks. They serve to quantify the inherent capacity of households to endure shocks. Conversely, the measure of realized resilience is ascertained prior to and subsequent to the occurrence of shock episodes, with emphasis on how households bounce back from explicitly defined shocks.

Asfaw (2022) also points out in his MSc thesis that there are considerable resemblances between the two prevailing methods of measuring resilience. When gauging the resilience potential of a household through a shared dataset, the measures of RIMA and TANGO exhibit a notable likeness.

Overview of RIMA Approach

The RIMA method is a novel quantitative approach that offers an explanation for the varying degrees of resilience among households in the face of shocks and stressors. This methodology presents an opportunity for more efficient design, delivery, monitoring, and evaluation of aid to populations in need, with a focus on fulfilling their specific requirements. Following its implementation in ten countries, the initial version of RIMA has undergone significant technical enhancements, culminating in the release of RIMA-II in early 2016.

It is believed that a household's ability to cope with drought and food insecurity at any given time would largely depend on the options it has for making a living, including its capacity for adaptation, access to assets, basic services, and social safety nets. The household resilience is analyzed by FAO-RIMA II analysis methods based on four "resilience pillars", as shown in Table 3:2 below: Pillars and proxy indicators of RCI. Access to enabling institutional and public service contexts is determined by the household's access to basic services (ABS). Assets that help a household support itself financially are included in the Assets (AST) pillar. Social safety nets (SSNs) are the network that a family can rely on in the event of a shock. Adaptive capacity (AC) describes a household's capacity to adjust to its operating environment as it changes. The estimation comes after the resilience analysis, which FAO regularly performs in numerous empirical scenarios (Uexkull et al., 2020). Due to the various levels of threat or risk that individuals are exposed to, resilience cannot be quantified as a single entity. An increasing number of groups from civil society and other sectors have created resilience indicators and emphasized them as essential elements of an effective assessment program. It's noteworthy that certain individuals believe that resilience and vulnerability cannot be directly observed or evaluated (Hinkel, 2011). According to the RMA II methodology, the initial step involves estimating a multidimensional resilience index as a latent construct through a two-step factor analysis (FAO, 1996)

Factor Analysis

The fundamental tenet of factor analysis is the obvious yet persuasive notion that, in order for two items to be associated, they must share an actual variable. Identifying and analyzing such underlying variables is possible through a series of methods known as factor analysis (Bernard, 2017).

Factor analysis, as described by Field (2013) is a method used to identify latent variables (factors) that explain the covariance among observed variables. It seeks to reveal the underlying structure in data by grouping highly correlated variables, assuming that observed variables are influenced by a smaller number of underlying factors. This technique is crucial for understanding relationships between variables and finds applications in fields such as psychology, social sciences, and market research. The basic and persuasive premise of factor analysis is that, if two or more phenomena are associated, they must share an underlying variable. A group of methods for locating and analyzing those underlying variables is known as factor analysis.

Field (2013) states that factor loadings in a particular analysis might be both regression and correlation coefficients. This is dependent on the factor rotation that is done, though. The factor/component loading, when orthogonal rotation is applied, is the correlation between the factor/component and the variable as well as the regression coefficient. Any underlying factors or components are considered to be uncorrelated. In other words, correlation and regression coefficient values are the same. However, when oblique rotation is used, it is believed that the underlying factors and components are correlated, which means that the resulting Pearson correlations between factors and variables will not match the corresponding regression coefficients Field (2013). Field (2013) contends that the importance of factor loading is dependent on the sample size, but acknowledging that researchers generally consider loadings with an absolute value of greater than 0.3 to be significant. Regarding this, Field (2013) suggests the crucial values that should be used to compare the factor loadings. As a result, according to Field (2013), a loading of 0.722 for the sample size of 50 can be regarded as significant; similarly, for 100, 200, 300, and 1000, the loading should be greater than 0.512, 0.21, 0.364, and 0.162, respectively. Field (2013) states that these numbers are based on a two-tailed alpha level of 0.01 to account for the necessity to evaluate multiple factor/component loadings. These crucial values teach us that, with ever-larger sample sizes, even relatively tiny loadings can have statistical significance.

Principal component analysis (PCA), also mentioned by Field (2013), is a dimensionality reduction technique that transforms a set of possibly correlated variables into linearly uncorrelated variables known as principal components. PCA aims to maximize the explained variance in the original dataset, identifying a new set of variables (components) that capture most of the information while reducing dimensionality. PCA is widely used in fields like image processing, finance, and genetics.

Both factor analysis and PCA serve as valuable tools for data exploration, pattern identification, and dimensionality reduction in complex datasets. The choice between the two depends on the nature of the data and the specific objectives of the analysis.

Additionally, as mentioned by Shrestha (2021), Factor Analysis is particularly useful when the focus is on determining logical subsets of variables that are relatively independent within a single set of variables.

Indeed, factor analysis can be broadly categorized into two main approaches: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Exploratory Factor Analysis (EFA):

Assume that any indicator or variable may be associated with any factor and this is the more common and widely used form of factor analysis. It is not based on any prior theory or predetermined factor structure. The primary goal of EFA is to identify underlying factors that explain the observed patterns of relationships among variables.

Confirmatory Factor Analysis (CFA): It used to confirm the factor structure and factor loadings of measured variables, based on a pre-established theory or model. Assume that each factor is associated with a specified subset of the measured variable. CFA involves testing a predefined hypothesis about the structure of the factors.

Structural Equation Modeling (SEM) Approach: CFA is integrated into the broader framework of SEM. SEM allows for the examination of relationships not only between observed variables and factors but also among factors themselves. This approach is more flexible and comprehensive.

The choice between EFA and CFA depends on the research objectives. EFA is suitable when the goal is to explore and uncover the underlying structure of variables, while CFA is appropriate when researchers want to test and confirm a specific factor structure based on existing theories or hypotheses (Brown, 2015). This study utilized confirmatory factor analysis, relying on the pre-existing resilience theory that defines resilience capacity based on four resilience pillars, as assessed in the previous topics.

Mathematically, the RIMA model calculates the resilience index as a function of the provided attributes, expressed as follows:

$RCI = f(ABS, AST, AC, SSN)$---------------------------------equation (4)

Where, RCI= resilience capacity index, ABS =access to basic service, AST = household's asset owned, AC= household's adaptive capacity and SSN =social safety net of the household.

Table 3:2 Pillars and proxy indicators of RCI

Pillars	Variables	Expected effects on resilience
	Access to improved water (1=yes)	+
	access to telecom (1=yes)	+
	Access to irrigation (1=yes)	+
ABS	Access to Save and credit service (1=yes)	+

	Access to early warning service (1=yes)	+
	Access to extension service (1=yes)	+
	Availability of road in the resident kebele (1=yes)	+
	Distance to health center (in minute)	_
	Distance to access public transport service (in minute) Distance to nearest by market (in minute)	_ _
AST	Wealth index	+
	Agricultural asset index	+
	Size of agricultural land measured in Timad	+
	Livestock size in TLU	+
AC	Income diversification index Livestock diversification index	+ +
	Household head’s ability to read and write	+
	Crop diversification index	+
	Dependency ratio = (above 64+below15)/economically active members	-
SSN	Cash transfers from formal sources in ETB Cash transfers from informal sources in ETB	+ +

Source: RIMA-II (2016)

3.5.3. Food security analysis method

The definition that ultimately brought these ideas together was put forth at the 1996 FAO Food Summit and reads as follows: "Everyone has physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life at all times." Availability, access, utilization, and stability are the four pillars that support this widely accepted definition (Upton et al., 2016). These pillars are inherently hierarchical, with availability being necessary but insufficient to guarantee access, which is necessary but insufficient for efficient utilization, and stability being necessary for all four pillars. Measuring food security should, in theory, come straight from the FAO definition. Correspondingly, the ideal food metric would satisfy four basic axioms: In principle, food security measurement should follow directly from the FAO definition. Correspondingly, the ideal food metric would satisfy four basic axioms:

- Relate to "all people," addressing both individuals and groups at any scale of aggregation, including geographic regions and political jurisdictions. We refer to this as the scale axiom.
- Apply "at all times," encompassing both predictable and unpredictable variability over time, or the "stability" dimension of food security. We refer to this as the time axiom.
- Capture the notion of "physical, social and economic access," as manifest in relation to various indicators of individual and collective well-being. This should capture both the "access" dimension, and implicitly also the "availability" dimension, as availability is a necessary (but not sufficient) condition for access. We refer to this as the access axiom.
- Ultimately relate to dietary, health, and/or nutrition outcomes required for "an active and healthy life," encompassing the "utilization" dimension of food security. We refer to this as the outcome's axiom. To date, no food security measure satisfies these four axioms. The global community has relied heavily on proxy measures that attend to one, two or perhaps three of these axioms. Many of these proxy measures are important and useful, but they are necessarily incomplete

This study measured food security through the household multidimensional food security index, which is developed by Maxwell et al. (2013).This method can capture all dimensions of food security and it is unique and inclusive of all the seven food security indicators such as coping strategies index (CSI), reduced coping strategies index (rCSI), household food insecurity and access scale (HFIAS), the household hunger scale (HHS), food consumption score (FCS), household dietary diversity scale (HDDS), and a self-assessed measure of food security (SAFS).

As Koyachew and Bamlaku (2021) point out that the advantage of using a multidimensional household food security index of food security measurement is to assess many food security dimensions better than that of measuring food security with a single indicator.

Seven food security indicators such as coping strategies index (CSI), reduced coping strategies index (rCSI), household food insecurity and access scale (HFIAS), the household hunger scale (HHS), food consumption score (FCS), household dietary diversity scale (HDDS), and a self-assessed measure of food security (SAFS) were considered in this method. Those indicators are answered through 24 questionnaires (see in Appendix I) which were developed by Maxwell et al. (2013). According to Maxwell et al. the status of household's food security status categorized as food secured, rarely food insecure, moderately food insecure and severely food insecure.

Recode Response to multidimensional food security indicators (MFI) questions (Q1 – Q24) as follows: Often = 1 recode as `1', Sometimes = 2 recode as `2' Rarely = 3 recode as `3' Never = 4 recode as `4'. The score obtained from the above response is a continuous measure for a recall period of one month (30 days) starting from questionnaire filled day to the past and the data collected from January 15 to February 20/ 2015 E.C. The score ranges from minimum of 24 (if the respondent answered all 24 questions are never) and maximum of 96 (if the respondent answered all 24 questions often). This scoring system is similar to the scoring system of HFIAS which is the score derived from 9 questions that scored minimum of 0 and maximum 27. However, as pointed out by Koyachew and Bamlaku (2021), unlike HFIAS scores, the MFI higher or lower score does not indicate the food (in)security experience of a household, because among 24 questions of MFI there is the question that answered often (4) that negatively related with food security status and also there is the questions that answered often (4) which positively related with food security status.

The status of household food security is classified based on the following cut-off functions the household who responds the questionnaires like any of NOTEAT up to SENDEAT =never, and PULSE and GRAIN = often, and EATSEED up to NOTWNT

=never and LIMITVAR up to WORRY = never or rarely, and SAFS = food secure or mildly food secure and DAIRY up to VEGET =rarely or sometimes or often is categorized on food secured status category. Moreover, if the households responded PULSE or GRAIN =sometimes, or any of EATSEED up to NOTWNT=rarely, or any LIMITVAR up to WORRY= sometimes, or SAFS= moderately food insecure, or any of DAIRY up to VEGET =never is categorized under rarely food insecure status. If any of NOTEAT up to SENDEAT = rarely, or PULSE or GRAIN = rarely, or any of EATSEED up to NOTWNT = sometimes, or any of LIMVAR up to WORRY = often, or SAFS = food insecure is categorized under moderately food insecure and if any of NOTEAT up to SENDEAT = sometimes or often, or any of PULSE or GRAIN = never, or any of EATSEED up to WORRY = often, or SAFS = food insecure is categorized under-severely food insecure status (Koyachew and Bamlaku, 2021, Maxwell et al.,2013).

Where, often =1, rarely =2, sometimes=3 and often=4 and those 1, 2, 3, and 4 are food secured, rarely food insecure, moderately food insecure and severely food insecure respectively (see table 4:14).

Table 4:14 Cut-offs of multidimensional household food security categories

Category	Response	MFI Prevalence in %
MFI Category = 1	If [(Q1–Q6=Never), or (Q7&Q8=Often), or (Q9-Q13=Never) or (Q14- Q18=Never or Rarely), or (Q19= Food Secure or Mildly Food Insecure) or (Q20-Q24= Often or Sometimes or Rarely)	$\frac{n\ of\ category1}{N} x100$
MFI Category = 2	If [(Q7–Q8=Sometimes) or (Q9-Q13=Rarely) or (Q14 – Q18=Sometimes), or (Q19=Mildly Food Insecure), or (Q20-Q24=Never)	$\frac{n\ of\ category2}{N} x100$

MFI Category = 3	If [(Q1-Q6=Rarely) or (Q7-Q8=Rarely) or (Q9-Q13=Sometimes) or (Q14-Q18=Often), or (Q19=Severely Food Insecure)	$\frac{n\ of\ category3}{N} x100$
MFI Category = 4	If [(Q1-Q6=Often/Sometimes), or (Q7 – Q8= Never) or (Q9-Q18=Often), or (Q19=Severely Food Insecure)]	$\frac{n\ of\ category4}{N} x100$

Source: adopted from (Koyachew and Bamlaku, 2021)

Where:

n is the number of households with MFI category 1, 2,3 & 4

1, 2, 3 & 4 are food secure, mildly food insecure, moderately food insecure & severely food insecure respectively

N is total number of households with MFI category or total surveyed household

The study has computed and reported the multidimensional food security status of households using descriptive statistics of prevalence in percentage. MFI prevalence was calculated to report multidimensional food security status of the households. The MFI prevalence refers to the percentage of households that fall in each food security category.

$$MFI\ \ Prevalence = \frac{Number\ of\ households\ in\ one\ MFI\ category}{Total\ number\ of\ households\ in\ all\ MFI\ categories} * 100\ldots \text{ equation (5)}$$

3.5.4. Interactive effect of households' shock exposure and resilience on food security outcomes

This subsection is the last objective of this study and it interconnects the prior three objectives and enables to frame the study overall assessment to point out collective results. The variables in this objective were not new rather somehow derived or revolved coming from the above just assessed objectives. Variables, which are four pillars of household resilience capacity, used to estimate the household aggregate resilience capacity index prior such as household’s access to basic service index, household’s asset index, households’ adaptive capacity index, and social safety net index were used as continuous independent variable to estimate the household’s resilience capacity effect on household food security status. In addition to that number of shocks those households faced in the past five years were also used as continuous explanatory variables and households’ multidimensional food security status were taking ordered categorical response variables. It ordered from 1(food secured) to 4(severely food insecure) status to make easy to interpret the relationship between response variable so called household multidimensional food security status and explanatory variables such as household aggregate resilience capacity index, households’ access to basic service index, households asset index, households adaptive capacity index, social safety net index and households shock-exposed in the past five year.

To analyze the interactive effects of shocks and resilience capacity pillars as well as household resilience capacity status on a household's food security status, ordinal logistic regression model was employed. For this specific objective, ordinal logistic regression was a suitable regression analysis technique that matches the data. Consequently, the investigator employed ordinal logistic regression analysis to explore the mutual influence of shocks and household resilience capacity pillars on households’ food security status. In order to employ the ordinal logistic regression model, the data must meet the following criteria: proportionate odd assumption, goodness of fit, pseudo-R-square, and checked multicollinearity problem. The variance inflation factor (VIF) measures how much the variance of the predicted regression coefficient is inflated when there is an issue with multicollinearity or correlation between the independent variables (Shrestha, 2020). According to Shrestha, the VIF is only the inversion of tolerance and the value of VIF =1 indicates that there is no correlation to each other of the explanatory variables. If the value of VIF $1<VIF<5$, it indicates that the independent variables are moderately correlated to each other. Problematic values of VIF $5<VIF<10$ indicate highly correlated variables, while multicollinearity difficulties are suggested when the value of VIF surpasses 10.

Ordinal logistic regression model

Three models are included in the logistic regression model: binary, multinomial, and ordinal (Derr, 2013). There are times, according to Derr (2013), when a result with several categories has an ordinal scale rather than a nominal one. Derr suggests that the multinomial logistic model be applied in this kind of situation. Nevertheless, this would neglect to include the outcome's ordinal nature, and as a result, the estimated odds ratios might not adequately address the analysis's problems regarding the relatively ordinal logistics brand (Hosmer & Lemeshow, 2000).The ordinal logistic regression model is a variant of the logistic regression model that is employed for the analysis of ordinal dependent variables that possess more than two categories (Parry, 2020) and Ordinal Logistic Regression entails the relationships between an ordered response variable and a set of predictor variables that can be continuous, discrete, dichotomous, or a mix of any of these. (Hosmer & Lemeshow, 2000). According to Liu (2015), ordinal logistic regression results can be interpreted using odds ratio. The proportional odds (PO) model, also called the cumulative odds model, and commonly used model for the analysis of ordinal categorical data, comes from the class of generalized linear models. It is a generalization of a binary logistic regression model when the response variable has more than two ordinal categories (Liu, 2009).

Hosmer & Lemeshow (2000) pointed out that it is also possible to create ordinal variable via categorization of an underlying continuous variable. In this study, the ordinal outcome household's food security status, which is coded as 1, 2, 3 and 4 (1=food secure,2 rarely food insecure, 3= moderately food insecure and 4=severely food insecure). The ordinal regression analysis could be stated as a latent variable model (Agresti, 2010). In this study a latent variable, y*i assumed, which is , here is the exact but unobserved dependent variable; x is the vector of independent variables, and β is the vector of regression coefficients which the study wish to estimate.

Odd ratio can be interpreted in percentage change in odd and it is calculated through (odd ratio-1) *100.Positive percentage change in the odds indicates increase in the odds, whereas negative percentage change indicates decrease in odds (Liu, 2015). As Liu points out, if the percentage change declares no changes in odds at all, it means that the predictor variable does not influence the odds of the success.

When using proportional odds models, we estimate the odds of being at or below a specific category (Y<-j) based on an ordered multiple-level outcome variable. In ordinal logistic regression, the chance of being at or below a category divided by the probability of being at or below the category is the odd of being at or below the category.

$$Odds(Y \le j) = \frac{p(Y \le j)}{p(y > j)}, \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \, equation(6)$$

Since the probability of being at or below a category and the probability of being above that category is complementary:

$$p(y \le j) + p(y > j) = 1, \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \, equation(7)$$

This equation can be modeled as:

$$Odds(y \le j) = \frac{P(y \le j)}{1 - p(y \le j)}, \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. \, equation(8)$$

The probability of being at or below a category $P(y \le j)$ is the cumulative probability since it equals the sum of the probability of all categories at or below that category:

$$p(y \le j) = p(y = 1) + p(y = 2) + \cdots p(y = j) \dots \dots \dots \dots \dots \dots \dots \dots \dots \, equation(7)$$

$$when\, j = 1,2,3 \dots \dots ..$$

CHAPTER FOUR: RESULTS AND DISCUSSION

Data analysis is performed to produce information that is both usable and helpful. The analysis can describe and summarize the data, find relationships between variables, compare variables, find differences between variables, and forecast outcomes, regardless of whether the data is qualitative or quantitative. The research method, which is sometimes referred to as the "heart" of the endeavor, is the source of the research results and discussion. The results and responses are provided in four subsections, following the specified sequence of specific objectives. The first subsection provides a brief overview of the agricultural and meteorological drought patterns that have occurred over time in the study areas, including the narration of existing experiences. The second subsection assessed a household's resilience capacity to recurring drought. The third subsection assessed the household’s multidimensional food security status and, the final subsection examined the interactive effect of household resilience capacity and households exposed to shock on their food security status.

4.1 Demographic and socio-economic characteristics of the households

A total of 326 survey questionnaire disseminated via the *Kobo* data collecting toolbox to the selected household, which takes one-month data collection period, which covered the dates from February 8 through March 7 in 2023. All of those questionnaires were returned. The survey had a total of 100% response rate. Out of the total 326 respondents, the majority, around 88% and 12%, are male- and female-headed households, respectively. The household heads vary in age by 13 years, with an average age of about 48. Additionally, the average family size, number of dependent household members, dependence ratio, and owner of cultivable land per household in Timad are roughly 6, 3, 1.05, and 6, respectively. 286 (86%) of the 326 respondents were married, 17 (5%) were divorced, 26 (8%) were widowed or widowers, and 3 (1%) were single household heads. Furthermore, out of the 326 respondents, 230 (71%) are illiterate, meaning they cannot read or write. Of the household heads, 47 (14%), 33 (10%), 14 (4%), and 2 (1%) can only read and write, including religious leaders, primary school graduates, secondary school graduates, and higher education graduates, respectively. The main livelihood of the households out of 326 respondents was on-farm for 263 (80.67%), non-farm for 18 (5.52%), and mixed for 45 (13.80%) of the households, in addition to that 184(56.44%) and 142 (43.56%) of the respondents were non-beneficiaries, and beneficiaries of PSNP respectively (see Table 4:1).

Table 4:1 Descriptive statistics of the households' demographic and socio-economic characteristics

Variables	Freq.	Percent
Male	286	87.73
Female	40	12.27
Total	326	100.00
Married	280	85.89
Divorced	17	5.21
Widowed/Widower	26	7.98
Single	3	0.92
Total	326	100.00
Illiterate	228	69.94
Literate	98	30.06
Total	326	100.00
On-farm	263	80.67
Non-farm	18	5.52
Mixed	45	13.80
Total	326	100.00
Not beneficiary	184	56.44
Beneficiary	142	43.56
Total	326	100.00
Variable	Mean	Std. Dev.
Age	47.604	13.104
Family size	5.997	2.267
Dependent members Dependency ratio	2.822 1.054	1.354 .837

Source: computed based on field survey 2023

4.2. Drought Assessment using Standard precipitation Index (SPI)

According to the SPI results shown in Figure 4:1, a SPI value of 0 indicates median precipitation, with the graph line depicting a decline, signaling a trend towards drier seasonal drought conditions, denoted by red shading. The intensity of red shading signifies the severity of drought, while green indicates wetter conditions. Additionally, the intermediate color, orange, represents near-normal precipitation levels, including transitional stages between drought and wetness (refer to Figure 4:1).

For the purpose of identifying the drought pattern of the study area, whether it increased or not over 30 years (1993–2022) period were classified into three categories: the first decade (from 1993 to 2002), the second decade (2003 to 2012), and the third decade (2013 to 2022). and the SPI drought analysis were carried out by considering the growing seasons of the study area, which are SPI3 embraces June, July, and August; those months are the main growing season for the study area, so called summer (kremt in local language) and the SPI6 considered the months from April to September especially SPI6 included three months those did not considered with SPI3 and those months have crucial role for grazing purpose and to grow two season crops like millet or sorghum crops.

According to this category, the drought pattern in *Meharit Kebele* at SPI3 is as follows: in the first decade 2 very wet years (1998 and 2001), 1 moderately dry year (1997) and the remain years were near normal; in the second decade, 1 moderately wet and the remaining years have been near normal; and in the third decade, one moderately dry year (2014), one extremely dry year (2015) and the remaining near normal. This indicates that both drought frequency and severity became slightly increased from 1993 to 2022. This result is partially in agreement with Haftu et al. (2022), as they stated there was a critical increased seasonal and annual drought from 1983 to 2016.

Nevertheless, regarding SPI6, the first decade revealed that all years were near normal and above except 1 moderately dry year (1997), in the second decade:2 moderately dry years happened and in the third decade:1 severely dry year (2015) was happened. This result indicates that both the drought frequency and severity have increased to some extent. Those drought years result in agreements with the studies of Haftu et al. (2022), and Abebe et al. (2020) (see Fig 4:1 and 4:2).

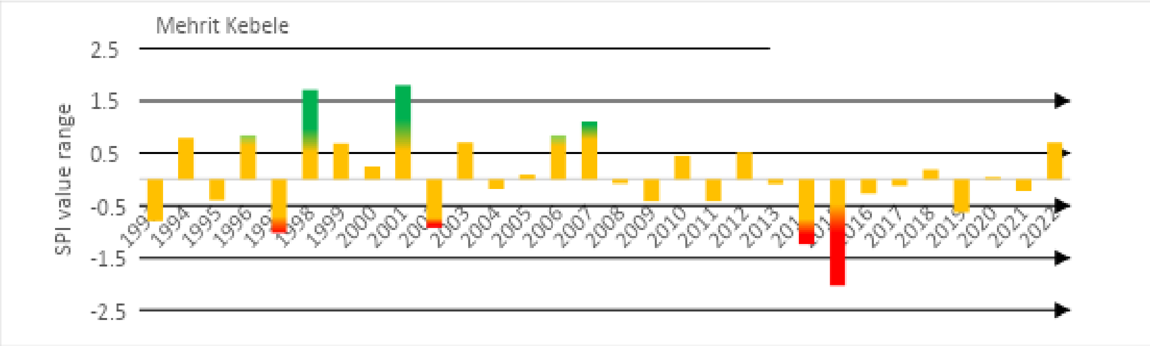

Figure 4:1 Drought patterns of Meharit Kebele using SPI-3

Source: own SPI-3 assessment result (2023)

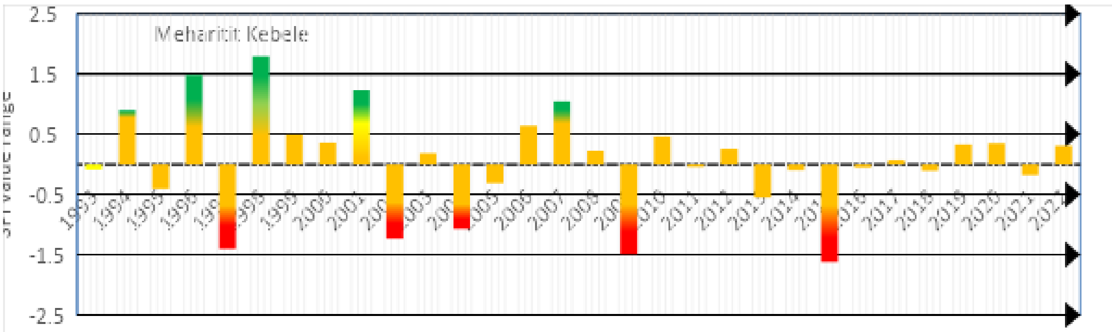

Figure 4:2 Drought patterns of Meharit Kebele using SPI-6

Source: own SPI-6 assessment result, 2023

Table 4:3 Standard precipitation index results for Meharit Kebele

SPI value	Drought intensity	First decade		Second decade		Third decade	
		Spi3	Spi6	Spi3	Spi6	Spi3	Spi6
2.0+	extremely wet	0	0	0	0	0	0
1.5 to 1.99	very wet	2	1	0	0	0	0
1 to 1.49	moderately wet	0	2	1	1	0	0
(-.99 to .99)	near normal	7	5	9	7	8	9
(-1 to -1.49)	moderately dry	1	2	0	2	1	0
(-1.5 to -1.99)	severely dry	0	0	0	0	0	1
(-2 and less	extremely dry	0	0	0	0	1	0

Source: Own SPI assessment result 2023

The FGD result in this kebele indicates that both the frequency and severity of drought become critically increased. As the FGD agreement result indicates, after 2008 they didn't get sufficient rainfall to grow crops and grazing.

The FGD repetitively shared experience was:

> *Drought is not new for us since we were born and it is popular that we live with ups and downs of drought and related challenges for years even from our ancestors, but the frequency and severity become increased especially after the year 2000 in the Ethiopian calendar. We have got sufficient and productive rainfall of 1 year in 4 years in this district, specifically in this kebele, there is no other option to grow crops if the rain fails (absence). Not only are we challenged to grow crops but also deficiency of water for home consumption and for animal consumption is always worse. Due to this our herds dramatically decreased; most households lost all of the available animals. Thu, their live fall on the hands of aid and some lives by migrated to neighbor districts like misraq (east) Belesa, Metema, Dehana district, Arma-chiho, Gonder and even we displaced far from our district like Bahir Dar, Gojam and Addis Ababa (FGD,2023).*

In *Menderecherkos Kebele*, the SPI3, for the first decade 1-year (1993) were moderately dry year; the second decade were all near normal; whereas in the third decade, 2 moderately dry (2014 and 2019) years and 1 severely dry year (2015) were happened this result in line with Haftu et al. (2022) (see figure 4:3).

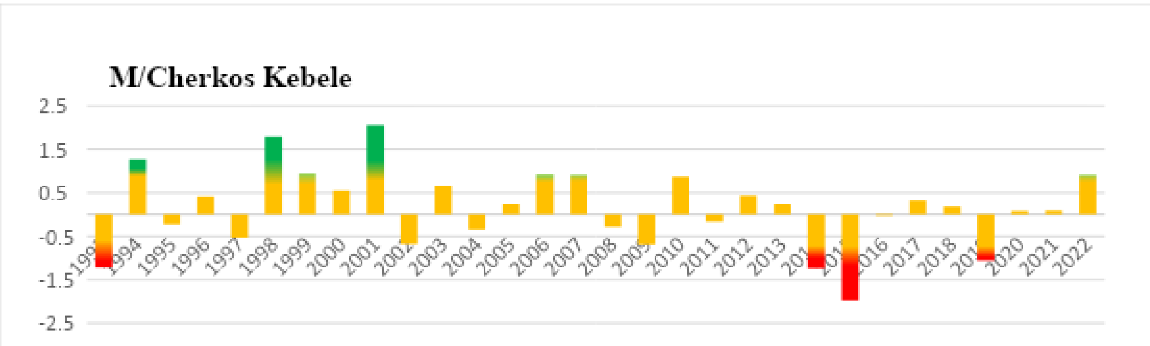

Figure 4:3 Drought patterns of M/Cherkos Kebele using SPI-3

Source: own SPI-3 assessment result 2023

In SPI6, first decade 1 extremely wet (1998), 1 very wet (2001) and 2 moderately wet years were happened; second decade 1 moderately dry (2004) and 1 severely dry (2009) year were happened; in third decade 1year was severely dry (2015) and the remaining years have been near normal, this result harmony with Abebe et al. (2020, Haftu et al. (2022) (see figure 4:4).

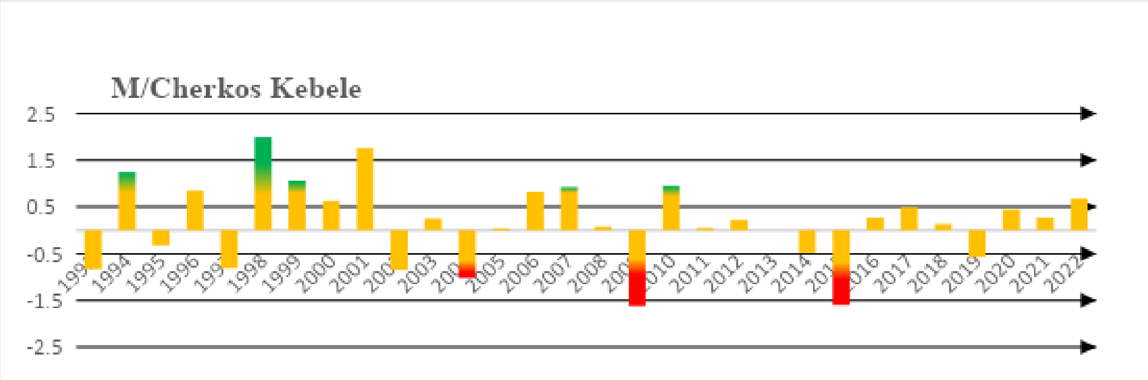

Figure 4:4 Drought patterns of M/Cherkos Kebele using SPI-6

Source: own SPI-6 assessment result, 2023

Table 4:4 Standard precipitation index results for M/Cherkos Kebele

SPI value	Drought intensity	First decade		Second decade		Third decade	
		Spi3	Spi6	Spi3	Spi6	Spi3	Spi6
2.0+	extremely wet	1	1	0	0	0	0
1.5 to 1.99	very wet	1	1	0	0	0	0
1 to 1.49	moderately wet	1	2	0	0	0	0
(-.99 to .99)	near normal	6	6	10	8	7	9
(-1 to -1.49)	moderately dry	1	0	0	1	2	0
(-1.5 to -1.99)	severely dry	0	0	0	1	1	1
(-2 and less	extremely dry	0	0	0	0	0	0

Source: own SPI assessment result, 2023

In *Tirshiman Kebele* in the time scale three of the first decade, 2 very wet, 1 moderately wet,1 moderately dry year and the remaining near normal years happened. Second decade, 1 moderately wet and nine near-normal years were occurred, in the third decade: 1 moderately dry and 1 severely dry year occurred. This result is in line with the result of Abebe et al. (2020, Haftu et al. (2022) and Senamaw et al. (2021).

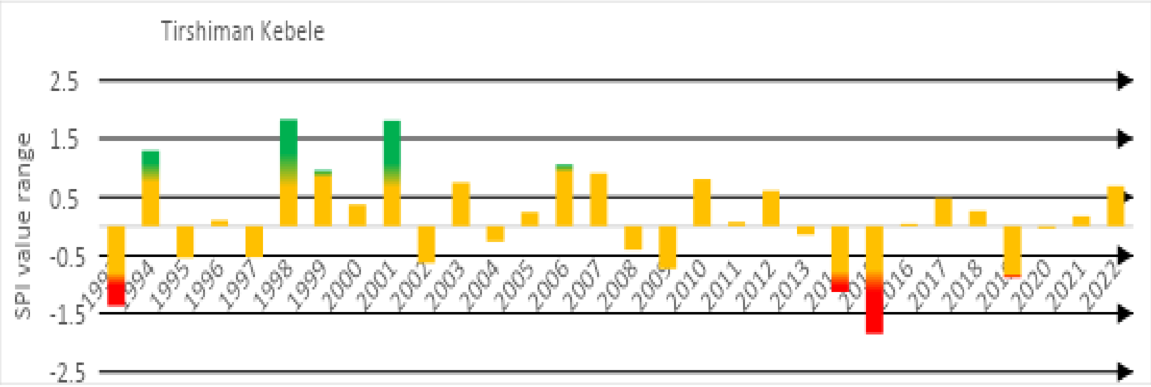

Figure 4:5 Drought patterns of Tirshiman Kebele using SPI-3

Source: own SPI assessment result, 2023

In SPI-6 of *Tirshiman Kebele* there were two severe drought years, one year in the second decade (2009) and the other in the third decade that was (2015), whereas the SPI reveals the year 1994 was a very wet year. This result is in harmony with the study of Abebe et al. (2020, Haftu et al. (2022), and Senamaw et al. (2021).

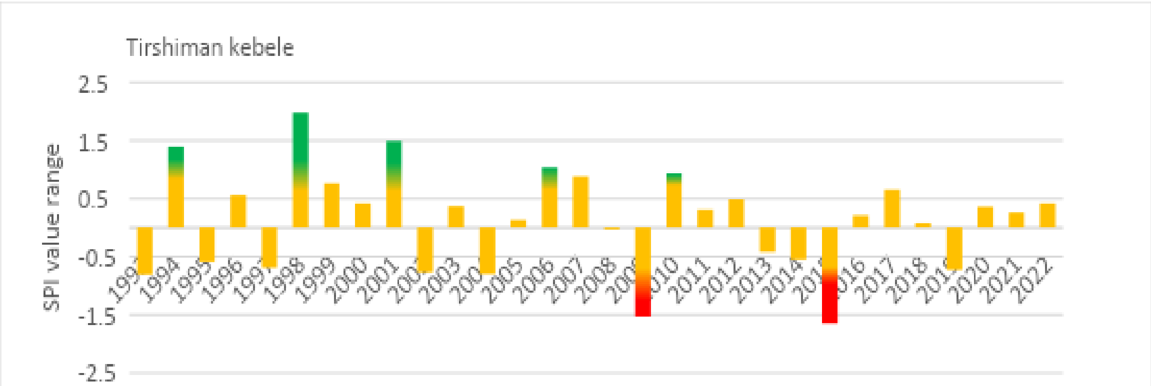

Figure 4:6 Drought patterns of Tirshiman Kebele using SPI-6

Source: Source: own SPI assessment result, 2023

Table 4:5 Standard precipitation index results for Tirshiman Kebele

SPI value	Drought intensity	First decade		Second decade		Third decade	
		Spi3	Spi6	Spi3	Spi6	Spi3	Spi6
(2.0+)	extremely wet	0	0	0	0	0	0
(1.5 to 1.99)	very wet	2	1	0	0	0	0
(1 to 1.49)	moderately wet	1	2	1	1	0	0
(-.99 to .99)	near normal	6	7	9	8	8	9
(-1 to -1.49)	moderately dry	1	0	0	0	1	0
(-1.5 to -1.99)	severely dry	0	0	0	1	1	1
(-2 and less)	extremely dry	0	0	0	0	0	0

Source: own SPI assessment result, 2023

The analysis of drought patterns across three kebeles reveals similar trends overall, with notable differences observed in Meharit kebele compared to the other two. In both three and six-time scales, Meharit exhibits distinct variations. For instance, in the three-time scale, years like 1993, 1997, 2002, 2009, 2014, 2015, and 2019 show SPI values ranging from -0.8 to 2.03, indicating significant fluctuation. Conversely, Menderecherkos kebele demonstrates more consistent SPI values within a narrower range. Similarly, in the six-time scale, Meharit's SPI values fluctuate notably across the same years, while Tirshiman kebele maintains more stable SPI values. This analysis underscores the importance of understanding local variations in drought patterns, which can inform targeted interventions and resilience-building efforts. The overall drought pattern indicates significant increment of both drought frequency and severity this result in harmony with Yitbarek and Huseyin, 2020) and Senamaw et al. (2021).

The drought frequency and severity are increasing in *Sehala Seyemt District* also confirmed by KII, who is the early warning expert of *Sehala Seyemt District*.

The early warning expert said that:

> *Sehala Seyemt District is a frequently drought prone area relative to other districts in wag Hemra zone. The rainfall in Sehala Seyemt District is erratic. Even though the known productive crop growing season in this district started in mid-June to the beginning of September, the late start and early cessation of rainfall became the trend. In addition to that the absence of rainfall throughout the year and also it occurs consecutively. Due to this the drought occurrence in this district becomes increased" (KII, 2023).*

Causes of recurrent drought

One key informant from the *district* Natural Resource Management department head provided the main concepts about the causes of recurrent drought in the study area as follow:

> *The rough topography of the Wag Hemra zone, in general, and the study area, in particular, is marked by mountains, high escarpments, and deeply incised valleys. These are the most frequent features of both areas. With a mean annual rainfall ranging from 150 to 700 mm, the summer season, which begins in mid-June and ends in early September, experiences the largest rainfall. The primary causes of the recurring drought in the study area are irregular and unpredictable rainfall patterns. Farmers in rain-dependent areas experience meteorological droughts when rain falls outside the long-term patterns of precipitation amount and distribution. These types of droughts can lead to agricultural conditions and other types such as hydrological and socioeconomic droughts (KII, 2023).*

This outcome agrees with the investigation of Souverijns et al. (2016), and Yitbarek and Huseyin, 2020). The drought occurred when the amount of rainfall varies from 700mm to lower 150 mm, because the drought is the deviation rainfall amount from long term trends. Especially this rainfall deviation occurred in the main growing season the crop grow failed leads to agricultural drought and so on other drought types. According to the key informant interviews provided information, drought can be caused by factors such as late onset, early cessation of rainfall, short and prolonged dry periods, and high frequency and moderate-to-severe intensity of drought events. The probabilities of dry spell lengths during different seasons, particularly during crop growing periods, contribute to the risk of drought. This result is in line with (Ott and Longnecker, 2016), who point out that high mean annual rainfall does not necessarily fix the occurrence of drought, as rainfall variability can still lead to risks such as drought with moderate-to-severe intensity. Variability in rainfall patterns, including late onset, early cessation, and dry spells, can contribute to drought conditions despite high mean annual rainfall levels. Drought risks are prevalent during the crop growing periods in both spring and autumn seasons, regardless of the mean annual rainfall levels.

Other FGDs result in each *Keble* also repetitively confirms the above KIIs idea as shown below:

> *Human activities like deforestation, population growth, increased herd size and plowing of steep slope causes dry out of head waters and springs and it leads to drought, however the main drought causes in this district is lack of or insufficient precipitation. The precipitation may be absences throughout the year or consecutive years, late starting or early cessation of summer rain are the main causes of drought (FGD, 2023).*

4.3 Measuring households' resilience capacity using food and agricultural organization resilience index measurement analysis-II

The emotional, psychological, and physical well-being of a person, as well as their capacity for problem-solving, access to social networks, and in-person stress management techniques, all contribute to their capacity for resilience (Kamara et al., 2019). Building and strengthening one's resilience capacity can help one maintain overall well-being and overcome hardship. Resilience, however, is a latent variable not directly measured but inferred from other observed indicators or proxy variables.

To measure the resilience status of households, which is the second objective of this research, it must pass through a two-step factor analysis. The first was dimension reduction to get the four dimensions of resilience, and the second was to measure the household's resilience capacity index based on the first computed resilience dimensions. Before, all four defining pillars of resilience, such as access to basic services (ABS), assets (AST), social safety nets (SSN), and adaptive capacity (AC), were selected based on RIMA-II (2016) resilience index measurement and analysis-II and computed as follows using factor analysis as mentioned above before trying to test resilience. Table 4:6 shows the descriptive statistics of the resilience explanatory variables; the resilience explanatory variables were selected based on literature reviewed mainly from Alinovi et al. (2010), RIMA-II (2016) and Mekonnen (2021).

Table 4:6 Resilience explanatory variables

	Households' dependency ratio	1.054	.837
Latent variables	Observed variable	Freq.	Percent
	Access to improved water(yes)	31	9.51
ABS	Access to telecom(yes)	185	56.75
	Access to irrigation(yes)	59	18.10
	Access to saving & credit institute(yes)	64	19.63
	Access to early warning service(yes)	70	21.47
	Access to extension service(yes)	96	29.45
	Access to road(yes)	130	39.88
		Mean	Std. Dev.
	Distance to health center(in-minute)	184.58	96.416
	Distance to nearest public transport (in minute)	178.47	103.958
	Distance to nearest market (in minute)	182.20	99.736
	Total cultivable land size (in-Timad)	5.706	2.916
AST	Agricultural asset index	92.601	23.814
	Total livestock (in TLU)	5.867	4.888
	Total non-agricultural asset index	27.969	31.424
	Crop diversification index	36.503	16.704
	Income diversification index	27.21	26.087
	Livestock diversification index	73.369	31.555
AC		**Freq.**	**Percent**
	Households head ability to read & write (yes)	107	32.82
		Mean	
SSN	Formal transfer cash (in ETB)	1225.77	
	In-formal transfer cash (in ETB)	623.988	

Source: computed based on field survey (2023)

Measuring Household Resilience Capacity pillars

Access to basic service (ABS)

Access to basic service by itself latent variable which explained by an observed variables such as access to improved water, access to telecom service, access to saving and credit institutes, access to irrigation, access to extension service, access to paved road in the kebele, distance to health center, distance to access public transport service and distance to nearest by market. To get this latent variable principal component factor method of factor analysis was employed. Before executed factor analysis variable were inverted those have inverse relationship with access to basic service such as distance to health center, distance to access public transport service and distance to nearest by market, if the distance to accessed those service far from the household's residence the household's accessibility becomes less and also their resilience capacity expected being less if other variables constant. After applying the inverse calculation of the above listed variables factor analysis has been executed and three factors are retained based on Kaiser-Meyer-Olkin (KMO) criterion which states that factors extracted should be its eigenvalue greater than1 (Field, 2013). Moreover, the KMO measure of sampling adequacy is 0.70. This value can fully fill the criterion of KMO minimum requirement of which is 0.5. Since the Kaiser-Meyer-Olkin (KMO) measure can be computed and serves as a representation of the ratio between the squared correlation among variables and the squared partial correlation among variables. The KMO metric, which falls within the range of 0 to 1, provides an indication of the degree of diffusion in the correlation pattern. A KMO value of 0 denotes a substantial disparity between the sum of partial correlations and the sum of correlations, thus signifying a lack of appropriateness for factor analysis. Conversely, a value that approaches 1 suggests that correlation patterns are relatively compact, and therefore factor analysis is expected to yield factors that are distinct and reliable (Field, 2013).

The cumulative proportion of the three extracted factors is 0.64, which indicates the amount of variance explained by those extracted factors is 64 % (see in appendix III table 1). As shown in the table 4:7 below access to improved water, availability of paved road in the kebele, access to health center, distance to get public transport service and distance to nearest market have high factor loading on factor 1 respectively, access to telecommunication service, access to saving and credit service and access to irrigation have higher loading factor on factor 2 and access to extension service and access to early warning service have high loading factor on factor 3 (see table 4:7).Among ten variables that used to estimate ABS distance to nearest by market, distance to access to public transport service and access to early warning service are the positive and substantive variables or those have higher loads respectively. This implies that to improve household resilience, high attention pay for those substantive variables is important. As a result, three retained factors were extracted and composed based on their eigenvalues. In both PCA and factor analysis, not all factors are retained and the process of deciding how many factors to keep is called extraction. Therefore, eigenvalues associated with a variate indicate the substantive importance of that factor. Due to this, it is logical to retain only factors with larger than one eigenvalue (see in appendix III table 1). The KMO can be calculated for individual, and multiple variables, and it represents the ratio of the squared correlation between variables to the squared partial correlation between variables. The KMO statistic varies between 0 and 1. A value of 0 indicates that the sum of partial correlations is large relative to the sum of correlations, indicating diffusion in the pattern of correlations (hence, factor analysis is likely to be inappropriate). A value close to 1 indicates that patterns of correlations are relatively compact and so factor analysis should yield distinct and reliable factors as follows.

$$ABS = \frac{factor1 * 0.3 + factor2 * 0.21 + factor3 * 0.13}{3}$$

Where:

- ABS is access to basic service
- Factor1, factor2 and factor3 are extracted latent variables

The operation output from the above function is further used to estimate a household's resilience capacity index.

Table 4:7 Factor loadings and correlations for access to basic service dimension

Variable	Factor1	Factor2	Factor3	Uniqueness
Access to improved water	0.671	0.008	0.137	0.530
access to telecom	-0.460	-0.649	0.361	0.237
Access to irrigation	0.484	0.555	-0.131	0.440
Access to Save and credit service	0.115	0.654	-0.006	0.559
Access to early warning service	-0.065	0.423	0.748	0.258
Access to extension service	0.366	0.582	0.326	0.422
Availability of paved road in the kebele	0.417	-0.480	0.511	0.334
Distance to health center	0.633	-0.346	-0.059	0.476
Distance to access public transport service	0.850	-0.253	-0.062	0.210
Distance to nearest by market	0.895	-0.223	-0.062	0.146
Bartlett test of sphericity; chi2(45) = 1179.48 Prob>chi2 = 0.0000 KMO measure of Sampling Adequacy = 0.70 Extraction method: Principal component factor (pcf)				

Source: Computed based on Field Survey (2023)

Non-agricultural asset index

Non-agricultural wealth index is one among the variables used to predict latent variable of asset; however, non-agricultural asset index by itself is not an observed variable rather it is explained by other observed variables. For this objective households having to Mobile phone, Households having to Television or Radio, Households having to Timbre or Iron made bed and Households having to Jewelry and luxury goods were selected based on different literatures and the study community’s condition. These observable variables were executed and predicted latent variables of non-agricultural asset index using the factor analysis family so called polychoric PCA method. The polychoric PCA method is a non-parametric approach to the analysis of dichotomous item responses, and according to kiwanuka et al. (2022), Kolenikov and Angeles (2004) factor analysis involving categorical or skewed variables; it is often suggested to utilize the polychoric correlation matrix. This method differs from traditional factor analysis, which relies on Pearson's correlation coefficient, as it estimates the correlation between two ordinal or categorical variables. The polychoric correlation matrix proves especially advantageous when dealing with variables that possess ordered categories or when the assumptions of normality are compromised. The executed result retains one component with eigenvalues greater than 1, this component explained 78 % of the total variance of the observed variables and this predicted component score further used to predict household's asset index (see more in table 4:8 and 4:9), it Contains the correlation between the component and the variables and also Eigenvalues and proportions.

Table 4:8 Scoring coefficients of non-agricultural asset variables

Variable	Response	Coeff. 1	Coeff. 2	Coeff. 3
Households having to Mobile phone	No	-0.441369	-1.100921	-0.078907
	Yes	0.172104	0.429284	0.030768
Households having to Television or Radio	No	-0.244150	0.051342	0.342319
	Yes	0.655669	-0.137880	-0.919305
Households having to Timbre or Iron made bed	No	-0.285825	0.106674	-0.032422
	Yes	0.589380	-0.357030	0.066856
Households having to Jewelry and luxury goods	No	-0.207516	0.075005	-0.251214
	Yes	0.713583	-0.257920	0.863847

Source: Computed based on Field Survey, 2023

Table 4:9 Scoring coefficients of non- agricultural asset variables

Variable	Response	Coeff. 1	Coeff. 2	Coeff. 3
Households having to Mobile phone	No	-0.441369	-1.100921	-0.078907
	Yes	0.172104	0.429284	0.030768
Households having to Television or Radio	No	-0.244150	0.051342	0.342319
	Yes	0.655669	-0.137880	-0.919305
Households having to Timbre or Iron mad bed	No	-0.285825	0.106674	-0.032422
	Yes	0.589380	-0.357030	0.066856
Households having to Jewelry and luxury goods	No	-0.207516	0.075005	-0.251214
	Yes	0.713583	-0.257920	0.863847

Source: Computed based on Field Survey, 2023

Agricultural asset index

Ax, Sickle, ploughing tools locally called *Mofer-qember*[3]*Plows* and water pumps (which are used for irrigation purposes or other) are the most common agricultural asset that explain observed variables without forgetting livestock asset even if it is calculated in TLU independently for this purpose. From those observed variables one factor based on Kaiser-Meyer-Olkin (KMO) criteria of eigenvalue greater than 1 should be retained as a factor. This retained factor accounted for 0.689(68.9%) of the total variance. The mentioned observed variables all have high positive loading weight on the retained factor except one, which is availability of water pump with -0.166 negative correlations. As shown in table: the observed variable of households having of full plowing tools (locally *mofer qenber*) have highly correlation with the latent variable or retained factor by recording 0.95 weight followed by 0.934,0.931 and 0.88 loading factor of having plow, having Sickle and having ax are respectively. It implies that almost all observed variables have strong correlation with latent factor except the availability of water pumps, which have weak correlation with the latent factor (see table 4:10). The score of this extracted factor is further used to predict a household's asset index.

Table 4:10 Factor loadings and correlations for agricultural asset index

Variable	Factor1	Uniqueness
Having Ax	0.879	0.227
Having Sickle	0.931	0.133
Having full Plowing tools (localyMofer_kenber)	0.950	0.097
Having Plow	0.934	0.127
Availability of water pump	-0.166	0.973
Bartlett test of sphericity; chi2(10) = 1628.65 Prob>chi2 = 0.0000 KMO measure of Sampling Adequacy = 0.76 Extraction method: Principal component factor (pcf)		

Source: Computed based on Field Survey (2023)

[3]Denotes the traditional and locally used tools for agricultural plowing.

Asset

An asset is one pillar of the latent variable so called resilience, but an asset by itself is not an observed variable rather it is predicted from observed variables such as livestock size, cultivable land size in timad[4], non-agricultural asset index and agricultural asset index. To get this asset index, two-step factor analysis was employed. The first was employed to get the non-agricultural and agricultural asset index separately and the second was employed for the final aggregated asset index. Livestock size changed into tropical livestock unit (TLU[5]) using the conversion factor of 0.7 for cattle, 0.5 for donkeys and 0.1 for small ruminants (Baars, 2000, Mekonen, 2021). In addition, the normalization technique of the min-max method was applied to make all units free and make index values minimum 0 and maximum 1 as the follow below formula.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{equation (8)}$$

Where:

- X is the original value
- X_min is the minimum value in the dataset
- X_max is the maximum value in the dataset

After all asset indexes were predicted by factor analysis and extracted two factors based on Kaiser-Meyer-Olkin (KMO) criterion of eigenvalue greater than 1. Among this agricultural asset index, and non-agricultural asset index have strong association with factor1, whereas livestock size and cultivable land size highly associated with factor2 based on the weight of the factor loading, since factor loading explains the relationship between observed variable and the extracted variance .While the proportion of variance explained quantifies how much of the total variance is explained by a particular factor, and so 72% of the total variance accounted for by the

[4] Local land size measurement units in the study area equivalent to 0.25 hectare.
[5]TLU standardizes different types of livestock into a single unit of measurement. The conversion factor of 0.7 for cattle, 0.5 for donkeys and 0.1 for small ruminants (Baars, 2000).

retained and combined factors (see table 4:11 and) and also see more Table 4 in appendix III about Eigenvalue and proportion of asset index .

Table 4:11 Factor loadings and correlations for asset index

Variable	Factor1	Factor2	Uniqueness
Households owned livestock size	0.419	0.683	0.358
Households owned cultivable land size	0.127	0.821	0.310
Households owned non-agricultural asset index	0.849	-0.240	0.222
Households owned agricultural asset index	0.848	-0.220	0.232
Bartlett test of sphericity; chi2(6) = 162.61 Prob>chi2 = 0.0000 KMO measure of Sampling Adequacy = 0.5159 Extraction method: Principal component factor (pcf)			

Source: Computed based on Field Survey (2023)

Adaptive capacity

Households' adaptive capacity to drought or food insecurity is explained through literacy status of the household head, dependency ratio of the household, income diversification status, crop diversification status and livestock diversification status of the household. To do so, factor analysis method has been applied. Prior to performing factor analysis for adaptive capacity of the household, crop diversification index, livestock diversification index and income diversification indices of the household have been estimated, since they are also latent variables and explained by other observable variables. To estimate those diversification indices factor analyses also employed including polychoric PCA for categorical and dummy variables. Polychoric PCA is an extension of principal component analysis and which is recommended method of factor analysis when observed variables are categorical or ordered and dummy (kiwanuka et al., 2022).

Crop diversification index

Household crop diversification is a latent variable as mentioned in the above paragraph, so it is predicted by households' experience of growing diverse crop types. For this purpose, different common crops were selected and collected data during survey time on whether or not they grew each priorly selected crop in the past one growing season. Those selected crops were Millet, Sesame, Teff and Mung bean (local name Masho) crops. As mentioned before, to estimate the household's crop diversification index polychoric PCA method was employed, since the questionnaire was a yes or no type dummy character question. After executing polychoric PCA two latent variables so called components were extracted that eigenvalue greater than 1 and those components 66.9% accounted for, see more about Eigenvalues and proportions of crop diversification in appendix III table 4). The scoring coefficient of each crop and each category are different for components (see in appendix III table 5).

$$CD_{Index} = \frac{P1 * 0.411 + p2 * 0.258}{2}$$

Where:

- CD is crop diversification index
- P1 is extracted component one
- P2 is extracted component two

This result further used as input variable when estimating one pillar of resilience so called adaptive capacity index

Livestock diversification

Livestock diversification is one explanatory variable for a household's adaptive capacity. Livestock like ox, milking cow, other Cattel's like (Bull and heifer), Donkey and small ruminants were used to predict livestock diversification index of the household. An extension of the PCA analysis method called polychoric PCA was employed to predict livestock diversification index. The latent variables are also extracted based on the component that have an eigenvalue greater than1 of Kaiser-Meyer-Olkin (KMO) criterion. Based on this KMO criterion one component is retained and it explains 73% of common variance (see in appendix III table 6).

Income diversification index

Income diversification is also another latent variable that used to explain the latent variable adaptive capacity of the households. This latent variable was extracted from observed variables like, income whether or not earned in the past twelve months from crop income from animal production, income from trade, income from rents, income from vegetables and fruits and income from Apicultural products. To estimate income diversification, index the same as the above indices polychoric PCA method employed and three components extracted based on the Kaiser-Meyer-Olkin (KMO) criterion of eigenvalue greater than 1 retain as a factor together with their combination account for 72% of the total variance (see in appendix III table 8 and 9).

$$INC\_DIV_{Index} = \frac{P1 * 0.411 + P2 * 0.222 + P3 * 0.150}{2}$$

Where:

- INC_DIV is income diversification
- P1, P2 and P3 are extracted latent variables

This result is further used as an input variable when estimating one pillar of resilience, the so-called adaptive capacity index.

Aggregated adaptive capacity index

Adaptive capacity is one of the resilience pillars which is an unobserved variable that is estimated by income diversification index, livestock diversification index, crop diversification index, dependency ratio of the household and household head literacy status. To produce adaptive capacity of the household factor analysis was employed. Based on the Kaiser-Meyer-Olkin (KMO) criterion, the relevant statistical requirements of goodness for factor analysis were checked and then all were satisfied (see table 4:12). Based on Kaiser-Meyer-Olkin (KMO) criterion of eigenvalue greater than 1 have been two factors extracted and these explain 54.9% of the total variance (see in appendix III table 11). Among observed variables weights on the extracted factors the household's livestock diversification index has the highest loading factor that recorded weight of 0.816 followed by household heads literacy status and crop diversification index respectively (see table 4:12). The higher the loading factor indicates the importance the variable is and interventions and policies should be pay attention to those that have higher factor loading in order to improve the adaptive capacity of the households.

$$AC_{Index} = \frac{P1 * 0.295 + p2 * 0.254}{2}$$

Where:

- AC is adaptive capacity
- P1 and P2 are extracted latent variables

The result obtained from this function is further used to estimate the research's interesting subject called resilience capacity index.

Table 4:12 Factor loadings and correlations for aggregated adaptive capacity index

Variable	Factor1	Factor2	Uniqueness
Households' income diversification index	0.480	0.601	0.408
Households' livestock diversification index	0.816	-0.204	0.293
Households crop diversification index	0.737	-0.356	0.330
Dependency ratio of the household	-0.030	0.333	0.888
Household heads literacy status	0.189	0.793	0.335
Bartlett test of sphericity; chi2(10) = 100.74 Prob>chi2 = 0.0000 KMO measure of Sampling Adequacy = 0.5027 Extraction method: Principal component factor (pcf)			

Source: Computed based on Field Survey, 2023

Aggregated households' resilience capacity index

Household resilience capacity index per se is unobserved; it is measured through proxy indicators through two stage factor analysis. This study identified those proxy indicators of a household's resilience, before going to measure it based on literature reviewed as stated in the household resilience method of analysis part of the RIMA-II approach. These proxy indicators are access to basic service (ABS), asset index (AST), adaptive capacity index (AC) and social safety net (SSN).ABS, ASST and AC are predicted through factor analysis methods which is the first stage that used to dimension reduction method distinctly to those pillars as shown in the above subtopics, but SSN is explained two observed variables which are formal and informal transfer of in-cash (Alinovi et al., 2010).To run factor analysis at list three variables are needed according to Tabachnick and Fidell (2007) mentioned in (Asfaw, 2022). But the two variables that explain SSN are two, which cannot fulfill the minimum required to run factor analysis. To get SSN the average has been taken and logarithmic transformation statistical methods and min max normalization methods were applied to manage the outliers, plus to make it unit free. On average the household's resilience capacity pillar such as ABS, AST, AC and SSN was 0.547, 0.532, 0.52 and 0.328 respectively (see table 4:13).

Table 4:13 Descriptive statistics for four resilience capacity pillars

variables	Mean
Access to basic service (ABS)	.547
Asset index (AST)	.532
Adaptive capacity index (AC)	.52
Social safety net (SSN)	.328

Source: Computed based on Field Survey, 2023

The Kaiser-Meyer-Olkin (KMO) measure is utilized to ascertain if the observed variables possess adequate commonality to justify a factor analysis and checks the entire criterion to run second stage factor analysis and the entire statistical requirements are satisfied. After all, checking the aggregated household's resilience estimated one factor retain based on the Kaiser-Meyer-Olkin (KMO) rule of eigenvalue greater than 1. The extracted factor explains 65.75 % of the total variance. Then, this factor value predicts a household's resilience capacity status, since the above all consecutively applied factor analysis was to get this point. As shown in table 4:14 All variables are directly associated with this retained factor except social safety net (SSN) which is negative (-0.286) and this negative association implies that cash transfer from friends, families or relatives, government interventions and non-governmental organizations delivered cashes to the needy or extremely poorer individual or households as aid or lifesaving assistance, means that the detection of substantive importance of variables to households' resilience was done by examining the size of their component loadings, where negative loadings may signify factors that contribute inversely to resilience . In the study area of this research poverty stricken or needy is the criteria to receive the food aid for life saving actions. This result or negative association of SSN to household resilience is in agreement with the work by Atara et al. (2020), Haile et al. (2022), the result could imply that receiving food assistance over a longer period of time could have an adverse impact on household resilience, they confirm that negative factor values or associations between underlying factors and variables can indicate an inverse relationship, where an increase in one variable leads to a decrease in another. According to Haile et al. (2022) the four pillars' estimated coefficients are statistically significant at the 0.01 level, indicating their significance in impacting resilience in Ethiopia's rural areas. Particularly, households show stronger resilience when they have more assets, better access to basic services, and a higher adaptive capacity. Fascinatingly, the model's inclusion of Social Safety Nets (SSN) confronts in reverse with our original theory. Remarkably, safety nets appear to support households' food entitlement, improve their capacity to cover basic needs, and lessen the effects of large negative shocks. This shows that among households in rural areas, SSNs contribute positively to resilience building and vulnerability reduction. Therefore, without additional funding for health and education as well as sustainable livelihood activities, safety nets will not be able to increase resilience over time. The negative coefficient emphasizes how emergency response, resilience building, and development promotion are not complementary.

Whereas this finding odds from the finding of Gambo et al. (2016), they stated as SSN possess positive and substantial effect with household resilience building. All of the variables show loading weights, but the asset index has a higher loading factor (0.831) when we prioritize it over the other variables (see factor loading in Table and eigenvalues and proportions in (see in appendix III table 11), which are access to basic services (0.819), adaptive capacity index (0.75), and social safety net, respectively. For the purposes of this research, the most crucial component of household resilience was asset status. If a household has comparatively better asset status, then it is closer to being resilient. As the table above demonstrated, assets are the outcome of numerous observed variables that construct comparatively superior assets. This result is confirmed by the work of Gambo et al. (2016), Kebede et al. (2016). The second most important attribute of households to being resilient in this research is ABS that possesses a positive effect. This result is consistent with the conclusion of (Alinovi et al., 2010), found that supplying of public service is beyond the household's control, but it plays critical role to access and build asset, as well as to improve households' life style including enhancing their adaptive capacity and it highlighting the importance of support systems (infrastructure and institutions) that make livelihoods function. Better access to the healthcare, schools, and functional markets improves quality of life and access to services which safeguards labor productivity, thereby increasing resilience capacity (see table 4:14).

Table 4:14 Factor loadings and correlations for aggregated household's resilience capacity index

Variable	Factor1	Uniqueness
Access to basic service (ABS)	0.819	0.329
Asset index (AST)	0.831	0.310
Adaptive capacity index (AC)	0.750	0.438
Social safety net (SSN)	-0.286	0.918
Bartlett test of sphericity; chi2(6) = 222.82 Prob>chi2 = 0.0000 KMO measure of Sampling Adequacy = 0.6814 Extraction method: Principal component factor (pcf)		

Source: Computed based on Field Survey, 2023

Some scholars, such as Beyene et al. (2023) categorized the resilience status of households into four groups: non-resilient, moderately resilient, resilient, and highly resilient. Following this classification, the present study assessed that 48.77% of households fell into the non-resilient category, 24.54% into the moderately resilient category, 15.34% into the resilient category, and 11.35% into the highly resilient category (see table 4:15).This categorizing is based on degrees their resilience status and categorizing household resilience based on these criteria allows for a nuanced understanding of the varying degrees of vulnerability and capacity among households. It helps identify priority areas for intervention and support, targeting resources more effectively to enhance household resilience and well-being.

Table 4:15 Household resilient capacity status

Resilience capacity index	Freq.	Percent	Cum.
Non resilient	159	48.77	48.77
Moderate resilient	80	24.54	73.31
resilient	50	15.34	88.65
High resilient	37	11.35	100.00
Total	326	100.00	

Source: Computed based on Field Survey, 2023

4.4 Households multidimensional food security status

As depicted in table 4:16, below out of 326 household 77(23.62%), 50(15.34%), 105(32.21%) and 94(28.83%) are food secured, rarely food insecure, moderately food insecure and severely food insecure respectively which is the prevalence of MFI. The highest prevalence of MFI in the surveyed household was moderately food insecure followed by severely food insecure and food secured status respectively (see table 4:16).

Table 4:16 Descriptive Statistics of the Household multidimensional Food Security Status prevalence

Households' multidimensional food security status	Freq.	Percent	Cum.
Food secured	77	23.62	23.62
Rarely food insecure	50	15.34	38.96
Moderately food insecure	105	32.21	71.17
Severely food insecure	94	28.83	100.00
Total	326	100.00	

Source: Computed based on Field Survey, 2023

Based on the data presented in Table 4:17, it is evident that the distribution of household resilience varies across different levels of food security. Among food-secure households, the majority exhibit high resilience, comprising 44.16% of all food-secure households (34 households). Additionally, a significant portion of food-secure households demonstrate moderate resilience, accounting for 29.87% (23 households). Resilient households are less common within this category, representing 3.90% (3 households).

Rarely food insecure households predominantly display moderate resilience, constituting 46% (23 households) of this group. Resilient households are also present but to a lesser extent, comprising 38% (19 households).

In contrast, moderately food insecure households are predominantly non-resilient, with 62.86% (66 households) falling into this category. Moderately resilient households are less common among moderately food insecure households, making up 27.62% (29 households) of this group. Severely food insecure households overwhelmingly lack resilience, with 93.62% (88 households) classified as non-resilient. Only a small proportion of severely food insecure households demonstrate moderate resilience, accounting for 5.32% (5 households).

Overall, non-resilient households are primarily concentrated among moderately (66 households) and severely (88 households) food insecure categories. Moderate resilient households are predominantly found among food-secure (23 households) and rarely food insecure (23 households) categories. Resilient households are mainly associated with food-secure (20 households) and rarely food insecure (19 households) categories, with high resilience primarily observed among food-secure households (34 households).

Positive Association:

A higher proportion of food-secure and rarely food insecure households exhibit higher resilience levels, particularly in the moderate and high resilient categories.

Negative Association:

A significant number of moderately and severely food insecure households are non-resilient, indicating lower resilience levels among these vulnerable groups.

Table 4:17 Cross-tabulation of Household MFI and RCI

Households MFI	Resilience capacity index				
	Non resilient	moderate resilient	resilient	high resilient	Total
Food secure	0	23	20	34	77
Rarely food insecure	5	23	19	3	50
Moderately food insecure	66	29	10	0	105
Severely food insecure	88	5	1	0	94
Total	159	80	50	37	326

Source: Computed based on Field Survey, 2023

4.5 The interactive effect of shocks and resilience capacity on household multidimensional food security status

To analyze the interactive effects of shocks and resilience capacity pillars as well as household resilience capacity status on a household's food security status, ordinal logistic regression model was employed.

Ordinal logistic regression model

Ordinal Logistic Regression is effective model to describe the effect of independent variables on a categorical response variable (Josephat & Ismail, 2012). Due to the order nature of the response variable, the current study employed the Ordinal Logistic Regression. The rationale for using Ordinal Logistic Regression for this study was that the dependent variable of the study, households' food security status is categorical and ordered variable. The dependent variable household's multidimensional food security status has four ranked levels, food secure, rarely food insecure, moderately food insecure and severely food insecure.

Assumptions of Ordinal Logistic Regression

Multicollinearity among the independent variables was therefore not an issue for the regression coefficients, as indicated by the research's mean VIF score of 1.14, which indicates a moderate correlation. As a result, all explanatory variables were included in the model estimation process (see in appendix III table 12). Using the ordinal logistics regression model requires that the significance value at the 95% confidence interval be less than 0.05 for model fit. Before employing the model, it was convenient to find out if the model gives adequate predictions. There are various ways to check the fitness of the ordinal logistic regression model. Consequently, having a significance level below 0.05, so the model fit information guarantees that the significance is 0.000, as table 4:18 illustrates. As a result, the analyses of this particular objective were completed in a comprehensive way, and the researcher continues to the following evaluation of overall goodness of fit.

Table 4:18 Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	881.438			
Final	481.086	400.352	5	.000

Source: Computed based on Field Survey, 2023

The overall model fit (goodness of fit) of the model significance value is greater than 0.05 declares good fit. Therefore, the significance value of Pearson and Deviance in table 4:19 ascertains the observed data is consistent with the fitted model.

Table 4:19 Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	711.956	970	1.000
Deviance	481.086	970	1.000

Source: Computed based on Field Survey, 2023

According to the pseudo-R-square result, the ordered logit model was found to be a suitable indicator of the ordered response models' predictive ability. Singh (200), states that an adjusted R2 of more than 75% is considered very high; 50–75% is good; 25–50% is fair; and less than 25% is poor. Based on the study data, the model's 45.4% may be classified as fair. However, R-Squared (or R2) does not perform well since ordinal regression is predicated on specific assumptions, as noted by lmquist et al. (2021), Because of its intrinsic bias; Stata is rarely used, even when it produces a bogus R2. However, a number of articles, including Field (2013, 2018), employed the Nagelkerke Pseudo R-Square SPSS figure that was produced (see table 4:20). Nagelkerke value is a measure of the strength of association in logistic regression, indicating how well the model fits the data. According to Field (2013, 2018), it is a pseudo-R-squared value that ranges from 0 to 1, with higher values indicating a better fit of the model to the data.

Table 4:20 Pseudo R-Square

Cox and Snell	.707
Nagelkerke	.758
McFadden	.454

Source: Computed based on Field Survey, 2023

Following the fulfillment of all assumptions and test statistics needed to execute the ordered logit model, the researcher proceeded to perform an ordinal logistics regression analysis, examining the interplay between the multidimensional food security status of households and their access to basic services, assets, adaptive capacity, social safety, and shock exposure. With a 95% confidence interval, the model is statistically significant overall, as indicated by the chi-square value of X2 = 196.636 and the accompanying P-value of 0.000. It means that there is a substantial association between the ordinal outcome variable and at least one of the explanatory variables in the model.

Interpretation ordinal logistic regression result using odds ratio

The analysis presented in Appendix III, Table 14, indicates a negative association between the predictor variable "access to basic services" (ABS) and the multidimensional food insecurity status of households, with a β coefficient of -6.133. Additionally, the odds ratio (odds = 0.002) corresponding to this association is less than one, indicating a significant negative relationship. The statistical significance is evidenced by the p-value ($P < 0.01$ or 1%), which is reported as $P = 0.000$, suggesting a high level of significance.

Interpreting these findings, it can be concluded that as the ABS predictor variable increases by one unit, the odds of a household experiencing a higher level of food insecurity (or a worse food security status) decrease by a factor of 0.002, holding all other variables constant. This implies a positive correlation between ABS and household food security, meaning that higher levels of access to basic services are associated with better food security outcomes. This aligns with the findings of Alinovi et al. (2010), suggesting that access to basic services plays a critical role in enhancing households' resilience to risks and crises, including food crises and threats to food security.

Regarding the AST predictor, the multidimensional food insecurity status of the household is highly significant negative association ($\beta = -5.329$) (see in appendix III table:14) at $P<0.01$ or 1% ($P = 0.000$), and odds = 0.005, which is less than one. An increase of one unit in the predictor variable AST, while keeping all other explanatory variables constant, is associated with a 0.005 decrease in the likelihood of being in a specific category of households with a more adverse food security status, as detailed in Table 4:21. This observation is consistent with the findings of Gambo et al. (2016), highlighting the importance of assets as a substantial coping mechanism during challenging periods.

In relation to the multidimensional food insecurity status of households, the adaptive capacity (Ac) predictor has a highly significant (i.e., significant at $P<0.01$ or 1 % ($P = 0.000$)) (see table 4:21) influence with $\beta = -4.696$ (see in appendix III table :13) which is negative, and odds = 0.009, which is less than one. When one unit increases the predictor variable AC, it means that, under the assumption that all other predictor variables held constant, the odds of being beyond a specific category of households' food insecurity status (i.e., having a worse food security status) reduces less likely by 0.009 (see table 4:21). Meaning that, AC is positively associated with household food security status (i.e., better food security status). This implication is in line with the studies by Egamberdiev et al. (2023) Stats that AC plays a positive and substantial role in food security status (i.e., having better food security status). The ordinal logit result of this study also indicates negative association with food insecurity status (i.e., having worse food security status), on the other hand AC has positive association with households' food security status (i.e., having better food security status).

Regarding the Social Safety Net (SSN) predictor, $\beta = .720$ (see in appendix III table :13) indicates a positive relationship, and odds = 2.055 indicate a substantial but non-significant ($P = 0.095$) impact on the multidimensional food insecurity status of the household. It suggests that SSN has no effect, either positive or negative, on any of the several categories of food insecurity status for households (see table 4:21). The direct or positive association between SSN and food insecurity status result is in line with what Olawuyi and Ijila (2023) studied. The reason for this is that receiving assistance from friends and family in the form of cash transfers and remittances, as well as government-funded social intervention and investment programs, among other social safety nets, should serve as a support system and buffer for people by "delivering targeted transfers and livelihood supports to needy households (extremely poor) and vulnerable individuals or households" from shocks and stressors. On the contrary of this result Tefera et al. (2017) found that, the partially positive or direct relation of SSN for family's resilience to food security due to families received SSN from diver's sources, so some are used to increased food security like remittance and some are not.

In terms of the predictor for households that had many shocks over the previous five years, has positive association (β=0.269) (see in appendix III table :14), Odds=1.308, which is greater than one, and it is significant at P<5 or 5%(P=0.04). It suggests that, under the assumption that all other variables are in an immutable state, the odds of being beyond a specific category of households' food insecurity status (i.e., having a worse food security status) are increase more likely by1.308 for every unit increase in predictor variable shock (see table 4:21). It suggests that if a household experiences more shocks, their ability to eat would be in jeopardy and this outcome is in line with the research conducted by Smith and Frankenberger (2018) Similar to what this study discovered, other articles examined by Kasie et al. (2018), Knippenberg and Hoddinott (2019) also supported the negative effects of shocks, particularly droughts, on food security.

Interpretation ordinal logistic regression result using marginal effect

The marginal effect (dx/dy) for the Food Secure category is 0.488. A one-unit increase in access to basic services is associated with an increase of 0.488 in the probability of being in the Food Secure category, holding other variables constant. This suggests that higher levels of access to basic services are positively associated with a higher likelihood of being in the Food Secure category. Marginal effect for the Rarely Food Insecure category is 0.037, it reveals, that a one-unit increase in access to basic services is associated with a smaller increase of 0.037 in the probability of being in the Rarely Food Insecure category. This indicates that the impact of access to basic services on the probability of being in this category is relatively smaller compared to the Food Secure category.

The marginal effect (dx/dy) for the Moderately Food Insecure category is −0.003, which indicates one-unit increase in access to basic services is associated with a decrease of 0.003 in the probability of being in the Moderately Food Insecure category. This suggests that higher levels of access to basic services are associated with a slightly lower likelihood of being in the Moderately Food Insecure category.

The marginal effect (dx/dy) for the Severely Food Insecure category is −0.522, which reveals one-unit increase in access to basic services is associated with a significant decrease of 0.522 in the probability of being in the Severely Food Insecure category.

This indicates that higher levels of access to basic services are strongly associated with a lower likelihood of being in the Severely Food Insecure category. In summary, these interpretations provide insights into how changes in access to basic services are associated with changes in the probabilities of different food security categories. Higher levels of access to basic services appear to be strongly associated with a lower likelihood of severe food insecurity (see table 4.21). Consistent with the research by Alinovi et al. (2010), this outcome underscores the significance of Access to basic service (ABS) as a pivotal factor affecting households' capability to navigate risks and respond to crises. These challenges encompass various issues, notably the food crisis and threats to food security.

The marginal effect (dx/dy) for the Food Secure category is 0.424. If it interprets a one-unit increase in the variable "Asset" is associated with an increase of 0.424 in the probability of being in the "Food Secure" category, holding other variables constant. This suggests that higher levels of assets are positively associated with a higher likelihood of being in the "Food Secure" category.

The marginal effect (dx/dy) for the "Rarely Food Insecure" category is 0.032 indicates a one-unit increase in "Asset" is associated with a smaller increase of 0.032 in the probability of being in the "Rarely Food Insecure" category. This indicates that the impact of assets on the probability of being in this category is relatively smaller compared to the "Food Secure" category.

The marginal effect (dx/dy) for the Moderately Food Insecure category is −0.003. which conveys that a one-unit increase in "Asset" is associated with a decrease of 0.003 in the probability of being in the "Moderately Food Insecure" category. This suggests that higher levels of assets are associated with a slightly lower likelihood of being in the Moderately Food Insecure category.

The marginal effect for the Severely Food Insecure category is −0.453, it conveys that a one-unit increase in Asset (dx/dy) is associated with a significant decrease of 0.453 in the probability of being in the Severely Food Insecure category. This indicates that higher levels of assets are strongly associated with a lower likelihood of being in the Severely Food Insecure category. In summary, these interpretations provide insights into how changes in the variable Asset are associated with changes in the probabilities of different food security categories. Higher levels of assets appear to be strongly associated with a lower likelihood of severe food insecurity and a higher likelihood of being food secure (see table 4.21). This discovery aligns with the findings of Gambo et al. (2016), emphasizing that the availability of assets serves as a significant coping mechanism during challenging periods.

The marginal effect (dx/dy) for the Food Secure category is 0.374, which illustrates a one-unit increase in the variable Adaptive Capacity is associated with an increase of 0.374 in the probability of being in the "Food Secure" category, holding other variables constant. This suggests that higher levels of adaptive capacity are positively associated with a higher likelihood of being in the "Food Secure" category.

The marginal effect (dx/dy) for the Rarely Food Insecure category is 0.028, which disclosed a one-unit increase in Adaptive Capacity is associated with a smaller increase of 0.028 in the probability of being in the Rarely Food Insecure category. This indicates that the impact of adaptive capacity on the probability of being in this category is relatively smaller compared to the Food Secure category.

The marginal effect (dx/dy) for the Moderately Food Insecure category is −0.002, which implies a one-unit increase in Adaptive Capacity is associated with a decrease of 0.002 in the probability of being in the Moderately Food Insecure category. This suggests that higher levels of adaptive capacity are associated with a slightly lower likelihood of being in the Moderately Food Insecure category.

The marginal effect (dx/dy) for the Severely Food Insecure category is −0.400, which implies a one-unit increase in Adaptive Capacity is associated with a significant decrease of 0.400 in the probability of being in the Severely Food Insecure category. This indicates that higher levels of adaptive capacity are strongly associated with a lower likelihood of being in the Severely Food Insecure category. In summary, these interpretations provide insights into how changes in the variable Adaptive Capacity are associated with changes in the probabilities of different food security categories. Higher levels of adaptive capacity appear to be strongly associated with a lower likelihood of severe food insecurity and a higher likelihood of being food secure (see table 4.21). This result is in harmony with Alinovi et al. (2010), Egamberdiev et al.

(2023), those authors indicated that having a higher level of adaptive capacity increases the likelihood of reducing food insecurity.

The marginal effect (dx/dy) for the Food Secure category is −0.021, which implies a one-unit increase in the variable Exposure to Shocks is associated with a decrease of −0.021 in the probability of being in the Food Secure category, holding other variables constant. This suggests that higher levels of exposure to shocks are negatively associated with the likelihood of being in the Food Secure category.

The marginal effect (dx/dy) for the Rarely Food Insecure category is −0.002, which implies a one-unit increase in Exposure to Shocks is associated with a smaller decrease of −0.002 in the probability of being in the Rarely Food Insecure category. This indicates that the impact of exposure to shocks on the probability of being in this category is relatively smaller compared to the "Food Secure" category.

The marginal effect (dx/dy) for the Moderately Food Insecure category is 0.000, which indicates a one-unit increase in Exposure to Shocks is associated with no change (0.000) in the probability of being in the Moderately Food Insecure category. This suggests that exposure to shocks does not have a significant impact on the probability of being in this category.

The marginal effect (dx/dy) for the Severely Food Insecure category is 0.023, which implies a one-unit increase in Exposure to Shocks is associated with an increase of 0.023 in the probability of being in the Severely Food Insecure category. This indicates that higher levels of exposure to shocks are positively associated with a higher likelihood of being in the Severely Food Insecure category. In summary, these interpretations provide insights into how changes in the variable Exposure to Shocks are associated with changes in the probabilities of different food security categories. Higher levels of exposure to shocks appear to be associated with a lower likelihood of being food secure and a higher likelihood of being severely food insecure (see table 4.20). This result is in harmony with Kasie et al. (2018), Knippenberg and Hoddinott (2019), Smith and Frankenberger (2018), according to scholars' conclusion, increased household's shocks could threaten the ability to access food.

Table 4:21 Interactive effect of shocks and resilience capacity on household multidimensional food security status

MFI	Odds ratio	St. Err.	p>|z|	Marginal effect(dy/dx) food security status			
				FS	Rarely FI	Moderately FI	Severely FI
ABS	0.002	0.707	0.00***	0.488	0.037	-0.003	-0.522
AST	0.005	0.722	0.00***	0.424	0.032	-0.003	-0.453
AC	0.009	0.964	0.00***	0.374	0.028	-0.002	-0.400
SSN	2.055	0.446	0.106	-0.057	- 0.004	0.000	0.061
Shock	1.308	0.131	.04**	-0.021	-0.002	0.000	0.023
Mean dependent var=2.663				SD dependent var =1.130			
Pseudo r-squared =0.454				Number of obs =326			
Chi-square =196.636				Prob > chi2 =0.000			
Akaike crit. (AIC)= 497.086				Bayesian crit. (BIC)= 527.381			

*** p<.01, ** p<.05, * p<.1 it implies that significance at 1%, 5% and 10%

Source: Computed based on Field Survey, 2023

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

An upward trend in drought frequency and intensity was observed in the study area. The survey results indicated that 48.77% of households were non-resilient, 24.54% were moderately resilient, 15.34% were resilient, and 11.35% were highly resilient. This indicates a higher portion of the surveyed households were vulnerable to shock and they were unable to resist and bounce-back better from shocks. From the latent variable resilience attributes, AST, ABS, and AC exhibited positive factor loadings and correlations of 0.831, 0.819, and 0.750, respectively. The variables with the higher load indicate the most important it is and the greater attention that should be paid to it. Therefore, when designing a policy, the policymaker should have to consider those variables by giving priority to those variables which have the highest loads.

According to Multidimensional Food Insecurity (MFI) analysis, the prevalence of food insecurity was distributed as follows: 23.62% food-secure, 15.34% rarely food-insecure, 32.21% moderately food-insecure and 28.83% severely food-insecure. This result implies above half of the surveyed households were chronically food insecure. The ordinal logistic regression results indicated that among the five explanatory variables, three were negatively significant at 1% those are AST, ABS and AC, and shock was positively significant at 5% this indicates the existence of high interactive effect of resilience attributes and shocks on food security.

In general, this study illuminates the concerning rise in long-term drought trends plus, assessing household resilience, multidimensional food security, and the interconnected effects of shock exposure and resilience capacity, the research provides crucial insights into the challenges faced by communities in the study area. The implications underscore the urgent need for strategic interventions to change less resilience households into resilience and to boost resilience households more and address the evolving dynamics of food security issues in the context of dynamic shock. As we navigate the intricate findings of this study, it becomes evident that sustainable initiatives are imperative to fortify communities against the diverse impacts of shocks and stressors. This research contributes to the ongoing discourse on creating a more secure and resilient future for households in the study area and offers valuable lessons for broader contexts.

5.2 Recommendations

In light of the study's results, the researchers have proposed recommendations for various stakeholders involved in community-focused initiatives aimed at enhancing resilience and addressing the challenges posed by increasing drought trends. These recommendations give priority to community empowerment, the promotion of sustainable practices, and fostering collaborative efforts to build a more secure and sustainable future for all residents. The study reveals that based on SPI value of the study area increased the observed upward trend in drought frequency and intensity, a significant proportion of households are non-resilient and also sizable portion of the surveyed households are experienced worst food security status and also there are important variables to enhance food security status of the households such as AST, ABS and AC. The conclusions drawn from this research have led to the formulation of the following recommendations:

- ☞ Implement Drought Mitigation Strategies: Given the observed upward trend in drought frequency and intensity, it is imperative to implement and strengthen drought mitigation strategies in the study area. This may include the development of water management systems, including building of water reservoirs, the promotion of drought-resistant crops and animals, and the establishment of early warning systems to enhance community preparedness.
- ☞ Enhance Household Resilience Building Programs: as the study reveals that a significant portion of the served households are less resilience, to enhance the resilience of these households the stakeholders such as communities by itself, governmental and non-governmental organizations, NGOS, National and international developmental organization should focusing on the identified resilience pillars, especially paying more attentions for households asset building and improve access to basic services are prioritized.
- ☞ Address Food Insecurity through Targeted Interventions: Design and execute initiatives targeted at tackling the diverse aspects of food insecurity in the research area. Customize interventions according to recognized proxy indicators such as CSI, rCSI,

HFIAS, FCS, HDDS, HHS, and SAFS. Take into account community-specific strategies to enhance food accessibility, dietary variety, and overall food security.

☞ Recognize the interconnection between household resilience and food security. Integrate resilience-building measures into food security planning and vice versa. This holistic approach can help create synergies and ensure a comprehensive strategy to address the challenges faced by households in the context of dynamic shocks.

☞ Advocate for policies that address the evolving dynamics of food security and resilience in the study area. Additionally, invest in capacity-building programs for local institutions and community leaders to ensure effective implementation and sustainability of interventions. "As policymakers, it is crucial to respond to the compelling evidence presented in the study regarding long-term drought trends in Sehala Seyemt District. Our recommendations are designed to guide the development and implementation of policies that prioritize resilience to shock by enhancing access to basic service, adaptive capacity of the household and asset development. These measures aim to ensure a resilient and sustainable future for the region.

☞ This study utilized remote sensing precipitation data and applied the Standardized Precipitation Index (SPI) as a drought assessment method due to a lack of available station data in the study area and limited efforts. To enhance the clarity and relevance of the research implications, future investigations will incorporate more than one alternative drought assessment method and utilize data from station sources. Additionally, this study employed a cross-sectional dataset to assess household resilience, multidimensional food security status, and self-reported shocks. A panel dataset would better capture these intricacies than a cross-sectional dataset because of the multidimensional and dynamic nature of these difficulties. It is advised that panel datasets be used in future studies to more thoroughly explore these intricate problems.

REFERENCE

ABADI, N., TECHANE, A., TESFAY, G., MAXWELL, D. & VAITLA, B. 2018. The impact of remittances on household food security.

ABEBE, A. M., AREGA, B. B. & MEHRETE, B. F. 2020. Spatial and temporal drought incidence analysis in the northeastern highlands of Ethiopia. *Geoenvironmental Disasters*, 7.

ABEBE, S., ADANE, W., AYALEW, A., GEBEREHANA, G. & WUBESHET, B. 2019. Major Resource Bases and Constraints for development of Wag Hemra zone: A Short Synopsis.

ABEGAZ, B. & KEBEDE, G. 2022. Analysis of climate variability and its impact on crop yield over Wag Hemra zone, Ethiopia. Journal of Earth and Environmental Sciences Research, 4, 1-12.

ABENET, F., SIMACHEW, K., GOBU, L., SIMIE, T., ADUGNA, W., ANBESSIE, M., YAKOB, Z. & SOMANE, A. 2016. Child malnutrition and associated factors among drought affected pastoralists in the Somali Region, Eastern Ethiopia. J Nutr Health Sci, 3, 402.

Agresti, A. (2010). Analysis of Ordinal Categorical Data (2nd ed.). New York: Wiley.

AKBARI, K. & BEGDELI, M. 2018. The Role of social media in Increasing Social Tolerance. *Transcendent Policy,* 6**,** 147-166.

ALEMAYEHU, A. & BEWKET, W. 2016. Local climate variability and crop production in the central highlands of Ethiopia. *Environmental Development,* 19**,** 36-48.

ALINOVI, L., MANE, E. & ROMANO, D. 2010. Measuring household resilience to food insecurity: application to Palestinian households. *Agricultural survey methods***,** 341-368.

ALMQUIST, Y. B., ÅKESSON, C. & BRÄNNSTRÖM, L. 2021. An applied guide to quantitative methods with Stata. Research Reports in Public Health Sciences.

AMBA, S., BHOWMICK, A. & KUMNEGER, E. 2022. Meteorological Drought Monitoring Based on Satellite CHIRPS Product over Gamo Zone, Southern Ethiopia. *Advances in Meteorology,* 2022.

ANDREW, D. J., FRANCIS, M. N., GRETEL, P. & SERA, L. Y. 2013. What are we assessing when we measure food security? A compendium and review of current metrics. *Adv Nutr,* 4**,** 481-505.

ANSAH, I. G. K., GARDEBROEK, C. & IHLE, R. 2019. Resilience and household food security: a review of concepts, methodological approaches and empirical evidence. *Food Security,* 11**,** 1187-1203.

ASFAW, T. 2022. *Rural Household Resilience to Food Insecurity: The case of Meket District,*

North Wollo Zone, Amhara National Regional State, Ethiopia. MSc thesis.

ASHENAFI, Y. K., SHAO, G., WANG, X. & WU, S. 2021. Quantification of drought severity change in Ethiopia during 1952–2017. *Environment, Development and Sustainability,* 23**,** 5096-5121.

ASMAMAW, M., MERETA, S. T. & AMBELU, A. 2019. Exploring households' resilience to climate change-induced shocks using Climate Resilience Index in Dinki watershed, central highlands of Ethiopia. *PloS one,* 14**,** e0219393.

ATARA, A., TOLOSSA, D. & DENU, B. 2020. Analysis of rural households' resilience to food insecurity: Does livelihood systems/choice/matter? The case of Boricha district of sidama zone in southern Ethiopia. *Environmental Development,* 35**,** 100530.

AZEB, A. M. & VAN LAERHOVEN, F. 2018. The interplay between planned and autonomous adaptation in response to climate change: Insights from rural Ethiopia. *World Development,* 107**,** 87-97.

BAARS, R. 2000. Costs and returns of camels, cattle and small ruminants in pastoral herds in eastern Ethiopia. *Tropical Animal Health and Production,* 32**,** 113-126.

BACHEWE, F. 2009. *The state of subsistence agriculture in Ethiopia: Sources of output growth and agricultural inefficiency*, University of Minnesota.

BAHTA, Y. T. 2022. Nexus between coping strategies and households' agricultural drought resilience to food insecurity in South Africa. *Land,* 11**,** 893.

BATHAIY, S. S., CHIZARI, M., SADIGHI, H. & ALAMBEIGI, A. 2021. Social media and farmer's resilience to drought as an environmental disaster: A moderation effect. *International Journal of Disaster Risk Reduction,* 59**,** 102209.

BAYISSA, Y. A., MOGES, S. A., XUAN, Y., VAN ANDEL, S. J., MASKEY, S., SOLOMATINE, D. P., GRIENSVEN, A. V. & TADESSE, T. 2015. Spatio-temporal assessment of meteorological drought under the influence of varying record length: The case of Upper Blue Nile Basin, Ethiopia. *Hydrological Sciences Journal,* 60**,** 1927-1942.

BAYISSA, Y. A., TADESSE, T., SVOBODA, M., WARDLOW, B., POULSEN, C., SWIGART, J. & VAN ANDEL, S. J. 2019. Developing a satellite-based combined drought indicator to monitor agricultural drought: A case study for Ethiopia. *GIScience & Remote Sensing,* 56**,** 718-748.

BEKELE, S., KIINDIE, T., MENALE, K., TSEDEKE, A., PRASANNA, B. & ABEBE, M. 2014. Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and climate extremes,* 3**,** 67-79.

BERNARD, H. R. 2017. Research methods in anthropology: Qualitative and quantitative approaches, Rowman & Littlefield.

BEWKET, W. Rainfall variability and crop production in Ethiopia: Case study in the Amhara region. Proceedings of the 16th international conference of Ethiopian studies, 2009. Norwegian University of Science and Technology Trondheim, Norway, 823-836.

BEYENE, F., SENAPATHY, M., BOJAGO, E. & TADIWOS, T. 2023. Rural household resilience to food insecurity and its determinants: Damot Pulasa district, Southern Ethiopia. *Journal of Agriculture and Food Research,* 11**,** 100500.

BEYENE, F., SENAPATHY, M., BOJAGO, E. & TADIWOS, T. 2023. Rural household resilience to food insecurity and its determinants: Damot Pulasa district, Southern Ethiopia. *Journal of Agriculture and Food Research***,** 100500.

BORCHERS, A. & PIELER, T. 2010. Programming pluripotent precursor cells derived from Xenopus embryos to generate specific tissues and organs. *Genes (Basel),* 1**,** 413-26.

BROWN, T. A. 2015. *Confirmatory factor analysis for applied research*, Guilford publications.

CALLOWAY, E. E., CARPENTER, L. R., GARGANO, T., SHARP, J. L. & YAROCH, A. L. 2022. Development of three new multidimensional measures to assess household food insecurity resilience in the United States. *Frontiers in Public Health,* 10**,** 1048501.

CAMMALLERI, C. 2021. GAR Special Report on Drought 2021. *GAR Special Report on Drought 2021.* United Nations Office for Disaster Risk Reduction.

CARLETTO, C., ZEZZA, A. & BANERJEE, R. 2013. Towards better measurement of household food security: Harmonizing indicators and the role of household surveys. *Global Food Security,* 2**,** 30-40.

CEGLAR, A. 2008. Drought indices. *Drought Management Center for Southeastern Europe, Biotechnical Faculty, University of Ljubljana, Slovenia, Report*.

CHIWAULA, L. & WAIBEL, H. 2009. The role of shocks and risks for the livelihoods of small-scale fishing communities of Hadejia-Nguru Wetlands in Nigeria.

CINNER, J. E., ADGER, W. N., ALLISON, E. H., BARNES, M. L., BROWN, K., COHEN, P. J., GELCICH, S., HICKS, C. C., HUGHES, T. P. & LAU, J. 2018. Building adaptive capacity to climate change in tropical coastal communities. *Nature Climate Change,* 8**,** 117-123.

D'ERRICO, M. & SMITH, L. 2019. Comparison of FAO and TANGO measures of household resilience and resilience capacity. Working paper.

DANIE, L. & FIRAFIS, H. 2021. Climate Change Induced Shocks, Consequent Impacts, Vulnerability and Farmers Endeavor to Adapt in Northern Highland: Implication for Designing Household and Community Level Strategies.

DANIEL, A. T., TESHALE, W. & FIRAFIS, H. 2022. Journal of Agriculture and Food Research. *Journal of Agriculture and Food Research,* 8**,** 100312.

DAWADI, S., SHRESTHA, S. & GIRI, R. A. 2021. Mixed-methods research: A discussion on its types, challenges, and criticisms. *Online Submission,* 2**,** 25-36.

DEREJE, H., ABRHAM, S. & ALEMU, A. 2021. Does building the resilience of rural households reduce multidimensional poverty? Analysis of panel data in Ethiopia. *Scientific African,* 12**,** e00788.

Derr, B. (2013). Ordinal Response Modeling with the LOGISTIC Procedure. Statistics and
Data Analysis

DEVEREUX, S. & SUSSEX, I. 2000. *Food insecurity in Ethiopia*, Institute for Development Studies Brighton, UK.

DFID 2011. Defining disaster resilience: A DFID approach paper. Department for International Development London.

DILLMAN, D. A., SMYTH, J. D. & CHRISTIAN, L. M. 2014. Internet, phone, mail, and mixed-mode surveys: The tailored design method, John Wiley & Sons.

DINKELMAN, T. 2017. Long- run health repercussions of drought shocks: evidence from South African homelands. *The Economic Journal,* 127**,** 1906-1939.

DUFOUR, C., KAUFFMANN, D. & MARSLAND, N. 2014. *Strengthening the links between resilience and nutrition: A proposed approach*, Intl Food Policy Res Inst.

EGAMBERDIEV, B., BOBOJONOV, I., KUHN, L. & GLAUBEN, T. 2023. Household resilience capacity and food security: evidence from Kyrgyzstan. *Food Security***,** 1-22.

ERIAN, W., PULWARTY, R., VOGT, J., ABUZEID, K., BERT, F., BRUNTRUP, M., EL-ASKARY, H., DE ESTRADA, M., GAUPP, F. & GRUNDY, M. 2021. GAR Special Report on Drought 2021.

FAO 1996. Rome declaration on world food security and world food summit plan of action. FAO Rome, Italy.

FAO 2018. The Malawi Social Cash Transfer Programme increases Household Resiliency.

FAO. 2013. *Resilient Livelihoods: Disaster Risk Reduction for Food and Nutrition Security*, Emergency and Rehabilitation Division, Food and Agriculture Organization of ….

FARAHANI, H. & JAHANSOOZI, M. 2022. Analysis of rural households' resilience to drought in Iran, case study: Bajestan County. *International Journal of Disaster Risk Reduction,* 82**,** 103331.

FIELD, A. 2013. *Discovering statistics using IBM SPSS statistics,* sage.

FIELD, A. 2018. *Discovering Statistics Using IBM SPSS Statistics,* Sage Publications.

FOX, N., HUNN, A. & MATHERS, N. 2009. Sampling and sample size calculation. *East Midlands/Yorkshire: The National Institutes for Health Research. Research Design Service for the East Midlands/Yorkshire & the Humber*.

FRANKENBERGER, T., CAMPBELL, J., NJOKA, J., SPANGLER, T. & NELSON, S. 2012. Building resilience to food security shocks in the Horn of Africa. *Discussion notes*.

FUENTES, I., PADARIAN, J. & VERVOORT, R. W. 2022. Spatial and temporal global patterns of drought propagation. *Frontiers in Environmental Science*, 140.

GADISO, W. J., ALEMU, B. A. & SHETE, M. 2023. Unpacking regional variations of multidimensional food security in rural Ethiopia: insights for policy. *International Journal of Social Economics*.

GAMBO, B. A., DIAW, A. & WÜNSCHER, T. 2016. Factors affecting rural households' resilience to food insecurity in Niger. *Sustainability*, 8, 181.

GAUTAM, M. 2006. Managing drought in sub-Saharan Africa: Policy perspectives.

GEBREMEDHIN, G. H., TANG, Q., LI, W., LIU, X. & ZHANG, X. 2020. Drought: Progress in broadening its understanding. *Wiley Interdisciplinary Reviews: Water*, 7, e1407.

GETACHEW, A. M. 2018. Drought and its impacts in Ethiopia. *Weather and Climate Extremes*, 22, 24-35.

GETAMESAY, B., DESALEGN, Y. A., TADESSE, T. Z., KASSAHUN, T. & AMARE, B. 2021. Comparative Analysis of Meteorological Records of Climate Variability and Farmers' Perceptions in Sekota District, Ethiopia. *Climate Services*, 23, 100239.

GOKCEKUS, M. A. Y. A. 2020. Causes and Effects of Drought in Northern Parts of Ethiopia.

GOSHME, D. 2019. Food security in Ethiopia: Review. *International Journal of Research Studies in Agricultural Sciences,* 5**,** 1-7.

HAFTU, B. G., GELANA, A. R., KASSAHUN, T. B. & GUDINA, L. F. 2022. Temporal and spatial characteristics of drought, future changes and possible drivers over Upper Awash Basin, Ethiopia, using SPI and SPEI. *Environment, Development and Sustainability***,** 1-39.

HAILE, D., SEYOUM, A. & AZMERAW, A. 2021. Does building the resilience of rural households reduce multidimensional poverty? Analysis of panel data in Ethiopia. *Scientific African,* 12**,** e00788.

HAILE, D., SEYOUM, A. & AZMERAW, A. 2022. Food and nutrition security impacts of resilience capacity: Evidence from rural Ethiopia. *Journal of Agriculture and Food Research,* 8**,** 100305.

HAKUZA, A. & WAITA, J. 2008. Review and analysis of existing drought risk reduction policies and programs in Uganda.

HERMANS, K. & GARBE, L. 2019. Droughts, livelihoods, and human migration in northern Ethiopia. *Regional Environmental Change,* 19**,** 1101-1111.

HINKEL, J. 2011. "Indicators of vulnerability and adaptive capacity": towards a clarification of the science–policy interface. *Global environmental change,* 21**,** 198-208.

HIRVONEN, K., SOHNESEN, T. P. & BUNDERVOET, T. 2020. Impact of Ethiopia's 2015 drought on child undernutrition. *World Development,* 131**,** 104964.

Hosmer, D. W., & Lemeshow, S. (2000). Applied Logistic Regression (2 ed.). New York: A
Wiley I& Sons, Inc.

JAKKU, E. & LYNAM, T. 2010. What is adaptive capacity. *Report for the south east Queensland climate adaptation research initiative*.

JAMBO, Y., ALEMU, A. & TASEW, W. 2021. Impact of small-scale irrigation on household food security: evidence from Ethiopia. *Agriculture & Food Security,* 10**,** 1-16.

JJEMBA, E., SINGH, R. & ARRIGHI, J. 2017. Extreme drought in Ethiopia stretches drought management systems. *Red Cross Red Crescent Climate Centre, The Hague. Available at: https://cdkn. org/sites/default/files/files/Extreme-drought-in-Ethiopia-stretches-drought-management-systems. pdf*.

JOHN, W. C. 2014. Qualitative, Quantitative, and Mixed Methods Approaches (PDFDrive).

JONES, L. & TANNER, T. 2015. Measuring 'subjective resilience': using peoples' perceptions to quantify household resilience.

JONES, L., SAMMAN, E. & VINCK, P. 2018. Subjective measures of household resilience to climate variability and change. *Ecology and Society,* 23.

JONES, L. & TANNER, T. 2017. 'Subjective resilience': using perceptions to quantify household resilience to climate extremes and disasters. *Regional Environmental Change,* 17**,** 229-243.

JUANA, J., MAKEPE, P., MANGADI, K. & NARAYANA, N. 2014. The socio-economic impact of drought in Botswana. *International journal of environment and development,* 11**,** 43-60.

KALA, C. P. 2017. Environmental and socioeconomic impacts of drought in India: Lessons for drought management. *Applied Ecology and Environmental Sciences,* 5**,** 43-48.

KAMARA, J. K., AGHO, K. & RENZAHO, A. M. 2019. Understanding disaster resilience in communities affected by recurrent drought in Lesotho and Swaziland—A qualitative study. *PLoS One,* 14**,** e0212994.

KASIE, T. A., ADGO, E., BOTELLA, A. G. & GARCÍA, I. G. 2018. Measuring resilience properties of household livelihoods and food security outcomes in the risky environments of Ethiopia. *Revista Iberoamericana de Estudios de Desarrollo= Iberoamerican Journal of Development Studies,* 7**,** 52-80.

KASSAYE, A. Y., SHAO, G., WANG, X. & WU, S. 2021. Quantification of drought severity change in Ethiopia during 1952–2017. *Environment, Development and Sustainability,* 23**,** 5096-5121.

KEBEDE, A. A., TAYE, B. T. & WONDIE, K. Y. 2022. Factors associated with comprehensive knowledge of antenatal care and attitude towards its uptake among women delivered at home in rural Sehala Seyemit district, northern Ethiopia: A community-based cross-sectional study. *PloS one,* 17**,** e0276125.

KEBEDE, T., HAJI, J., LEGESSE, B. & MAMMO, G. 2016. Econometric analysis of rural households' resilience to food insecurity in West Shoa, Ethiopia. *Journal of Food Security,* 4**,** 58-67.

KIIM, H., PARK, J., YOO, J. & KIIM, T.-W. 2015. Assessment of drought hazard, vulnerability, and risk: A case study for administrative districts in South Korea. *Journal of Hydro-environment Research,* 9**,** 28-35.

KIIWANUKA, F., KOPRA, J., SAK-DANKOSKY, N., NANYONGA, R. C. & KVIST, T. 2022. Polychoric Correlation with Ordinal Data in Nursing Research. *Nursing Research,* 71**,** 469-476.

KNIPPENBERG, E. & HODDINOTT, J. 2019. Shocks, social protection, and resilience: Evidence from Ethiopia. *Gates Open Res,* 3**,** 702.

KOLENIKOV, S. & ANGELES, G. 2004. The use of discrete data in PCA: theory, simulations, and applications to socioeconomic indices. *Chapel Hill: Carolina Population Center, University of North Carolina,* 20**,** 1-59.

KOTHARI, C. R. 2004. *Research methodology: Methods and techniques*, New Age International.

KOUROUMA, J. M., EZE, E., KELEM, G., NEGASH, E., PHIRI, D., VINYA, R., GIRMA, A. & ZENEBE, A. 2022. Spatiotemporal climate variability and meteorological drought characterization in Ethiopia. *Geomatics, Natural Hazards and Risk,* 13**,** 2049-2085.

KOYACHEW, E. K. & BAMLAKU, C. A. 2021. Does irrigation improve household's food security? The case of Koga irrigation development project in northern Ethiopia. *Food Security,* 13**,** 291-307.

KOYACHEW ENKUAHONE KASSIE & ALEMU, B. A. 2021. Does irrigation improve household's food security? The case of Koga irrigation development project in northern Ethiopia. *Food Security,* 13**,** 291-307.

KRISHNAMURTHY, P. K., HOBBS, C., MATTHIASEN, A., HOLLEMA, S., CHOULARTON, R., PAHARI, K. & KAWABATA, M. 2013. Climate risk and food security in Nepal—analysis of climate impacts on food security and livelihoods. *CCAFS Working Paper*.

LELAMO, L. L., SHENKUT, B. T. & ABDILAHI, A. H. 2022. Drought characteristics and pastoralists' response strategies in Korahey zone, Somali regional state, Eastern Ethiopia. *Scientific African,* 16**,** e01254.

LIOU, Y.-A. & MULUALEM, G. M. 2019. Spatio–temporal assessment of drought in Ethiopia and the impact of recent intense droughts. *Remote sensing,* 11**,** 1828.

LIU, X. 2009. Ordinal regression analysis: Fitting the proportional odds model using Stata, SAS and SPSS. *Journal of Modern Applied Statistical Methods,* 8**,** 30.

LIU, X. 2015. *Applied ordinal logistic regression using Stata: From single-level to multilevel modeling*, Sage publications.

LIU, X., ZHU, X., PAN, Y., LI, S., LIU, Y. & MA, Y. 2016. Agricultural drought monitoring: Progress, challenges, and prospects. *Journal of Geographical Sciences,* 26**,** 750-767.

LLOYD-HUGHES, B. 2014. The impracticality of a universal drought definition. *Theoretical and Applied Climatology,* 117**,** 607-611.

LOKOSANG, L. B., RAMROOP, S. & ZEWOTIR, T. 2016. The effect of weakened resilience on food insecurity in protracted crisis: the case of South Sudan. *Agriculture & Food Security,* 5**,** 1-8.

MAXWELL, D., COATES, J. & VAITLA, B. 2013. How do different indicators of household food security compare? Empirical evidence from Tigray. *Feinstein International Center***,** 1-19.

MAXWELL, D., VAITLA, B., TESFAY, G. & ABADI, N. 2013. Resilience, Food Security Dynamics and Poverty Traps in Northern Ethiopia. Analysis of a Biannual Panel Data Set, 2011–2013. *Feinstein International Center, Friedman School of Nutrition Science and Policy at Tufts University, Boston*.

MECHLEM, K. 2004. Food Security and the Right to Food in the Discourse of the United Nations. *European Law Journal,* 10**,** 631-648.

MEKONEN, G. 2021. *Rural Household Resilience in Libokemkem District, Amhara National Regional State, Ethiopia.*

MEKONNEN, A. & WOLDEAMLAK, B. 2015. Trends and spatial patterns of drought incidence in the omo- gibe river basin, Ethiopia. *Geografiska Annaler: Series A, Physical Geography,* 97**,** 395-414.

MEKONNEN, Y. A. & GOKCEKUS, H. 2020. Causes and Effects of Drought in Northern Parts of Ethiopia.

MENGISTU, A., ARGAW, A. & SEID, T. M. 2018. Climate Resilience Index as a tool to explore households' resilience to climate change-induced shocks in Dinki watershed, central highlands of Ethiopia Households' resilience to climate change impacts. *bioRxiv***,** 382358.

MERA, G. A. 2018. Drought and its impacts in Ethiopia. *Weather and climate extremes,* 22**,** 24-35.

MERA, G. A. 2018. Drought and its impacts in Ethiopia. *Weather and climate extremes,* 22**,** 24-35.

MEZA, I., SIEBERT, S., DÖLL, P., KUSCHE, J., HERBERT, C., EYSHI REZAEI, E., NOURI, H., GERDENER, H., POPAT, E., FRISCHEN, J., NAUMANN, G., VOGT, J. V., WALZ, Y., SEBESVARI, Z. & HAGENLOCHER, M. 2020. Global-scale drought risk assessment for agricultural systems. *Natural Hazards and Earth System Sciences,* 20**,** 695-712.

MOHAMED, A. A. 2017. Food security situation in Ethiopia: a review study. *International journal of health economics and policy,* 2**,** 86-96.

MOHAMMED, A., ESUBALEW, T., HABTAMU, M. & MEZEGEBU, A. 2018. Income diversification and food security situation in Ethiopia: A review study. *Cogent Food & Agriculture,* 4**,** 1513354.

MOHAMMED, Y. & YIMAM, A. 2021. Analysis of meteorological droughts in the Lake's Region of Ethiopian Rift Valley using reconnaissance drought index (RDI). *Geoenvironmental Disasters,* 8**,** 1-16.

MORTON, J. F. 2007. The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the national academy of sciences,* 104**,** 19680-19685.

MUSIE, M., SEN, S. & SRIVASTAVA, P. 2019. Comparison and evaluation of gridded precipitation datasets for streamflow simulation in data scarce watersheds of Ethiopia. Journal of hydrology, 579, 124168.

NANJUNDESWARASWAMY, T. & DIVAKAR, S. 2021. Determination of sample size and sampling methods in applied research. *Proceedings on Engineering,* 3**,** 25-32.

NAWAZ, M., IQBAL, M. F. & MAHMOOD, I. 2021. Validation of CHIRPS satellite-based precipitation dataset over Pakistan. Atmospheric Research, 248, 105289.

NAZARETH, E. 2014. Remote sensing and GIS based agricultural drought assessment in East Shewa Zone, Ethiopia. *Tropical ecology,* 55**,** 349-363.

NJOROGE, N. & WAMBUGU, L. 2021. The search for understanding of Mixed Method Research among Graduate students. A Case of Learners in the School.

NOONI, I. K., HAGAN, D. F. T., ULLAH, W., LU, J., LI, S., PREMPEH, N. A., GNITOU, G. T. & LIM KAM SIAN, K. T. C. 2022. Projections of Drought Characteristics Based on the CNRM-CM6 Model over Africa. *Agriculture,* 12**,** 495.

OLAWUYI, S. O. & IJILA, O. J. 2023. Correlates of farmers' resilience to food insecurity in South-West Nigeria. *International Journal of Research in Business and Social Science (2147-4478),* 12**,** 330-341.

PANAGOULIA, D. & DIMOU, G. Definitions and effects of droughts. Proceedings of the conference on Mediterranean water policy: building on existing experience, Mediterranean water network, Valencia, Spain, 1998.

PARRY, S. 2020. Ordinal logistic regression models and statistical software: What you need to know. *Cornell Statistical Consulting Unit, pg***,** 1-4.

PAWAR, N. 2021. 6. Type of Research and Type Research Design.

PHILIP, S., KEW, S. F., VAN OLDENBORGH, G. J., OTTO, F., O'KEEFE, S., HAUSTEIN, K., KIING, A., ZEGEYE, A., ESHETU, Z. & HAILEMARIAM, K. 2018. Attribution analysis of the Ethiopian drought of 2015. *Journal of Climate,* 31**,** 2465-2486.

POLLARD, C. M. & BOOTH, S. 2019. Addressing food and nutrition security in developed countries. MDPI.

RIMA-II, F. 2016. Resilience Index Measurement and Analysis—II. *Food and Agriculture Organization of the United Nations: Rome, Italy*.

SALIMI, H., ASADI, E. & DARBANDI, S. 2021. Meteorological and hydrological drought monitoring using several drought indices. Applied Water Science, 11, 1-10.

SAULNIER, D., DIXIT, A., NUNES, A. R. & MURRAY, V. 2020. Disaster Risk Factors–Hazards, exposure, and vulnerability. *WHO Guidance on Research Methods for Health Emergency and Disaster Risk Management.* World Health Organization.

SCHROEDER, K. & SMALDONE, A. Food insecurity: a concept analysis. Nursing forum, 2015. Wiley Online Library, 274-284.

SENAMAW, A., ADDISU, S. & SURYABHAGAVAN, K. 2021. Mapping the spatial and temporal variation of agricultural and meteorological drought using geospatial techniques, Ethiopia. *Environmental Systems Research,* 10**,** 1-17.

SENAMAW, A., ADDISU, S. & SURYABHAGAVAN, K. 2021. Mapping the spatial and temporal variation of agricultural and meteorological drought using geospatial techniques, Ethiopia. *Environmental Systems Research,* 10**,** 1-17.

SHRESTHA, N. 2020. Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics,* 8**,** 39-42.

SHRESTHA, N. 2021. Factor Analysis as a Tool for Survey Analysis. *American Journal of Applied Mathematics and Statistics,* 9**,** 4-11.

SIBHATU, K. T. & QAIM, M. 2017. Rural food security, subsistence agriculture, and seasonality. *PloS one,* 12**,** e0186406.

SMITH, L. C. & FRANKENBERGER, T. R. 2018. Does resilience capacity reduce the negative impact of shocks on household food security? Evidence from the 2014 floods in Northern Bangladesh. *World Development,* 102**,** 358-376.

SOLOMON, A., MAGGIO, G. & PALMA, A. 2018. Climate Resilience Pathways of Rural Households. Evidence from Ethiopia. *Evidence from Ethiopia (October 2018). SWPS,* 18.

SOUVERIJNS, N., THIERY, W., DEMUZERE, M. & VAN LIPZIG, N. P. 2016. Drivers of future changes in East African precipitation. *Environmental research letters,* 11**,** 114011.

SSASSI, M. 2018. Food Security Basics. *Understanding Food Insecurity.* Springer.

SUNDAY, N., KAHUNDE, R., ATWINE, B., ADELAJA, A. & GEORGE, J. 2022. How specific resilience pillars mitigate the impact of drought on food security: Evidence from Uganda. *Food Security***,** 1-21.

SVOBODA, M. & FUCHS, B. 2022. World Meteorological Organization (WMO) and Global Water Partnership (GWP), 2016: Handbook of Drought Indicators and Indices. *Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines. Series,* 2.

SVOBODA, M., HAYES, M. & WOOD, D. 2012. Standardized precipitation index: user guide.

TASSEW, M. 2022. The effects of flooding and drought on clean water accessibility in Ethiopia.

TEFERA, A. S., AYOADE, J. & BELLO, N. 2019. Comparative analyses of SPI and SPEI as drought assessment tools in Tigray Region, Northern Ethiopia. *SN Applied Sciences,* 1**,** 1-14.

TEFERA, A. S., AYOADE, J. O. & BELLO, N. J. 2019. Drought Occurrence Pattern in Tigray Region, Northern Ethiopia. *Journal of Applied Sciences and Environmental Management,* 23**,** 1341.

TEFERA, N., DEMEKE, M. & KAYITAKIIRE, F. 2017. Building sustainable resilience for food security and livelihood dynamics: The case of rural farming households in Ethiopia. *European Commission: Ispra, Italy*.

TEMAM, D., UDDAMERI, V., MOHAMMADI, G., HERNANDEZ, E. A. & EKWARO-OSIRE, S. 2019. Long-term drought trends in Ethiopia with implications for dryland agriculture. *Water,* 11**,** 2571.

TESFAHUN, K., AGRANDIO, A., ENYEW, A. & GARCIA, I. 2017. *Household resilience to food insecurity: Shock exposure, livelihood strategies and risk* *response options: The case of Tach-Gayint District, Amhara Region, Ethiopia.* University of Jaume I.

THIEDE, B. 2016. Resilience and development among ultra-poor households in rural Ethiopia. *Resilience,* 4**,** 1-13.

TOFU, D. A., WOLDEAMANUEL, T. & HAILE, F. 2022. Smallholder farmers' vulnerability and adaptation to climate change induced shocks: The case of Northern Ethiopia highlands. *Journal of Agriculture and Food Research,* 8**,** 100312.

TWONGYIRWE, R., MFITUMUKIIZA, D., BARASA, B., NAGGAYI, B. R., ODONGO, H., NYAKATO, V. & MUTONI, G. 2019. Perceived effects of drought on household food security in South-western Uganda: Coping responses and determinants. *Weather and Climate Extremes,* 24**,** 100201.

UEXKULL, N. V., D'ERRICO, M. & JACKSON, J. 2020. Drought, resilience, and support for violence: Household survey evidence from DR Congo. *Journal of conflict resolution,* 64**,** 1994-2021.

VAITLA, B., TESFAY, G., ROUNSEVILLE, M. & MAXWELL, D. 2012. Resilience and livelihoods change in Tigray, Ethiopia. *Somerville, MA: Tufts University, Feinstein International Center*.

VAN LOON, A. F. 2015. Hydrological drought explained. *WIREs Water,* 2**,** 359-392.

VICENTE-SERRANO, S. M., QUIRING, S. M., PENA-GALLARDO, M., YUAN, S. & DOMINGUEZ-CASTRO, F. 2020. A review of environmental droughts: increased risk under global warming? *Earth-Science Reviews,* 201**,** 102953.

VISTE, E., KORECHA, D. & SORTEBERG, A. 2013. Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology,* 112**,** 535-551.

WANG, W., ERTSEN, M. W., SVOBODA, M. D. & HAFEEZ, M. 2016. Propagation of drought: from meteorological drought to agricultural and hydrological drought. Hindawi.

WMO & GWP 2016. World Meteorological Organization (WMO) and Global Water Partnership (GWP), 2016: Handbook of Drought Indicators and Indices. *Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines. Series,* 2.

YARED, E. & SALE, A. 2022. Impact of War on Livestock and Forage Products and Marketing in Wag hmare Zone, Ethiopia.

YARED, T. A., DESALEGN, Y. A., TADESSE, T. Z. & KASSAHUN, T. B. 2022. Impact of climate variability on household food security in Godere District, Gambella Region, Ethiopia. *Climate Services,* 27**,** 100307.

YIMER, M., FANTAW, Y., MENFESE, T. & KIINDIE, T. 2017. Meteorological drought assessment in north east highlands of Ethiopia. *International Journal of Climate Change Strategies and Management*.

YITBAREK, A. M. & HUSEYIN, G. 2020. Causes and Effects of Drought in Northern Parts of Ethiopia. *Civil and Environmental Research*.

ZELEKE, T., GIORGI, F., DIRO, G. & ZAITCHIK, B. 2017. Trend and periodicity of drought over Ethiopia. *International journal of climatology,* 37**,** 4733-4748.

ZHONGMING, Z., LINONG, L., XIAONA, Y., WANGQIANG, Z. & WEI, L. 2012. Drought contingency plans and planning in the Greater Horn of Africa: a desktop review of the effectiveness of drought contingency plans and planning in Kenya, Uganda and Ethiopia.

ZONE, H. 2005. Ethiopia. *Journal of Agricultural Economics and Rural Development, 2 (4): 054,* 59.

APPENDICES

Appendex I : Household Survey Questionnaire

- Informed consent

I am MSc student at Bahir Dar University. Now I'm collecting information to conduct research, which would be used for MSc thesis.

Dear interviewee, this survey's goal is to systematically and impartially assess the household's exposure to climate related shocks (specifically drought shocks), its consequences and household's resilience capacity. To this end, the data would be collected from randomly selected households of three Kebeles of Sehala Seyemt District. As a result, I respectfully ask you to continue participation in order for this study to be successful. Please complete the questionnaire honestly. I guarantee that all responses will be kept anonymous, your answers would be held in complete confidence, and no one would be recognized in the study. I acknowledge your understanding and cooperation in advance.

General Instructions

No need of writing any personal information
Make a tick mark, or circle while responding to the questions with a choice
All responses required to be answered by a household
Please clearly justify the questions that need your suggestions

Name of enumerator: ________________________________

Date and time of interview: ___________________________

SECTION1. Details of the respondent

1.1. Kebele: ______________________________

1.2. Village: ______________________________

1.3. Sex_________

1.4. Age_________

1.5. Position of the respondent in the household:

Household head Son/daughter

Spouse Relative

SECTION: 2. Demographic Characteristics of the household

2.1. Sex of the household head A. Female (0) B. Male (1)

2.2. Age of the HH (year of completed): _________(Years)

2.53. What is the religion of the HH head?

A. Orthodox C. Catholic

B. Protestant D. Muslim E. Other (specify)

2.4. What is the marital status of the HH?

A. Single B. Married C. Divorced D. Widowed/widower E. Separated/Deserted

2.5. Are you literate? A. yes B. No

2.5.1. If the above answer is yes, what is level of education?

A. Read and Write B. Primary school completed C. High school completed D. Higher institution education completed E. Other (Specify)

2.6. What is/are the main occupation/s of the household?

A. Unemployed B. Subsistence farmer C. Artisan/skilled D. tradesman/woman E. Petty trade F. governmental employee G. others (specify)

2.6.1. If subsistence farmer, in which activity are you engaged?

A. Crop production C. Mixed farming

B. animal production D. If other specify

2.7. Household size: Male ___________ Female ____________ Total: __________

2.8. Number of dependent household members: Children (below 15 years): _____Adults (above 64 years) _______

SECTION3: Resilience capacity pillars indicator questionnaires'

3.1. Pillar One: - access to basic services (ABS) indicators

3.1.1. Do you or your households access improved water source? (Yes=1, no=0)

3.1.1.1. If yes, how long do you or any one of your household members take to fetching (in minutes) ______?

3.1.2. How far/how long is the health center (in Kilometers or minutes) ____________?

3.1.3. Do you or your households are access electricity? (Yes=1, no=0)

3.1.3.1. If yes, to what purpose do you or your households use it ___________?

3.1.4. Do you or your households can access telecom? (Yes=1, no=0)

3.1.5. How far/how long is the school from this household village (in min or km) ________?

3.1.5. How far/ how long to public transport (in km or min) _____________?

3.1.6. Does the household access Veterinary service? A. Yes B. No

3.1.6.1. If yes, how far or how long did you take to reach (in km or minutes) __________?

3.1.7. Are the household get access to irrigation? A. yes B. No

3.1.8. Is there any saving institute available in your Kebele? A. Yes B. No

3.1.8.1. If yes, can you get credit in those institutes? A. Yes B. No

3.1.9. How long/how far is the nearest market to the household's village_______________?

3.1.10. Which early warning services are the household can access? A. Conventional B. Expert based or scientific C. None of them

3.1.11. Did you or any member of the household get extension service before this time? A. Yes B. No

3.1.12. Is there better road access in your Kebele? A. Yes B. No

3.2. Pillar two: - Asset (AST) indicators

3.2.1. Do you have cultivable land? A. Yes B. No

3.2.1.1. If yes, how many cultivable lands in timad (kada) do you have_________?

3.2.1. Wealth index

3.2.1.1. Do you have mobile jewelry (gold, silver)? A. yes B. No

3.2.1.2. Do you have a mobile phone? A. yes B. No

3.2.1.3. Do you have Television/Radio? A. yes B. No

3.2.1.4. Do you have a bed ("timbre made or shibo? A. yes B. No

3.2.2. Agricultural asset index

3.2.2.1. Do you have a water pump (it may be pedal and hand dug well)? A. yes B. No

3.2.2.2. Do you have a plow? A. yes B. No

3.2.2.3. Do you have workable Moferkenber? A. yes B. No

3.2.2.4. Do you have sickle? A. yes B. No

3.2.2.5. Do you have an ax? A. yes B. No

3.2.3. Livestock size in TLU

3.2.3.1. Which livestock do you have? A. Cattle B. Camels C. Donkeys/mules/horses D. Sheep and goats

3.3. Pillar three: -Adaptive capacity (AC) indicators

3.3.1. Ability to read and write HH

3.3.2. Dependency ratio of the household = (above 64+below15)/economically active members) ______

3.3.3. Crop diversification index

3.3.3.1. Did you produce wheat/barley last year? A. Yes B. No

3.3.3.2. Did you produce millet last year? A. Yes B. No

3.3.3.3. Did you produce rice last year? A. Yes B. No

3.3.3.4. Did you produce maize last year? A. Yes B. No

3.3.3.5. Did you produce beans last year? A. Yes B. No

3.3.4. Livestock diversification index

3.3.4.1. Do you have an ox? A. Yes B. No, If ye, how many oxen do you have__________________?

3.3.4.2. Do you have a milking cow? A. Yes B. No

If yes how many milking cows do you have_____________?

3.3.4.3. Do you have other cattle? A. Yes B. No

If yes how many oxen do you have____________________?

3.3.4.4. Do you have Equines? A. Yes B. No

If yes how many Equines do you have________________?

3.3.4.5. Do you have sheep & goat? A. Yes B. No

If yes how many sheep and goat do you have___________?

3.3.5. Income diversification index

3.3.5.1. Did you get income from crop production? A. Yes B. No

3.3.5.2. Did you get income from animal production? A. Yes B. No

3.3.5.3. Did you get income from any form of trade? A. Yes B. No

3.3.5.4. Did you get income from remittance? A. Yes B. No

3.3.5.5. Did you get income from any form of rent? A. Yes B. No

3.3.5.6. Did you get income from the sale of vegetables (pimento/spice, tomato, potato, garlic etc.? A. Yes B. No

3.3.5.7. Did you get income from the sale of perennial plants (such as banana, mango, avocado, and eucalyptus? A. Yes B. No

3.4. Social safety net (SSN)

3.4.1. Did the household get any cash transfers from formal sources in ETB?

3.4.2. Did the household get any cash transfers from informal sources in ETB?

Section 4; weather related Shocks, Risks and Response Options that taken by household's

4.1. During the past five year did your household experience any shock? A. Yes B. No

4.1.2. If yes which type of shock, did you experience ?

- Severe flooding
- Severe drought
- Livestock/crop disease
- Desert locusts damaged crop/grazing land
- Land inaccessible due to conflict
- Loss of crops/livestock/tree plantation due to conflict
- Road closures due to conflict
- Sharp food price increase
- Unavailability of agricultural or livestock inputs
- Sharp increase in price of agricultural or livestock inputs
- Sharp drop in price of agricultural, livestock or tree plantation products
- Death/severe illness of head of household/caregiver
- Conflict other than mentioning as a cause
- Other specify

4.1.3. How severe was the impact of the most significant shock on your income?

- Slight impact
- Moderate impact
- Strong impact
- Worst ever happened

4.1.4. How severe was the impact of the most significant shock on your food consumption?

- Slight impact
- Moderate impact
- Strong impact
- Worst ever happened

4.1.5. What did you do to mitigate income and food consumption impacts of the shocks you experienced in the last year?

- Sold livestock
- Slaughtered livestock
- Migrate (only some family members)
- Migrate (the whole family)
- Sent children or an adult to stay with relatives
- Took children out of school
- Got food on credit from a local merchant
- Took up new/additional work (casual labor, wage labor)
- Sold household items (eg, radio, bed)
- Sold productive assets (eg, plough, water pump)
- Took out a loan from friends or relatives
- Unconditional gift of money (not remittances) or food
- Sent children to work for money (eg, domestic service)
- Received emergency food aid from the government or NGO
- Received emergency cash transfer from the government or NGO
- Participated in government or NGO food-for-work or cash-for-work activities (conditional)
- Used own savings
- Relied on remittances from a relative that migrated
- Other (specify)
- Did nothing

4.1.6. To what extent was your household able to recover?

- Did not recover
- Recovered some, but worse off than before
- Recovered to same level as before
- Recovered and better off
- Don't know
- Refused to answer

4.2. Is the household a recipient of PSNP? A. Yes B. No

SECTION5: Multidimensional Food Security Indicator questionnaires

	Indicator	Name	Question	Response

				4	3	2	1
1	HFIAS/HHS	NOEAT	In the past 30 days, how often did you or any HH member have to go a whole day without eating?				
2	HFIAS/HHS	SLPHUN	In the past 30 days, how often did you or any HH member go to sleep at night hungry?				
3	HFIAS/HHS	NOFOOD	In the past 30 days, how often was there ever no food in your HH?				
4	CSI	SKIIPEAT	In the past month, how often has the HH had to skip entire days without eating?				
5	CSI	SENDBEG	In the past month, how often has the HH had to send HH members to beg?				
6	CSI	SENDEAT	In the past month, how often has the HH had to send HH members to eat elsewhere?				
7	FCS/HDDS	PULSE	In the past month, how often has the household eaten any pulses?				
8	FCS/HDDS	GRAIN	In the past month, how often has the household eaten any food made from grain?				
9	CSI	EATSED	In the past month, how often has the HH had to consume seed stock held for next season?				
10	CSI	WILD	In the past month, how often has the HH had to gather wild food, hunt, or harvest immature crops?				
11	CSI	FDCRED	In the past month, how often has the HH had to purchase food on credit?				
12	CSI/rCSI	BORROW	In the past month, how often has the HH had to borrow food, or rely on help from a relative?				
13	HFIAS	NOTWNT	In the past 30 days, how often did you or any HH member have to eat foods you did not want to eat?				
14	HFIAS	LIMVAR	In the past 30 days, how often did you or any HH member have to eat a limited variety of foods?				
15	HFAIS	PREFER	In the past 30 days, how often were you or any HH member not able to eat the Kinds of foods you preferred?				
16	CSI/rCSI	FWRMEAL	In the past month, how often has the HH				

			had to reduce the number of meals eaten in a day?				
17	CSI/rCSI	LMTPORT	In the past month, how often has the HH had to limit portion size at meal times?				
18	HFIAS	WORRY	In the past 30 days, how often did you worry that your HH would not have enough food?				
19	SAFS	SAFS	Self-assessed food security during past 30 days				
20	FCS/HDDS	DAIRY	In the past month, how often has the household eaten any dairy products?				
21	FCS/HDDS	EGGS	In the past month, how often has the household eaten any eggs?				
22	FCS/HDDS	MEAT	In the past month, how often has the household eaten any meat, fish?				
23	FCS/HDDS	FRUIT	In the past month, how often has the household eaten any fruits?				
24	FCS/HDDS	VEGET	In the past month, how often has the household eaten any vegetables?				

Source: Computed based on Field Survey, 2023

Appendix II : KII and FGD Interview Questionnaire

Name of Key informant________________________________

- ✔ Age __________sex______________
- ✔ Occupation ____________________________
- ✔ If other identification/qualities of the informant that support to this issue_______________

1. Do you think that this Kebele is drought-prone area?
2. If yes, to what extent is it?
3. What are the causes for this shock?
4. What is the effect of those shock on socio-economical, environmental, agricultural and if other?
5. What measures have been taking by households, communities, NGOs and government?
6. What are the effects of those taking measures?

7. Do the households in this district able to with stand for shocks? In addition, what about the food security issue in the household level?
8. If you have any suggestions interview status comments that you may leave before or additional idea you are welcome.

Focus group discussion agendas

1. Agenda one: what are causes of recurring drought in this Kebele?
2. Agenda 2: what are the consequences of this recurrent drought on different sectors?
3. Agenda3: How is the household level resilience capacity to shocks? Moreover, what about the household's level food security status?
4. Agenda 4: What Kind of solutions did the community find for this problem? What made a difference? What planned to be done for future? Is there a response from the governmental and non-governmental organizations to this drought problem? What changes have they brought about?

Interview status comments and suggestions_________________

Appendex III : Eigenvalues and proportions latent variables separately

Table 1: Eigenvalues and proportions of access to basic service

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.147	1.008	0.315	0.315
Factor2	2.138	1.035	0.214	0.528
Factor3	1.103	0.196	0.110	0.639
Factor4	0.907	0.129	0.091	0.730
Factor5	0.778	0.152	0.078	0.807
Factor6	0.626	0.179	0.063	0.870
Factor7	0.447	0.003	0.045	0.915
Factor8	0.445	0.189	0.044	0.959
Factor9	0.255	0.101	0.025	0.985
Factor10	0.154	.	0.015	1.000
Bartlett test of sphericity; chi2(45) = 1179.48 Prob>chi2 = 0.0000				
KMO measure of Sampling Adequacy = 0.70				

Extraction method: Principal component factor (pcf)

Source: Computed based on Field Survey, 2023

Table2: Eigenvalues and proportions of non-agricultural asset index

Components	Eigenvalues	Proportion explained	Cum. explained
1	3.131	0.783	0.783
2	0.679	0.170	0.953
3	0.137	0.034	0.987
4	0.053	0.013	1.000

Source: Computed based on Field Survey, 2023

Table 3: Eigenvalues and proportions of asset index

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.632	0.386	0.408	0.408
Factor2	1.246	0.554	0.311	0.720
Factor3	0.692	0.262	0.173	0.892
Factor4	0.430	.	0.107	1.000

Bartlett test of sphericity; chi2(6) = 162.61 Prob>chi2 = 0.0000

KMO measure of Sampling Adequacy = 0.5159

Extraction method: Principal component factor (pcf)

Source: Computed based on Field Survey, 2023

Table 4: Eigenvalues and proportions of crop diversification

Components	Eigenvalues	Proportion explained	Cum. explained
1	1.644099	0.411025	0.411025
2	1.030497	0.257624	0.668649
3	0.714949	0.178737	0.847386
4	0.610455	0.152614	1.000

Source: Computed based on Field Survey, 2023

Table 5: Scoring coefficients crop diversification

Variables	Responses	Coeff. 1	Coeff. 2	Coeff. 3

Millet	No	-0.802605	-0.694094	1.219423
	Yes	0.120079	0.103845	-0.182440
sesame	No	-0.293423	-0.466702	-0.463470
	Yes	0.355134	0.564855	0.560943
Masho	No	-0.620046	0.405651	-0.097495
	Yes	0.304913	-0.199482	0.047944
Teff	No	-0.537631	0.529789	-0.121898
	Yes	0.302869	0.298451	0.068670

Source: Computed based on Field Survey, 2023

Table 6: Eigenvalue of livestock diversification

Components	Eigenvalues	Proportion explained	Cum. explained
1	3.645690	0.729138	0.729138
2	0.582731	0.116546	0.845684
3	0.373073	0.074615	0.920299
4	0.279222	0.055844	0.976143
5	0.119285	0.023857	1.000000

Source: Computed based on Field Survey, 2023

Table 7: Scoring coefficients of livestock diversification

Variables	Responses	Coeff. 1	Coeff. 2	Coeff. 3
Ox	No	-0.727718	0.330682	0.287123
	Yes	0.149096	-0.067751	-0.058826
Milking cow	No	-0.353581	-0.873691	0.113171
	Yes	0.242058	0.598121	-0.077476
Other cattle	No	-0.424215	0.065523	0.863359
	Yes	0.279498	-0.043170	0.568832
Donkey	No	-0.641939	0.206557	0.293239
	Yes	0.167441	-0.053878	-0.076487
Small ruminate		-0.642506	0.398289	0.459577
(Goat and sheep)		0.161367	-0.100031	-0.115424

Source: Computed based on Field Survey, 2023

Table 8: Eigenvalue of income diversification

Components	Eigenvalues	Proportion explained	Cum. explained
1	2.394659	0.342094	0.342094
2	1.554665	0.222095	0.564189
3	1.053489	0.150498	0.714687
4	0.819149	0.117021	0.831709
5	0.634220	0.090603	0.922312
6	0.346215	0.049459	0.971771
7	0.197604	0.028229	1.000000

Source: Computed based on Field Survey, 2023

Table 9: Scoring coefficients of income diversification

Variables	Responses	Coeff. 1	Coeff. 2	Coeff. 3
Income from crop	No	-0.065411	-0.326919	0.696163
	Yes	0.037840|	0.189119	-0.402722
Income from animal production	No	0.182820	-0.643040	-0.340668
	Yes	-0.084998	0.298967	0.158386
Income from trade	No	-0.236424	0.044376	-0.007936
	Yes	0.411529	-0.184064	0.668928
Income from rents	No	-0.139318	0.062313	-0.226457
	Yes	0.411529	-0.184064	0.668928
Income from vegetables and fruits	No	-0.092654	-0.097029	0.028034
	Yes	0.714472	0.748217	-0.216176
Income from Apicultural products	No	0.183066	-0.227276	-0.197885
	Yes	-0.399384	0.495834	0.431713

Source: Computed based on Field Survey, 2023

Table 10: Eigenvalue and proportion of adaptive capacity

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.476	0.206	0.295	0.295
Factor2	1.270	0.276	0.254	0.549
Factor3	0.994	0.299	0.199	0.748

Factor4	0.695	0.128	0.139	0.887
Factor5	0.566	.	0.113	1.000

Bartlett test of sphericity; chi2(10) = 100.74 Prob>chi2 = 0.0000

KMO measure of Sampling Adequacy = 0.5027

Extraction method: Principal component factor (pcf)

Source: Computed based on Field Survey, 2023

Table 11: Eigenvalue and proportion of aggregated household resilience capacity

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.990	1.002	0.498	0.498
Factor2	0.988	0.420	0.247	0.745
Factor3	0.568	0.116	0.142	0.887
Factor4	0.453	.	0.113	1.000

Bartlett test of sphericity; chi2(6) = 220.38 Prob>chi2 = 0.0000

KMO measure of Sampling Adequacy = 0.6765

Extraction method: Principal component factor (pcf)

Source: Computed based on Field Survey, 2023

Table 12: Variance inflation factor

Variable	VIF	1/VIF
AST	1.31	0.764982
AC	1.28	0.778716
SSN	1.04	0.964610
shock	1.04	0.965869
ABS	1.02	0.984037
Mean VIF	1.14	

Source: Computed based on Field Survey, 2023

Table 13: Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[HMFSI = 1]	-10.424	.995	109.745	1	.000	-12.374	-8.474
	[HMFSI = 2]	-8.475	.925	83.979	1	.000	-10.288	-6.663
	[HMFSI = 3]	-4.797	.792	36.659	1	.000	-6.350	-3.244
Location	ABS	-6.133	.645	90.430	1	.000	-7.397	-4.869
	AST	-5.329	.683	60.903	1	.000	-6.668	-3.991
	AC	-4.696	.774	36.786	1	.000	-6.214	-3.179
	SSN	.720	.429	2.822	1	.093	-.120	1.561
	shock	.269	.135	3.969	1	.046	.004	.533

Link function: Logit.

Source: Computed based on Field Survey, 2023