ADDIS ABABA UNIVERSITY

COLLEGE OF DEVELOPMENT STUDIES

CENTRE FOR ENVIRONMENT AND DEVELOPMENT

ANALYSIS OF SURFACE WATER AVAILABILITY, DROUGHT, AND THE IMPACT OF SMALL-SCALE IRRIGATION ON FARMERS' LIVELIHOOD IN UPPER AWASH SUB-BASIN, ETHIOPIA

BY

HUSEN MARU AHMED

OCTOBER 2022

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ADDIS ABABA, ETHIOPIA

Declaration

I, the undersigned, declare that this is my original work, has never been presented at this or any other university, and that all the resources and materials used for the dissertation have been duly acknowledged.

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Dissertation Approval

Addis Ababa University

College of Development Studies

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This is to certify that the dissertation prepared by Husen Maru Ahmed, entitled "**Analysis of Surface Water Availability, Drought, and the Impact of Small-Scale Irrigation on Farmers' Livelihood in Upper Awash Sub-Basin, Ethiopia**," is presented in fulfillment of the requirements for the Degree of Doctor of Philosophy in Development Studies (Environment and Development) and meets the accepted standards concerning originality and quality.

Signed by the Examining Committee:

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List of Original Papers

This Dissertation is organized based on the following four peer-reviewed and published articles.

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List of Abbreviations and Acronyms

^0C	Degree Celsius
AEZ	Agro-Ecological Zone
ANOVA	Analysis of Variance
CWB	Climatic Water Balance
DEM	Digital Elevation Model
DVI	Drought Vulnerability Index
E	East
ETB	Ethiopian Birr
ETM+	Enhanced Thematic Mapper Plus
EUMETSAT	European Organizations for the Use of Meteorological Satellites
FAO	Food and Agricultural Organization of the United Nations
GIS	Geographic Information System
GPS	Geographic Positioning System
Ha	Hectare
HH	Household
HHL	Household Livelihood
HL	Highland
HRU	Hydrologic Response Unit
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
IPL	International Poverty Line
ITCZ	Inter Tropical Convergence Zone
KII	Key Informant Interview
KM^2	Square Kilometer
LL	Lowland
LULC	Land Use Land Cover
LVI	Livelihood Vulnerability Index
M	Meter
m.a.s.l.	Mean Above Sea Level
ML	Midland
Mm	Millimeter
MoWE	Ministry of Water and Energy

N	North
NASA	National Aeronautics Space Administration
NMA	National Meteorological Agency
NSE	Nash Sutcliff Efficiency
PBIAS	Percent Bias
PCA	Principal Components Analysis
PET	Potential Evapotranspiration
PSM	Propensity Score Matching
SE	Standard Error
SNNP	Southern Nations Nationalities and Peoples
SPEI	Standard Precipitation and Evapotranspiration Index
SPI	Standard Precipitation Index
SWAT	Soil and Water Assessment Tool
TLU	Tropical Livestock Unit
TM	Thematic Mapper
US	United Sates
USD	United Sates Dollar
USGS	United States Geological Survey
WLE	Water Land and Ecosystem
WMO	World Meteorological Organization
WUA	Water Users' Association

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CHAPTER ONE

1. General Introduction

1.1. Background of the Study

The changing climate harms hundreds of millions of people's lives and livelihoods worldwide (Klare, 2007). This threat becomes harmful when combined with human action in various forms (Rockström *et al*., 2009). Considering this harsh reality, its necessary to accelerate the incorporation of climate risk management into development activities in order to ensure that development proceeds along climate-resilient pathways (Munang *et al*., 2013).

The anthropogenic activities enhance climate change, thus, endangering human life globally (Gissi *et al*., 2021) as well as smallholder farmers and impeding food security, poverty alleviation, and sustainable development (Adom et al., 2022). According to Kunda (2018), an estimated 475 million smallholder farmers worldwide cultivate less than 2 hectares of land; many are destitute, face food insecurity, and live in highly precarious circumstances (Harvey *et al*., 2018).

Land use land cover (LULC) change brought by human activities (Shiferaw *et al*., 2019) and drought are among the core factors that affect the life of smallholder farmers (Gebru *et al*., 2020), especially in developing countries (Kumasi *et al*., 2019). Changes in a LULC have several negative consequences for smallholders. The ever-increasing urban expansion on surrounding agricultural land reduces agricultural production (Astuti *et al*., 2019), and the distortion of the hydrological cycle elements due to changes and affected surface water availability are among the impacts (Dibaba *et al*., 2020a). Climate change-induced drought will have a negative impact on agriculture (Javadinejad *et al*., 2021), food security (Durodola, 2019), and developing countries' economic development (Coulibaly *et al*., 2020), particularly for smallholder farmers who are dealing with rising temperatures and declining rainfall (Fadairo *et al*., 2020).

Water scarcity and drought are common occurrences in Sub-Saharan African countries (Lottering *et al*., 2022). Ahmed (2020) states that a 20% change in land use land cover and associated water scarcity has resulted in prolonged drought conditions. LULC change contributes to the fluctuation of surface water availability (Kafy *et al*., 2019). Smallholder farming primarily depends on naturally available rainfall in the case of rainfed agriculture

(Rodrigo-Comino *et al*., 2021) or surface water utilization in the case of irrigation (Schmitter *et al*., 2018).

In Ethiopia, persistent increases in temperature (Worku *et al*., 2020) and decreases in rainfall (Mekonen & Berlie, 2020) caused moisture stress for smallholder farming activities (Orke & Li, 2021), threatening farmers' livelihoods (Maru *et al*., 2021). As a result, droughts occur, resulting in starvation, displacement, and death (Maru *et al*., 2022). Drought significantly impacts Ethiopian farmers' livelihoods (Mekonen *et al*., 2020), as agriculture relies heavily on naturally available moisture (Araro *et al*., 2020). Farmers are less self-resilient to the impacts (Teklewold *et al*., 2019) due to their high level of poverty (Teka *et al*., 2019) and low level of asset possession (Zeleke *et al*., 2021), and the drought is recurring in nature (Anbacha & Kjosavik, 2019).

Agriculture, Ethiopia's dominant economic activity (Abesha *et al*., 2022), is highly vulnerable, being practiced on a small plot of land by smallholder farmers (Zerssa *et al.*, 2021). Rainfed agriculture suffers from uneven spatial and temporal rainfall distribution, resulting in food insecurity and poverty (Gidey *et al*., 2018). As a result, one of the Ethiopian agricultural sector development priorities is using small-scale irrigation to supplement rainfed agriculture (Passarelli *et al*., 2018). Surface water availability and the actual impacts of small-scale irrigation on the livelihoods of smallholder farmers must be analyzed and understood before expanding small-scale irrigation (Amare & Simane, 2017).

The Awash River Basin is Ethiopia's most heavily used river basin (Gedefaw *et al*., 2018). As a result, there is a high level of water utilization in the basin for small-scale irrigation, large-scale irrigation owned by the private and public sectors (Hailu *et al*., 2019), industry, and household purposes (Daba & You, 2022). Apart from this, drought is a common occurrence in Awash Basin. (Maru *et al*., 2021). According to Maru *et al.* (2022), nine severe to extreme drought episodes occurred in the basin during the past three decades. Challenges of surface water scarcity and drought impact smallholder farmers' livelihoods, which are already precarious due to various factors (Savari & Amghani, 2022). Small-scale irrigation is one option for reducing rainfed agriculture and thus increasing farmer resilience (Asfaw *et al*., 2019). In this case, the impact of small-scale irrigation on farmers' livelihoods must be understood (Assefa *et al*., 2022). This data is critical for expanding small-scale irrigation in previously undeveloped areas.

It is suggested to analyze the surface water availability, which can support small-scale irrigation (Dawit *et al*., 2022), to understand the impacts of water stress and drought on smallholder farmers' livelihoods. That is why the current study focused on analyzing surface water availability, drought, and the impact of small-scale irrigation on smallholder farmers' livelihoods in Ethiopia's upper Awash sub-basin.

1.2. Literature Review

1.2.1. The Impact of LULC Change on Streamflow and Surface Water Availability

The ever-increasing human actions due to increasing dynamics and human-environment interactions have significantly altered the LULC of areas (Li *et al.,* 2020). Changes in LULC type impact the elements of the hydrological cycle as well as the surface water balance (Nyatuame *et al.,* 2020). Climate variability and change also impact water availability at various watershed levels (Conway, 2005). Aside from the interaction between LULC change and climate change and variability significantly impact surface water availability (Dibaba *et al.,* 2020a). Human activities in their environment affecting LULC change must be studied pressingly to understand their impacts on surface water balance and availability (Fan *et al*., 2015). Understanding human action on LULC change and its subsequent impact on surface water helps formulate policies to preserve scarce water for various uses (Kumar Nayan *et al*., 2020).

Humankind's daily activities, such as agricultural expansion, deforestation, urbanization, and LULC, have impacted water flow pathways and balance over time (Welde & Gebremariam, 2017). Deforestation and urbanization, for example, increase surface runoff (Mansaray *et al*., 2016). The increased amount of barren land increases surface runoff (Chaemiso *et al.*, 2021).

Various methods could be used to investigate the effects of LULC changes on streamflow and surface water availability. One of the methods is the Soil and Water Assessment Tool (SWAT) model (Nie *et al*., 2011). The SWAT is a river basin model with continuous-time and semi-distributed processes. It was developed to assess how different management options affect nonpoint-source pollution and water resources in major river basins. (Arnold *et al*., 2012).

Because it can analyze LULC, streamflow, rainfall, temperature, humidity, wind, and solar radiation, the SWAT model is preferred for studying the impacts of LULC change. It can also simulate streamflow at various timeframes to better understand the effects of temporal variations on surface water. (Getachew *et al*., 2021).

1.2.2. Drought and its Assessment

Drought is an intricate natural phenomenon with a poorly defined term (Ruwanza *et al.*, 2022). Drought is a condition in which very little soil moisture is available due to decreased precipitation and/or increased evapotranspiration (Nicolai-Shaw *et al*., 2017). Droughts are classified historically into four types: meteorological, agricultural, hydrological, and socioeconomic (Mishra & Singh, 2010). Meteorological drought is associated with low precipitation (McKee *et al.*, 1993), agricultural drought with a lack of soil moisture (Bolten *et al*., 2009), hydrological drought with reduced streamflow (Nalbantis & Tsakiris, 2009), and socio-economic drought with water supply systems (Van Loon *et al*., 2016). A combination of two or more of these factors can also cause drought. Meteorological drought is the most common type because precipitation is the primary source of surface moisture (Javadinejad *et al.*, 2020).

Drought has a long and tragic history in Ethiopia. Droughts occurred in several parts of the country, displacing people, killing human and animal life, and causing severe socioeconomic crises (Haile *et al.*, 2019). It is also one of the extreme weather events affecting Ethiopians even today (Gebremichael *et al*., 2022). Droughts cause the loss of assets such as crops, livestock, as well as other productive assets due to a lack of water and other effects. Droughts significantly affected Ethiopia's agricultural output, with several places reporting complete crop failure and significant livestock mortality (Edossa *et al.*, 2010).

Drought is a persistent threat in the Awash basin. Approximately nine severe to extreme drought events have occurred in the basin over the last three decades (Maru *et al*., 2022). Droughts are more common in the basin's middle and lower reaches than in its upper reaches. Understanding droughts' magnitude, frequency, and duration require timely analysis (Liu *et al.*, 2021). Because meteorological drought is the cause of almost all other droughts, using it as a tool for other types of drought analysis makes sense (Kingston *et al*., 2015).

Meteorological drought characteristics can be studied using a variety of methods and techniques. The Standard Precipitation Index (SPI) calculates drought characteristics by comparing monthly precipitation deficits to long-term averages (Tirivarombo *et al*., 2018).

The main limitation of the SPI method of drought characteristics analysis is that it only considers precipitation. This method eliminates the possibility of evapotranspiration. To address this concern, Vicente-Serrano et al. (2010) developed the Standard Precipitation and

Evapotranspiration Index (SPEI) for meteorological drought analysis. This method outperforms SPI in calculating drought indices because it considers potential evapotranspiration. Using the SPI and SPEI methods to calculate meteorological drought is recommended because they have different capabilities in time and space (Liu *et al*., 2021).

1.2.3. Livelihood Vulnerability to Drought

Smallholder farm households' vulnerability is their proclivity to suffer adverse effects from drought on their livelihoods and their ability to cope with the stresses caused by those effects (Morton *et al*., 2007). Livelihood is a means of living for the farmers (Morse & McNamara, 2013). It is determined by the five capitals: physical, human, natural, financial, and social capital (Fang *et al.*, 2014). Drought has the potential to degrade these capitals of livelihood in various ways.

Household livelihood strategies in Ethiopia are particularly vulnerable due to the country's heavy reliance on rainfed agriculture and the threats associated with climate unpredictability and extremes (Mekonen & Berlie, 2020). Drought has a wide range of consequences for people's livelihoods. Drought has a particularly severe impact on livelihoods that rely on rainfed agriculture. Due to the sector's reliance on naturally occurring precipitation, crop failure and livestock deaths caused by a lack of precipitation result in famine, poverty, and food insecurity (Gentle & Maraseni, 2012).

The increasing frequency of droughts and other environmental issues such as land degradation, deforestation, and biodiversity loss have impacted rural households' livelihoods (Mekonen & Berlie, 2020). Another aggravating factor for the impact of drought on farmers' livelihoods in Ethiopia is a lack or low level of adaptive capacity for the effects of poverty (Senbeta & Olsson, 2020). Inadequate economic resources, low educational attainment, and limited infrastructure contributed to households' reduced adaptive capability and increased vulnerability (Shiferaw *et al*., 2014).

The IPCC's livelihood vulnerability index (LVI), according to Simane *et al.* (2016), has been used to quantify the magnitude of livelihood vulnerability to climate change and variability. Adapting the IPCC concept to drought, a drought vulnerability index (IPCC-DVI) was used to assess the vulnerability of livelihoods to the effects of drought (Maru *et al*., 2021). The method uses climatic and socioeconomic household survey data to calculate DVI using indicators derived from the five livelihood capitals. These indicators are combined into three vulnerability components: adaptive capacity, sensitivity, and exposure.

1.2.4. Small-Scale Irrigation and its Impact on Livelihood

Small-scale irrigation agriculture has been suggested in Ethiopia because rainfed agriculture is highly affected by climate change variability (Agutu et al., 2019). Irrigation and improved agricultural water management techniques may reduce the effects of climate variability, increase productivity per unit of land, and significantly increase annual crop volume (Awulachew et al., 2010). In response to severe droughts that caused widespread crop failure and famine in Ethiopia, the Ministry of Agriculture (MoA) began to build and operate modern small-scale irrigation systems in the 1970s (Simane et al., 2018). Since then, small-scale irrigation has become a source of income for smallholder farmers to supplement rainfed agriculture. It is believed that traditional small-scale irrigation schemes in Ethiopia are limited to 100 ha, whereas modern communal schemes are limited to 200 ha (Awulachew et al., 2005). Individual farm owners' lands vary in both cases. Farmers can grow crops during the dry seasons with small-scale irrigation, supplementing rainfed crop production (Makombe *et al*., 2007).

According to studies, small-scale irrigation has improved the livelihoods of Ethiopian smallholder farmers (Zeweld *et al*., 2015; Mengistie & Kidane, 2016; Tesfaye *et al*., 2021). It has helped farmers achieve food security and reduce poverty (Adugna *et al*., 2014). It has also increased smallholders' income by producing cash crops (Passarelli *et al*., 2018). Compared to farmers who only used rain-fed agriculture, small-scale irrigation households have diversified their sources of income by participating in on-farm, off-farm, and non-farm activities (Gebru *et al*., 2018).

Prior studies in Ethiopia focused on the impact of small-scale irrigation on food security (Durodola, 2019), poverty reduction (Adugna *et al.*, 2014), and income growth (Passarelli *et al.*, 2018).

Because livelihood is complex and must be understood from differing viewpoints (De Haan & Zoomers, 2003), it's essential to understand the effects of small-scale irrigation on farmers' livelihoods from various capitals (Savari & Zhoolideh, 2021).

1.3. Statement of the Problem

Diverse agroecological zones characterize the Awash basin, variations in the amount and seasonality of rainfall and temperature, and the occurrence of extreme climate events like drought and flood, particularly in the upper parts of the basin (Taye *et al*., 2018; Adane *et al*., 2020b). These diverse attributes in the basin contribute to high water demand for irrigation and other water abstraction schemes ongoing in the basin, thus, affecting the livelihood of the rural farming communities (Awulachew *et al.*, 2005; Gedefaw *et al.*, 2019). To this end, it is helpful to understand the impact of surface water availability for the promotion of small-scale irrigation in the basin (Taye *et al*., 2021), the drought characteristics, and their impact on the livelihood of farmers (Ayanu *et al*., 2015); and the impact of irrigation on the livelihood of farmers as a supplementary for the rainfed agriculture (Maru *et al*., 2021).

One of the major factors affecting streamflow and hence surface water availability is the LULC change (Chaemiso *et al*., 2021) by changing the surface's characteristics and vegetation, as well as the components of the hydrological cycle (Kumar *et al*., 2018; Mekonnen *et al*., 2018). The Awash Basin is noted for its high rate of LULC transition due to continued population growth, agricultural area expansion, and urbanization (Shawul & Chakma, 2019; Damtew *et al*., 2022). These LULC shifts increase the demand for the basin's water, resulting in water availability fluctuation.

Previous research in the Awash basin and elsewhere in Ethiopia discovered that LULC change affects surface runoff (Bekele *et al*., 2019; Bulti & Abebe, 2020; Tola & Setty, 2021). In studies, efforts were also made to analyze the effects of LULC changes on surface water availability (Chaemiso *et al*., 2021). They are, however, presented in a disconnected manner, with no clear relationship between the influence of the LULC change on streamflow and, thus, surface water availability. This can be accomplished by using the Soil and Water Assessment Tool (SWAT) and climatic water balance to assess the impact of the LULC transition on surface water and quantify the availability of surface water. The combined analysis of LULC change on surface water and subsequent surface water availability provides a comprehensive understanding of LULC dynamics and their implications for water usage, irrigation expansion, and watershed management (Rajaei *et al*., 2021).

Drought is common in the Awash basin (Emiru *et al.,* 2021). As a result, various drought studies in the basin have been undertaken (Edossa *et al.,* 2010; Belayneh *et al.,* 2014; Yadeta *et al.,* 2020b; Tareke & Awoke, 2022). Earlier studies used desk reviews and household surveys as data sources; station-based rainfall was only considered in drought analysis; as well as studies were unable to recommend whether to use the Standard Precipitation Index (SPI) or the Standard Precipitation and Evapotranspiration Index (SPEI) in drought analysis (Edossa *et al*., 2010; Murendo *et al*., 2011; Naumann *et al*., 2014; Tefera *et al*., 2019; Bhunia *et al*., 2020). Regardless of the methodologies, data sources, or spatial and temporal scales employed, these studies have contributed to a better understanding of historical and future drought probability in their respective focus regions.

According to this study, significant research gaps need to be filled to inform meteorological drought-related risk management. Given the importance of evapotranspiration in drought analysis, these gaps can be filled with SPEI (Jehan & Waqas, 2020); and gridded meteorology data are more temporally and spatially accurate than station data, in which data is missing as well as due to imitation in weather observatory density. (Esayas *et al*., 2018). In order to analyze drought, larger areas, such as basins, must be disaggregated into homogeneous AEZs, which many previous studies did not consider. Drought analysis includes examining farmers' livelihood conditions to withstand its effects (Zarafshani *et al*., 2016).

Further, smallholder farmers in the upper Awash sub-basin work in diverse agroecology and lead livelihood type and socioeconomic settings (Zerssa *et al*., 2021). As a result, their vulnerability to drought impacts may differ (Dilling *et al*., 2015). Several studies have been conducted in the upper Awash sub-basin and elsewhere in which some have concentrated on the general vulnerability of livelihoods to drought (Abeje *et al*., 2019; Asmamaw *et al*., 2020; Poudel *et al*., 2020a). These studies only used household survey data to determine livelihood vulnerability (Ahmed & Ma, 2020; Endalew & Sen, 2020). Some vulnerability studies (Dechasa *et al*., 2020) emphasized basin-wide livelihood vulnerability analyses while ignoring local and farmer-specific contexts. Some studies (Zhu *et al*., 2020) examined livelihood vulnerability using a small number of indicator variables.

The gaps mentioned above can be bridged by analyzing smallholders' livelihood vulnerability to climate-induced shocks, notably drought, integrating real-time climate data into the vulnerability assessment, and relying on local contexts in the analysis to understand the problem at the household level (by clustering farms based on their livelihood and activity profiling), and including as many indicators as possible to make the vulnerability analysis multidimensional. The current study focuses on these gaps to analyze smallholder farmers' livelihoods in response to drought, using agroecology and farm typology as analysis units.

One of the responses to the impacts of drought on farmers' livelihoods is small-scale irrigation (Enfors & Gordon, 2008). Small-scale irrigation is recommended for smallholder farmers to remedy rainfed agriculture's vulnerability to spatiotemporal rainfall variation (Frake *et al*., 2020). However, in expanding small-scale irrigation, a real impact on each farmer's livelihood capital helps identify farmers for its use (Yaro, 2013). Previous research found that small-scale irrigation improved farmers' livelihoods in this case (Adela et al., 2019). However, livelihood was conceived as a broad term like farmer income (Hagos & Mamo, 2014). Some studies looked at the effect of small-scale irrigation on food security and poverty reduction (Adugna *et al*., 2014). Most studies also used descriptive statistics to support their methodology (Mengistie & Kidane, 2016). Livelihood is complex and must be studied from multiple angles (Sun *et al*., 2021). To this end, this study will examine how small-scale irrigation affects smallholder farmers' livelihoods considering the five capitals (natural, physical, human, financial, and social). The current study thus focused on analyzing surface water availability as it is affected by LULC change, drought, the farmers' vulnerability to drought, and the impacts of small-scale irrigation on smallholder farmers' livelihood in Ethiopia's upper Awash sub-basin.

1.4. Research Questions

The current study answered the following four research questions:

i. How does LULC change effect streamflow and surface water availability in the upper Awash sub-basin, Ethiopia?
ii. What are the meteorological drought's magnitudes, frequency, return times, and hotspots in the upper Awash sub-basin?
iii. At what level is the smallholder farmers' livelihood vulnerable to drought across agroecology and farm typology in the study area; and
iv. What are the impacts of small-scale irrigation on the livelihood of smallholder farmers in the sub-basin?

1.5. Objectives of the Study

1.5.1. General Objective

The study's general objective was to contribute to the knowledge of the impact of LULC change on surface water availability, drought, the vulnerability of farmers' livelihood to drought, and the impact of small-scale irrigation on the livelihood of smallholder farmers in the upper Awash sub-basin, Ethiopia.

1.5.2. Specific Objectives

Specifically, the study addressed the following objectives:

i. To analyze the impact of LULC change on the streamflow and surface water availability in the upper Awash sub-basin, Ethiopia.
ii. To assess the agroecology-based meteorological drought and map its hotspot areas in the study area.
iii. To analyze the smallholder farmers' livelihood vulnerability to drought across agroecology and farm typology in the sub-basin.
iv. To investigate the impacts of small-scale irrigation on the farmers' livelihood in the sub-basin.

1.6. Conceptual Framework of the Study

In a study, a conceptual framework depicts the variables' expected relationships. It defines the relevant objectives for the research process and maps out how they interact to produce coherent results (Leshem & Trafford, 2007).

The current study starts with the concept of LULC change and its impacts on streamflow and surface water availability. The main driver of the LULC change in this study's context is human action (anthropogenic factors). The factors made the expansion of urban areas, barren lands, and shrinking grasslands at the catchment level. These LULC changes enhanced the surface water availability (Figure 1.1). The seasonal climatic water balance model depicted the decreasing trend for all seasons except the *Tsedey* season. This declining trend in climatic water balance contributed to monthly, seasonal, and annual meteorological drought events in the Awash Basin.

The agroecology-based meteorological drought analysis was conducted monthly, seasonally, and annually based on drought characteristics such as magnitude, frequency, and duration. Drought affected the farmers regarding crop failure, fodder shortage, food insecurity, social instability, and asset base degradation.

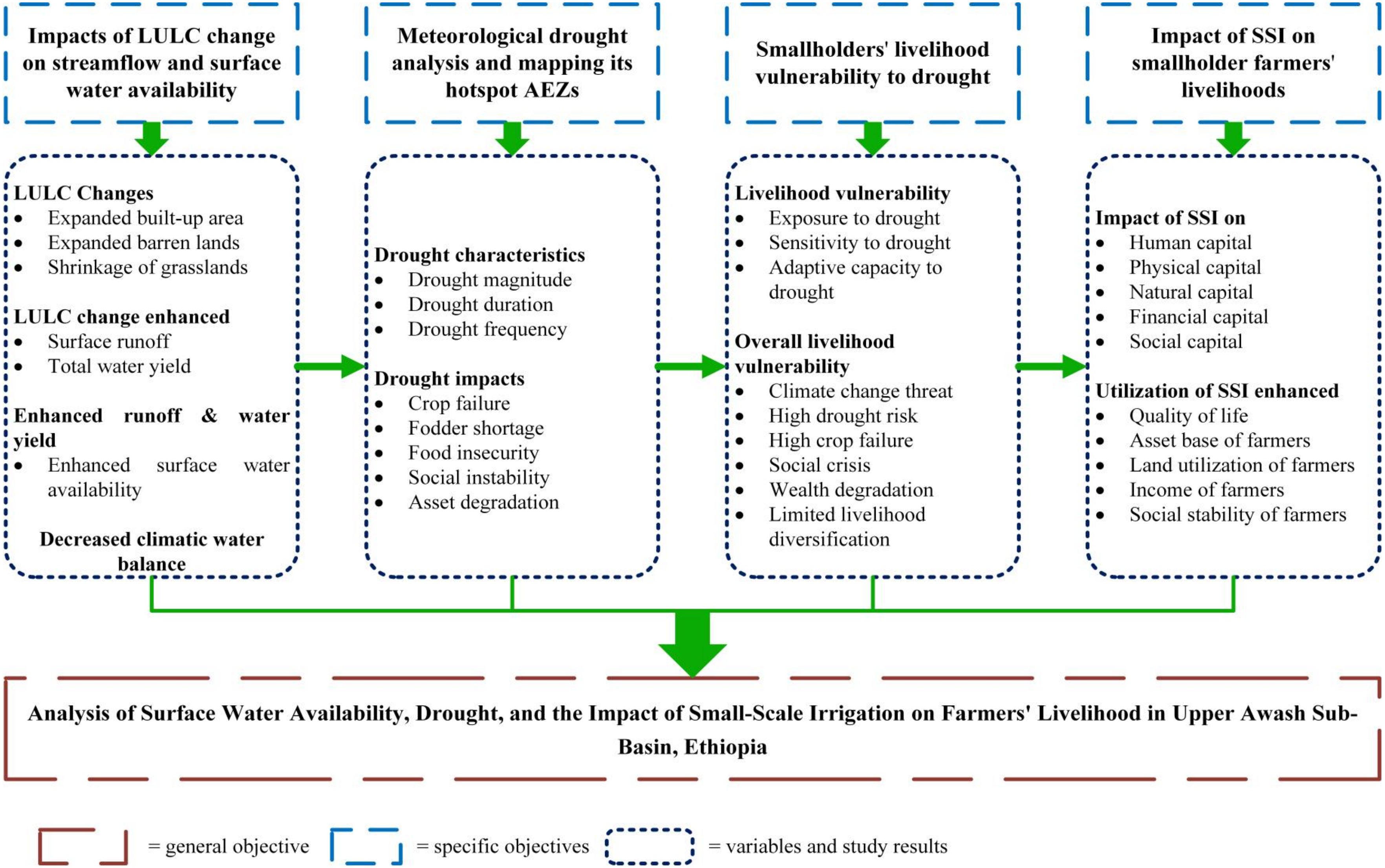


Figure 1.1. Conceptual framework of the study

Drought in a particular area affects the livelihood of inhabitants, especially smallholder farmers. Hence, the analysis of smallholder farmers' livelihood vulnerability to drought must follow. Accordingly, the vulnerability of farmers' livelihood to drought was characterized by high exposure and sensitivity and low adaptive capacity, which caused climate change threats, high drought risk, social crisis, wealth degradation, and limited livelihood options.

One of the options for drought-related livelihood challenges is the utilization of small-scale irrigation. In this regard, the utilization of small-scale irrigation contributed to a better quality of life (in terms of education and variety of food consumed), the enhanced asset base of farmers, increased income, and contributed to the social stability of the farmers (Figure 1.1).

1.7. Scope of the Study

The current study was conducted in Ethiopia's upper Awash sub-basin. Methodologically, different approaches were used based on the study's multidimensionality. Time series data (such as precipitation, temperature, streamflow, wind, and relative humidity); socio-economic survey data (from 396 sample farm households in the sub-basin); and spatial data (digital elevation model (DEM), soil, enhanced thematic mapper (ETM)) were used based on the objectives and requirements by individual chapters of the study. Thematically, the study focused solely on the impact of LULC change on streamflow and surface water availability, meteorological drought analysis, farmers' vulnerability to drought, and the impacts of small-scale irrigation on farmers' livelihoods. Temporally, the study employed various time scales based on the objectives included. Most of the climate data sets used in the study ranged from 1983 to 2016.Limitations of the Study

Academic requirement studies are completed with a limited amount of time and resources. These constraints may have an impact on the paper's quality. The current study has limitations as well. The first limitation is the spatial separation of the study's chapters. The first paper was on the upper Awash sub-basins Akaki catchment. This was due to the model's limitation - the Soil and Water Assessment Tool (SWAT), which works best in small study areas. The meteorological drought was calculated using meteorological data from the Awash basin level. As a result, paper two was done at the Awash basin level. Because the socioeconomic household survey data were collected from selected districts in the upper Awash sub-basin, the third and fourth papers were also conducted in the sub-basin. This study had temporal limitations because streamflow data in the basin was only available from 1990 to 2016; the first paper's timescale was from 1990 to 2016. Other papers used various time levels because meteorological data existed between 1983 and 2016. Because of the data availability, we were forced to use different temporal scales in the study papers.

1.8. Structure of the Study

There are six chapters in the dissertation. The first chapter focuses on the introductory section, which includes the background, problem statement, objectives, research questions, and study scope. This chapter also included a brief review of the literature.

The second chapter addresses the study's first objective: analyzing the impacts of LULC change on streamflow and surface water availability in the Akaki catchment. This chapter discussed the LULC change, streamflow, rainfall, temperature, and climatic water balance trends (1990-2016). This chapter included a SWAT simulation of streamflow with LULC maps from 1993 and 2016 and quantified surface water availability in the catchment.

Chapter three analyzes meteorological drought and maps its hotspot areas in the Awash basin. Using SPI and SPEI drought level measurement indices, the magnitude, frequency, return period, and spatial extent of the meteorological drought were discussed in this chapter. The drought analysis was based on the basin's agroecological zones. The chapter also includes drought hotspot areas in the Awash basin that were mapped using Arc GIS's Arc Map.

The fourth chapter analyzes the smallholder farmers' livelihood vulnerability to the drought in the upper Awash sub-basin. The Intergovernmental Panel on Climate Change's (IPCC) Drought Vulnerability Index (DVI) was used to develop indices showing smallholder farmers' drought vulnerability levels. The findings were compared in terms of agroecology and farm typology. The extent of the farmers' livelihood vulnerability to drought was also mapped regarding exposure, sensitivity, and adaptive capacity to add a spatial dimension to the indices.

Chapter five comprises the impact of small-scale irrigation on the livelihood of farmers in the upper Awash sub-basin. The impact of small-scale irrigation on the smallholder farmers' human, natural, physical, financial, and social capital was quantified using the propensity score matching model.

The sixth chapter discusses the paper's general summary, conclusions, and recommendations. This chapter also discusses the study's contributions to existing methodological, theoretical, empirical, and conceptual frameworks and the findings, recommendations, and policy implications.

CHAPTER TWO

2. Analysis of the Impacts of Land Use Land Cover Change on Streamflow and Surface Water Availability in Upper Awash Sub-Basin, Ethiopia

Abstract

The analysis of the LULC change impact on surface water availability provides a complete picture of the LULC dynamics and related water use, irrigation expansion, and watershed management. The current study analyzed the impact of LULC change on streamflow and surface water availability in the Akaki catchment of the Awash Basin, Ethiopia. SWAT and Climatic Water Balance (CWB) models were used. SWAT model was used to delineate the catchment, define the hydrological response unit (HRU), and calibrate and validate the daily streamflow based on the 1993 and 2016 LULC scenarios. The CWB was utilized to calculate the seasonal water balance of the Akaki catchment over 27 years. The study results indicated that from 1993 to 2016, built-up and barren land areas increased by 5.3% and 3.4%, respectively, while grassland areas decreased by 12.7%. The SWAT model was run and defined 15 sub-basins and 153 HRUs. SWAT calibration and validation were simulated over four years and observed and simulated daily streamflow were agreed upon using selected sensitive parameters. The SWAT model over-estimated the peak flows and simulated best the medium and low flows. The seasonal climatic water balance of the catchment depicted decreasing trend except for the *Tsedey (Birraa)* season. The SWAT model quantified the Akaki catchment's runoff to be 236.01mm and 272.59mm under the 1993 and 2016 LULC scenarios, respectively. The total water yield of the catchment was 366.7mm and 382.01mm for the 1993 and 2016 LULC scenarios, respectively. These results showed that surface runoff and the total water yield of the catchment increased. Based on the current study findings, surface water harvesting techniques are recommended to utilize the increased runoff, and total water yield and proactive management of flooding could decrease the impact of the flood hazard on life and property.

Keywords: LULC Change; Water Balance; Surface Water Availability; SWAT; Calibration; Validation

2.1. Introduction

The Land Use Land Cover (LULC) change caused by natural processes and anthropogenic alterations heavily influences the global hydrologic system (Kumar *et al*., 2018; Aragaw *et al*., 2022). These global hydrological processes can determine water availability in a river basin

(Chen *et al*., 2019; Yang *et al*., 2021). The change affects the soil and water relationship (Gashaw *et al*., 2018; Caballero *et al*., 2022). The impact can also affect surface and atmospheric systems, the main sources of surface water availability (Chaemiso *et al*., 2021; Senbore & Oke, 2021). Hence, the LULC change's impact on the hydrological processes at a river basin scale is still a timely topic of research worldwide (Senbeta & Romanowicz, 2021; Muhammed *et al*., 2021).

Managing the adverse impacts of LULC change on river basins in developing countries is difficult due to the ever-increasing population growth (Chaemiso *et al*., 2021; Daba & You, 2022). The reasons for this are the high rate of LULC change due to the rural-urban migration, increasing demand for agricultural land, and a high rate of unsustainable human-nature interactions (Acebes *et al*., 2021; Degefu *et al*., 2021). The LULC change caused fluctuations in the amount, duration, and pattern of streamflow and hence water availability in the river basins in many regions of Africa (Chanapathi & Thatikonda, 2020; Getachew *et al*., 2021; Measho *et al*., 2020).

In Ethiopia, studies showed that LULC change affected streamflow and hydrological cycle processes in different basins, sub-basins, and catchments (Dibaba *et al*., 2020a; Teklay *et al*., 2021; Affessa *et al*., 2022). For instance, a study by Hassen (2022) in Baro Basin indicated that converting forests, shrubs, and grasslands into agricultural lands affects the river's streamflow and evapotranspiration. Leta *et al*. (2021) extrapolated that for 2019–2050, surface runoff increased by 4.23 percent during the short rain season and 2.0 percent during the dry season due to LULC alterations in the Nashe watershed of the Blue Nile Basin. Cultivated land enhances streamflow throughout the major rainy season and decreases evapotranspiration, but there is unpredictability during the short rainy and dry seasons (Adnan & Atkinson, 2011; Hyandye *et al*., 2021). In Northwestern Ethiopia, according to Dibaba *et al*. (2020b), agricultural land expanded by 16 percent over the last 30 years, while forest land areas decreased by 12 percent. This indicated that significant changes in LULC change mean that the catchment's water balance components are further disrupted since infiltration is reduced and surface runoff is increased (Chilagane *et al*., 2021; Kiprotich *et al*., 2021).

Awash is a highly utilized river in Ethiopia (Berhe *et al*., 2013; Gedefaw *et al*., 2018). The sugar factories rely on the river's water for their sugarcane plantation, and small-scale irrigation schemes that use the river's water are common in the basin (Wendimu *et al*., 2016). Public and private investors own large-scale agricultural investments (Tufa *et al*., 2018). Moreover, due to the continuous population growth, agricultural land expansion, and urbanization in the Awash basin is known for its high rate of LULC change (Shawul & Chakma, 2019; Tadese *et al*., 2020a; Damtew *et al*., 2022). These LULC changes increase the burden on the water in the basin, and the net impact is the fluctuation in water availability.

Previous studies in the Awash basin and elsewhere in Ethiopia identified the impacts of LULC change on surface runoff (Woldesenbet *et al*., 2017; Gashaw *et al*., 2018; Birhanu *et al*., 2019; Dinka & Klik, 2019; Bulti & Abebe, 2020; Dibaba *et al*., 2020a). Studies also tried to assess the impacts of LULC change on surface water availability (Kumar *et al*., 2018; Tadese *et al*., 2020b; Chaemiso *et al*., 2021). These studies contributed to the current understanding of the impact of LULC changes on surface runoff and the water availability in the watershed. However, they are presented in a disentangled way, and the exact relationship between the impact of LULC change on streamflow and hence the surface water availability is missing. This can be achieved by applying the Soil and Water Assessment Tool (SWAT) to determine the impact of LULC change on surface water and quantify the surface water availability. The combined analysis of the LULC change on surface water and the subsequent surface water availability provides a complete picture of the LULC dynamics and related water use, irrigation expansion, and watershed management (Gebremicael *et al*., 2018; Aghsaei *et al*., 2020).

LULC change substantially impacts the hydrological processes and affects the process's elements at the basin and sub-basin levels (Dinka & Klik, 2019; Karakuş *et al*., 2019). By affecting important water balance elements like groundwater recharge, interception, infiltration, and evaporation, LULC change modifies the rainfall path and basin's water availability (Mekonnen *et al*., 2018; Wang *et al*., 2020; Nannawo *et al*., 2021). Hence, to fill the research gaps identified earlier, this study analyzed the impact of LULC change on streamflow using the SWAT model and, therefore, the surface water availability using the Climatic Water Balance model in the Akaki catchment of the Awash basin, Ethiopia.

2.2. Materials and Methods

2.2.1. Description of the Study Area

Akaki catchment is situated in the Awash basin, particularly in the upper part. The catchment is between 8°50'01"N and 9°13'10"N latitude and 38°43'42"E and 39°00'26"E longitude (Figure 2.1). The total area of the catchment is about 801.61 square kilometers. As shown in Figure 2.1, there are 15 streamflow outlets in the catchment.

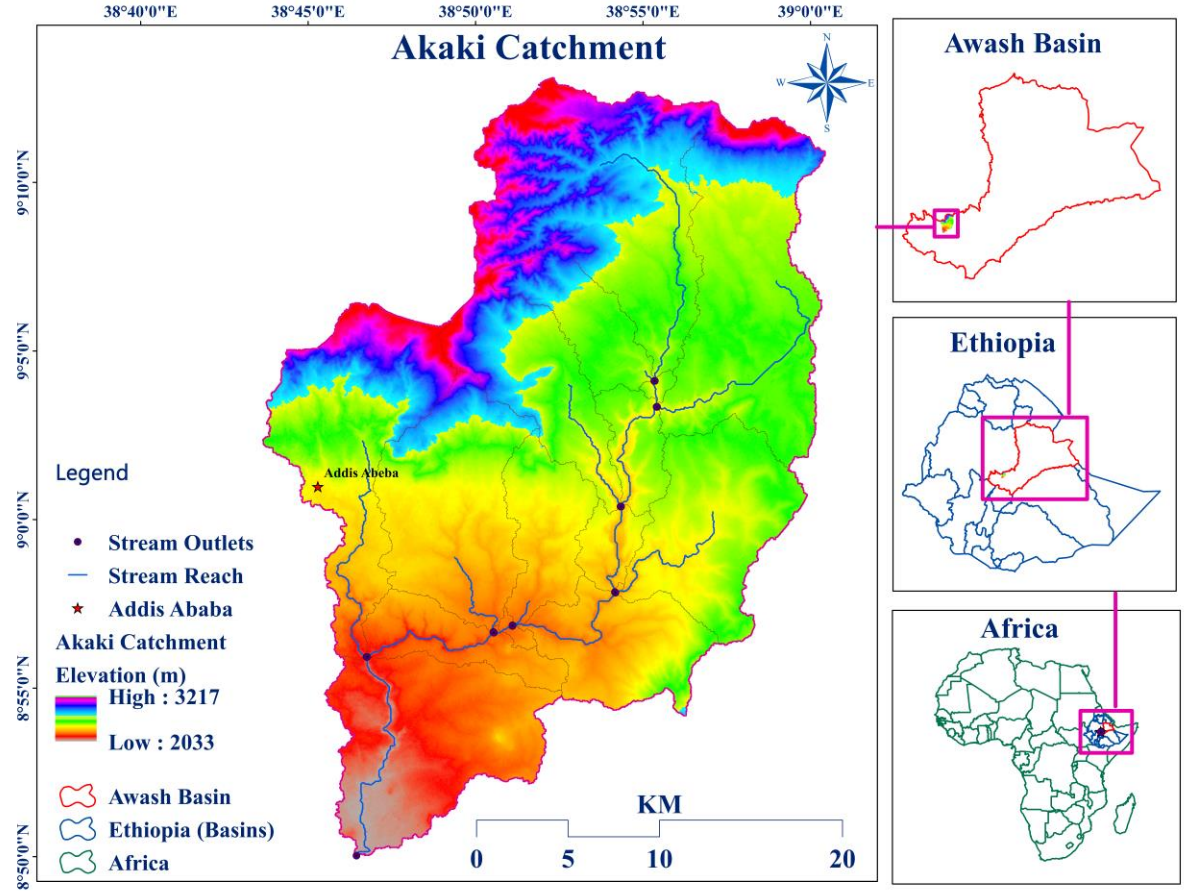


Figure 2.1. Location map of the study area, stream outlets, stream reaches, and elevation.

The elevation of the Akaki catchment ranges between 2033 to 3217 meters above mean sea level. The topography undulates the catchment's northern, western, and southwestern parts and creates a plateau. Rolling plains, steep riverbanks, valleys, hills, and mountains make up the physiographic elements of the area (Tolera & Chung, 2021). The Southern and South-Eastern parts of the catchment have gentle morphology and flat land regions (Zeberie, 2019).

Akaki catchment has a humid to subhumid climate in the highlands and a semiarid climate in the lowlands. The average annual temperature in humid and subhumid highlands is between 16 to 17 ^{o}C. The semiarid lowlands have a yearly mean temperature of 19 to 20 ^{o}C (Tessema *et al*., 2015). The catchment's daily maximum temperature range is between 17.1 and 36.3^{o}C, whereas the daily minimum is 0.6 to 26.1 ^{o}C. The rainfall is seasonal in the catchment. The major rainy season lasts from June to September, accounting for over 70% of total annual precipitation (Tolera & Chung, 2021). The daily range of total rainfall in the catchment is between 0 and 102 mm. The average annual rainfall in the catchment ranges from 800 to 1400 mm, depending on the elevation difference (Maru *et al*., 2021). Large-scale (mega) droughts and floods in the catchment are occasionally caused by the inter-annual variability of rainfall in the *Belg* and *Kiremt* seasons (Shawul & Chakma, 2020; Maru *et al*., 2022).

Akaki catchment was selected as a study area due to the availability of daily streamflow data from Ethiopia's Ethiopian Meteorological Institute (EMI) in better temporal coverage and a relatively small number of missing values. Other catchments in the Awash basin have non-tolerable missing values and limited temporal coverage in their daily streamflow data, which might have influenced the study results negatively.

2.3. Trend Analysis of streamflow, precipitation, and temperature

Before running the SWAT and Climatic Water Balance models, the time series trends of the hydro-meteorological data, such as streamflow, rainfall, and temperature, were conducted. The Mann Kendall Sen's slope was used to analyze the trends of the main hydro-meteorological datasets. Mann-Kendall trend analysis is a non-parametric analysis that detects monotonic trends in environmental, climate, or hydrological data (Asfaw *et al*., 2018). The model shows an increasing or decreasing trend in hydro-meteorological parameters. The model's tau value shows the trend's direction, and the slope indicates the magnitude of the change in the time series. The net result of all such increments and decrements yields the final value of S. The Mann-Kendall test statistic 'S' is calculated using Equation 2.1, based on Mann (1945) and Kendall (1948).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \tag{2.1}$$

where S is the Mann-Kendall statistics, x_i is a time series where the trend is done, which is ranked from $i = 1,2, \dots n-1$ and x_j, ranked from $j = i+1,2, \dots n$.

Each of the data points X_i is taken as a reference point which is compared with the rest of the data points X_j so that:

$$sgn(X_j - X_i) = \begin{cases} +1 \; if \; (X_j - X_i) > 0 \\ 0 \; if \; (X_j - X_i) = 0 \\ -1 \; if \; (X_j - X_i) < 0 \end{cases} \tag{2.2}$$

where X_i and X_j are the annual values in years i and j $(j > i)$, respectively.

It has been documented that when the number of observations is more than 10 (n _10), the statistic 'S' is approximately normally distributed with the mean and $E(S)$, becomes 0 (Kendall, 1948). In this case, the variance statistic is given as (Equation 2.3):

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{t=1}^{m} t_1(t_1 - 1)(2t_1 + 5)}{18} \tag{2.3}$$

where n is the number of observations and t_i are the ties of the sample time series. The test statistics Z_c is calculated as Equation 2.4:

$$Z = \begin{cases} \frac{S-1}{\sigma} & if\ S > 0 \\ 0 & if\ S = 0 \\ \frac{S+1}{\sigma} & if\ S < 0 \end{cases} \tag{2.4}$$

2.4. Model Description

Two models were used in the current study. The impact of the LULC change on streamflow was conducted using the SWAT model. The surface water availability was quantified using the Climatic Water Balance model.

2.4.1. SWAT Model

Since its origin at the beginning of the 1990s, SWAT has undergone continuous review and development of capabilities (Williams *et al.*, 2007). It reasonably has the most potential and computationally intensive capacity to operate on basins because it is physically based, semi-distributed, and uses a continuous-time hydrologic model (Daba & You, 2020). In particular, land change and management models affect the quality, quantity, agricultural water chemical yields, sediment, and water in large watersheds (Tolera & Chung, 2021). It simulates the other eight major elements, including hydrology, agricultural management, weather, crop growth, soil temperature, pesticides, nutrients, erosion, and sediment movement (Arnold *et al*., 1998).

There are different hydrological models used to simulate runoff at the catchment level. For instance, the lumped model best simulates snow-melt-based water balance (Cong *et al*., 2017). The ABCD model can simulate water balance and LULC change but has limited parameters for sensitivity analysis (Shahid *et al*., 2018). The SIMHYD model best simulates the impacts of climate change on runoff but cannot consider the impact of LULC change (Chiew *et al*., 2009). The SWAT model was chosen ahead of the other hydrological models due to its superior performance in simulating water balance as it is affected by the LULC change. The SWAT model's main limitation is its performance drops in larger study areas. To address this limitation, the current study focused on the Akaki catchment (a small part of the Basin) of the upper Awash sub-basin.

SWAT estimates major hydrological processes such as percolation, surface flow, infiltration, evapotranspiration (ET), aquifer flows, and shallow aquifer (Mapes & Pricope, 2020). It is a popular model for simulating the influence of LULC change on streamflow at the catchment level. It can simulate bulk input data such as LULC change, soil, streamflow, rainfall, temperature, and digital elevation model (Anand *et al*., 2018). The other quality of the SWAT model is that it is integrated with ArcGIS software as an extension. This makes the model suitable for simulating LULC change and its impact on streamflow (Belihu *et al*., 2020).

The SWAT model uses the water balance equation to simulate the hydrological cycle presented in Equation 2.5 (Neitsch *et al*., 2011).

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \tag{2.5}$$

where SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day i (mm), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm), and Q_{gw} is the amount of return flow on day i (mm).

The ArcSWAT was employed to set up the SWAT project, delineate the watershed, input DEM, LULC, soil, and slope data, integrate weather data, and run the SWAT model in Arc Map. This study used the ArcMap extension of ArcSWAT and the computer program SWAT-CUP 12 was used in this study. The SWAT-CUP model was utilized to calibrate and validate the SWAT model using streamflow data. This model enables the SWAT model's calibration, validation, sensitivity, and uncertainty analyses (Khalid *et al*., 2016).

In calibrating and validating the SWAT model, three performance metrics were applied. These are the R-Square Coefficient (R^2), Nash–Sutcliffe Efficiency (NSE), and Percent bias (PBIAS). The R^2 is a metric that measures the strength of the association between the data and the fitted regression line (Bennour *et al*., 2022). It ranges between 0 and 1; the closer the R^2 value to 1, the less error variance is. The NSE compares the relative magnitudes of the residual "noise" and the variance of the data. Its value is between $-\infty$ and 1, where NSE>0.5 is acceptable

(Schuol & Abbaspour, 2007). The relative bias, or PBIAS, determines whether the model data are greater or smaller than the observations. Its best value is 0 (Goshime *et al*., 2019).

2.4.2. Climatic Water Balance Model

Climatic Water Balance (CWB) is the difference between precipitation and potential evapotranspiration (PET). The net precipitation after the impact of PET defines the CWB. Therefore, CWB characterizes the water availability in an area using precipitation and PET as factors. Before applying the CWB model, it is necessary to calculate the PET for a specific time. Although there are different methods of PET calculations based on the data availability, the Hargreaves & Samani (1982) method is the most convenient one. The method uses the minimum and maximum temperatures and solar radiation to estimate PET using Equation 2.6.

$$PET = 0.0023(T_{mean} + 17.8)\sqrt{(T_{max} - T_{min})R_{a,}} \tag{2.6}$$

where PET is the potential evapotranspiration (mm/day), T_{mean} is the average temperature (in ^{o}C), T_{max} and T_{min} are the maximum and minimum temperatures (in ^{o}C), respectively, and R_a is extra-terrestrial radiation (in mm/day).

Then climatic water balance is the net difference between precipitation and potential evapotranspiration in a defined period (Equation 2.7).

$$CWB = P - PET \tag{2.7}$$

where CWB is climatic water balance (mm), P is precipitation (mm), and PET is potential evapotranspiration (mm/day).

2.4.3. Image Processing and Classification

After acquiring the Landsat Mapper and Enhanced Thematic Mapper Plus (ETM+) from the U.S. Geological Survey (USGS) Earth Explorer, image pre-processing was done to increase the image quality for classification. Geometrical (spatial georeferencing) and radiometric (image enhancement, noise, and dark object removals) corrections were made to enhance the image. Stacking was done using ENVI 5.3 software to bring the image bands together. Then the corrected image was brought to ArcMap 10.5, masking the image with the Akaki catchment. Using ERDAS Imagine 2015, supervised image classification was performed. The high-resolution image of Google Earth linked with ERDAS Imagine and knowledge about the study area aided the classification. Repeated classifications were done to increase the accuracy using the signature editor tool.

Individual pixels on the images were used as validation units for the image accuracy assessment. User's, producer's, overall, and Kappa Coefficient assessments were done as part of the accuracy assessment. User's accuracy measures commission mistakes that correspond to pixels from other classes that the classifier has categorized as belonging to the class of interest (Rwanga & Ndambuki, 2017). The producer's assessment indicates the number of omission mistakes corresponding to pixels belonging to the class of interest that the classifier missed (Thapa & Murayama, 2009). The overall accuracy refers to the percentage of correctly classified samples (Story & Congalton, 1986). The Kappa Coefficient quantifies the proportionate reduction in error caused by a classification algorithm (Fahsi *et al*., 2000).

2.5. Data Types and Sources

The current study simulated the SWAT model using the required datasets, including LULC, Digital Elevation Model (DEM), soil, 4km by 4km gridded meteorological data (precipitation, minimum and maximum temperature, relative humidity, solar radiation, wind speed), and observed streamflow gauged at Akaki station.

The LULC map was developed for two different years. Hence, the LULC was done for 1993 and 2016. The years were selected based on a previous study by Maru *et al*. (2022). These years are non-drought and drought years, respectively, in the Awash basin. This was done to link the SWAT model outputs with the water availability in wet and dry years. The Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) were input data for the LULC maps of 1993 and 2016, respectively. The data were accessed from the U.S. Geological Survey Earth Explorer site with a spatial resolution of 30m * 30m. Then, as shown in Figure 2.2**,** the LULC maps of 1993 (**a**) and 2016 (**b**) were developed to simulate the SWAT model.

The high-resolution ASTER Global Digital Elevation Model (ASTER-GDEM) was also obtained from the USGS Earth Explorer (Figure 2.3**a**). It was used as DEM input data for SWAT and to develop a slope map. The slope map of the study area was developed using the slope tool in ArcGIS using DEM as input data. The resolution of the ASTER-GDEM was 30m*30m, with the elevation ranges between 2033 and 3217 m above mean sea level (Figure 2.3**b**).

The LULC classes were defined based on the criteria presented in Table 2.1 below.

Table 2.1. Operational definition and description of different LULC in Akaki catchment.

LULC category	Description of the LULC category
Forest land	Montane evergreen forest, areas with closed or nearly closed canopies, and plantation forest
Barren land	The land lacks vegetation and consists primarily of exposed rocks and sands found on the surface of mountains and valleys and non-agricultural bare soils.
Grass land	Landscapes with grasses as the dominant vegetation type or areas dominated by natural grass and small shrubs, including traditional grazing areas and bare land covered in seasonal grass.
Water body	An area covered by surface water.
Agricultural land	Arable and fallow land is used to grow annual or perennial crops using rain-fed, small-scale, or commercial irrigation.
Built-up area	An area occupied by human settlement and urban infrastructures such as roads and offices
Bush and shrub land	Lands covered by small trees, bushes, and shrubs and sometimes mixed with grasses; are less dense than forest land.

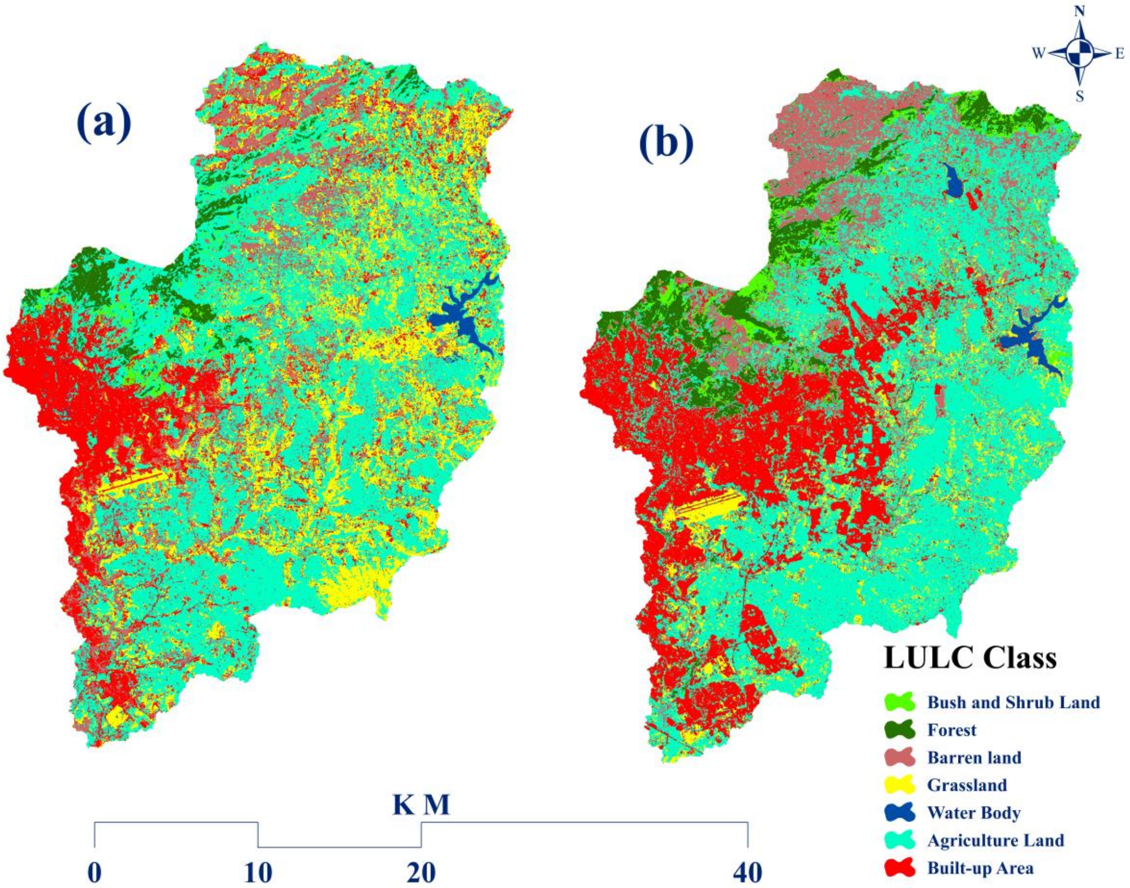


Figure 2.2. The LULC map of 1993 **(a)** and 2016 **(b)**

The soil data was found from the Food and Agriculture Organization (FAO) of the United Nations digital soil map of the world database and the Ministry of Water and Energy (MoWE). The soil types, codes, and attributes were manually entered into the SWAT user soil database (Figure 2.3**c**). There are six soil types in the Akaki catchment (Figure 2.3**c**). The Mollic Nitisols

(Vp1-3a-283) is the dominant soil type in the catchment, with 58.1% of the catchment's coverage. The Chromic Cambisols (Lc75-2b-3781) and Eutric Leptosols (Le19-3a-6578), covering 15.6% and 14.1% of the catchment's area, are the second and third largest soil types, respectively. The other soil types of the catchment are Rhodic Nitisols (Lv2-3b-3535), Eutric Arenosols (Be9-3c-26), and Pellic Vertisols (Ne61-2-3a-5938), which cover the rest area of the catchment.

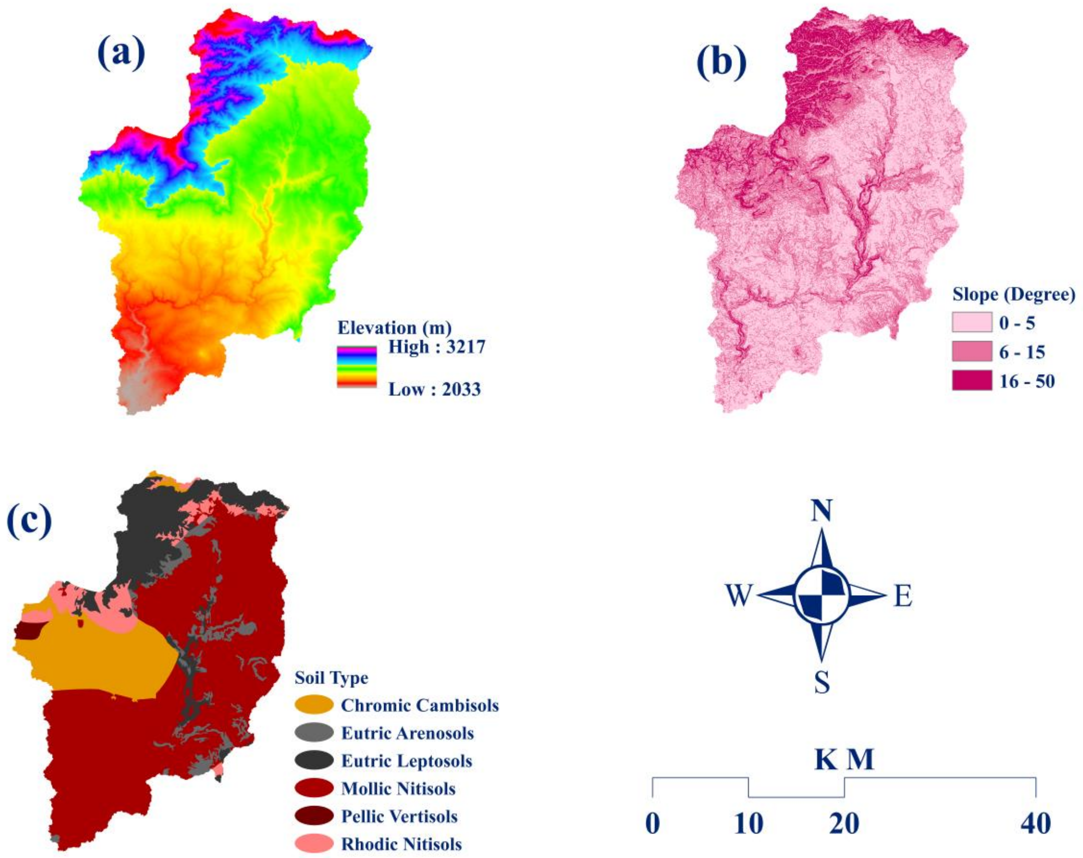


Figure 2.3. DEM **(a)**, Slope map **(b)**, and Soil type map **(c)** of the Akaki catchment

The meteorological data were obtained from two sources. Daily precipitation, minimum, and temperature (1990 – 2016) were accessed from Ethiopia's National Meteorological Agency (NMA). Due to the absence of the data in expected spatiotemporal scales from the NMA, the study area's daily relative humidity and wind speed were accessed from the mentioned-above USGS site by adding the location of stations. Ethiopia's MoWE provided the observed daily streamflow data (1990 – 2016).

The general methodological flow of the study that combines the use of SWAT, SWAT CUP 12, and R software is presented in Figure 2.4.

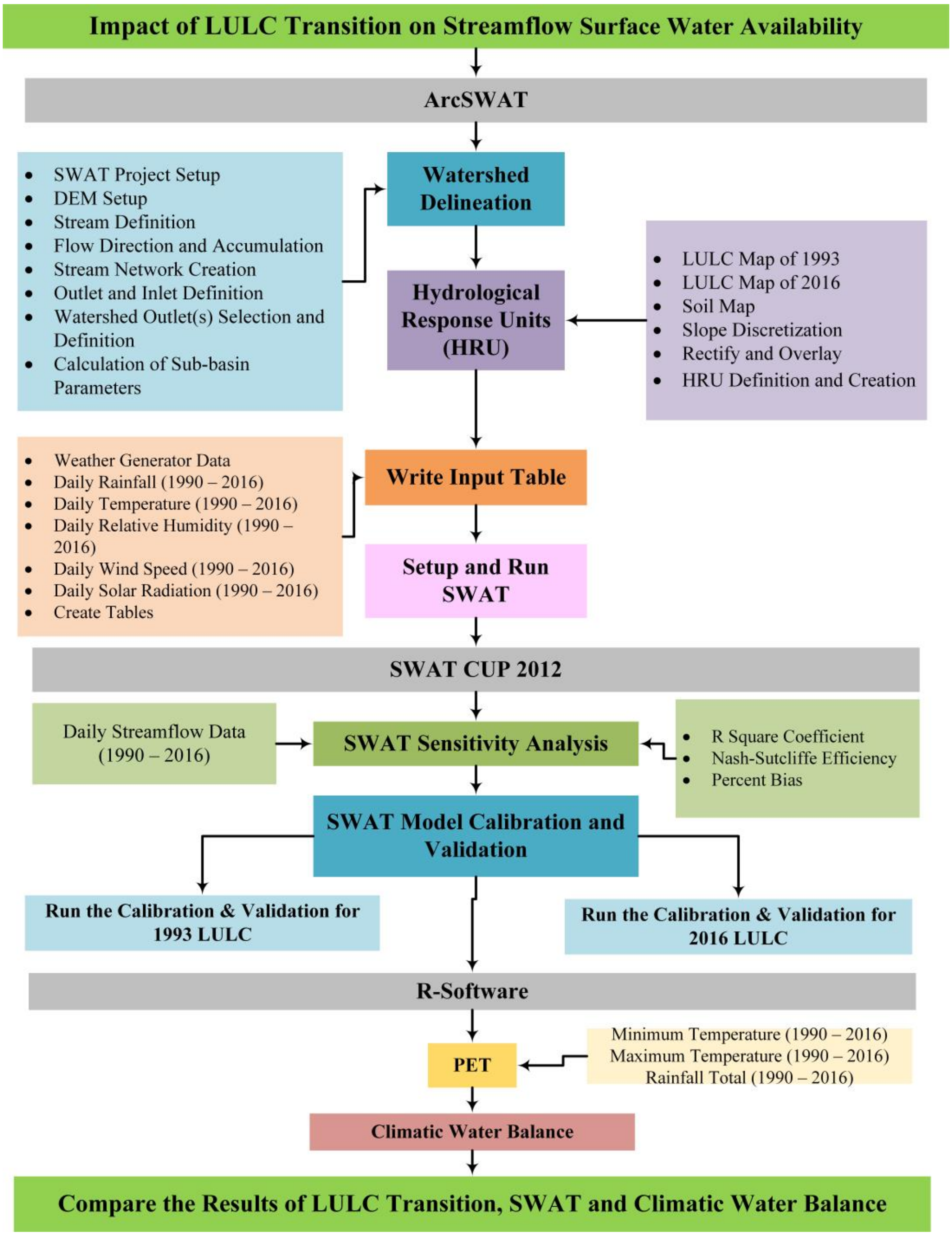


Figure 2.4. The general methodological flow of the study

2.6. Results and Discussions

2.6.1. Trend analysis of hydro-meteorological data

The results of the trend analysis are presented in Table 2.2. Accordingly, the annual streamflow trend in the Akaki catchment showed a statistically significant increasing trend at a 99% significance level over the study period. This means, over the last 27 years streamflow of the catchment was increasing. This might contribute to the increment of surface water in the catchment contributing to the increased surface water availability.

A study in the Awash basin by Tadese *et al*. (2019) indicated a statistically significant increasing trend of streamflow based on station data. An increasing trend of streamflow was also found in studies done in different parts of Ethiopia (Gebremicael *et al*., 2017; Gurara *et al*., 2021; Orke & Li, 2021; Malede *et al*., 2022).

As shown in Table 2.2, the total rainfall trend was statistically insignificant, with a P-value of 0.420. The rainfall trend was statistically insignificant in most parts of Ethiopia and the Awash basin (Mulugeta *et al*., 2019; Tadese *et al*., 2019). However, its seasonal variability was high (Esayas *et al*., 2018). In some cases, the rainfall appears during an unexpected season (Belay *et al*., 2017), is delayed from its usually expected season (Kassie *et al*., 2013), or shifts its appearance between two seasons (Orke *et al*., 2021). This high rate of variability affected the smallholder rainfed agricultural production and resulted in food insecurity and poverty in most rural areas in Ethiopia (Mekore & Yaekob, 2018; Mekonnen *et al*., 2021).

The 27-year-long trends also indicated that the maximum and minimum temperatures showed a statistically increasing positive trend at a 99% confidence level. This result indicates that the temperature rises in the study catchment, implying high evapotranspiration rates that could affect the surface water availability. This is because temperature increment and evapotranspiration have a direct positive relationship (Al-Sudani, 2019). As indicated by recent studies (Taye *et al*., 2018; Bekele *et al*., 2019; Daba & You, 2020; Emiru *et al*., 2021; Gebremiecael *et al*., 2022), the long-term temperature analysis in the Awash basin revealed an increasing trend.

Table 2.2. Mann Kendall and Sen's Slope trend analysis for hydro-meteorological data

Parameters	P-value	Tau (direction)	Sen's Slope
Streamflow (mm/day)	0.000***	0.266	0.0014
Total Rainfall (mm)	0.420	0.061	0.0000
Maximum Temperature (^oC)	0.000***	0.216	0.0003
Minimum Temperature (^oC)	0.000***	0.004	0.0001

***Significant at $p < 0.01$

2.6.2. LULC Classification Accuracy Assessment

The accuracy assessment results indicated a valid supervised image classification for the 2016 image with 96% of the user's accuracy and 96.38% of the producer's accuracy (how often does the classified map accurately depict actual ground features). The overall accuracy was 96%, and the Kappa coefficient was 95% (Table 2.3).

Table 2.3. Classification Accuracy Assessment Matrix (2016)

	Grassland	Agriculture land	Built-up Area	Forest	Bush & Shrub Land	Barren Land	Water Body	**Total User**	**Us. Acc. %**
Grassland	47	3	0	0	0	0	0	50	94
Agriculture land	1	49	0	0	0	0	0	50	98
Built-up Area	0	0	49	0	0	1	0	50	98
Forest	1	0	0	48	1	0	0	50	96
Bush & Shrub Land	0	0	0	0	50	0	0	50	100
Barren Land	0	3	0	0	0	47	0	50	94
Water Body	0	4	0	0	0	0	46	50	92
Total Producer	49	59	49	48	51	48	46	**350**	**96**
Pr. Acc. %	95.9	83	100	100	98	97.8	100	**96.38**	
Overall Acc. = 96%									
Kappa = 0.95									

Us. Acc. = User's Accuracy; Pr. Acc. = Producer's Accuracy; Acc. = Accuracy

2.6.3. Trends of LULC Change

Seven LULC classes, including Bush and Shrub Land (BSHL), Forest (FRST), Barren Land (BARR), Grassland (GRSL), Water Body (WATR), Agriculture Land (AGRL), and Built-up Area (BLTU), were classified from the supervised image classification to detect the changes. The classification was performed to detect changes in LULC between 1993 and 2016, with the results summarized in Table 2.4.

The results indicated that bush and shrubland, forest, barren land, and built-up area increased from 1993 to 2016, while grassland, water body, and agricultural land decreased. The built-up area was the highest gain LULC class with an increment of 42.08 km^2 (5.3%) between 1993 and 2016. This is because of the alarming expansion of Addis Ababa on the surrounding grasslands and agricultural land, which showed a significant decrement of 101.62 km^2 (12.7%) and 4.06 km^2 (0.5%), respectively. Addis Ababa has been expanded to the surrounding areas mainly because of condominiums and related housing constructions (Koroso *et al*., 2020). The increment in the urban area implies a greater tendency for higher surface runoff (Leta *et al*., 2021; Demissie, 2022).

Although its amount is insignificant (0.2%), the LULC change of water bodies exhibited a shrinking trend over 27 years (Table 2.4). Many previously conducted studies in Ethiopia (Elias *et al*., 2019; Regasa *et al*., 2021) and the Awash basin (Tadese *et al*., 2020a; Tessema *et al*.,

2020) have reported a shrinkage trend of water bodies. This could be due to the transformation of wetlands and swampy areas into bare land and the decrease in river water in the catchment.

On the other hand, the barren land and forest coverages showed an expansion trend in the Akaki catchment. In the Awash basin, as Damtew *et al*. (2022) reported, the barren land expanded mainly due to fuelwood gathering and overgrazing. Area coverage of the forest land has shown an expansion trend of 5.8% between 1993 and 2016 (Table 2.4). This could be linked to the country's recent recovery of forest resources (Betru *et al*., 2019) due to government and non-governmental organization-supported household and community-level reforestation and afforestation initiatives (Damtew *et al*., 2022).

The change of LULC in the catchment has many implications for the river's streamflow and surface water availability. LULC type, soil parameters, and yearly precipitation directly relate to average annual watershed stream flows. For instance, due to the impermeable cover and low infiltration in specific catchment areas, urban land has the largest potential for increased runoff (Chaemiso *et al*., 2021). The reduced water storage capacity of the expanded barren land and the shrinkage in grassland as of 2016 resulted in increased surface water runoff and lateral flows in the catchment.

Table 2.4. LULC changed between 1993 and 2016.

		1993		**2016**		**Gain**	**Loss**
S.N.	**LULC Class**	**LULC Area (sq. km)**	**%**	**LULC Area (sq. km)**	**%**	**%**	**%**
1	Bush and Shrub Land	12.54	1.56	26.86	3.35	1.8	0
2	Forest	22.91	2.86	46.48	5.80	2.9	0
3	Barren Land	77.65	9.69	104.78	13.07	3.4	0
4	Grassland	159.44	19.89	57.82	7.21	0	12.7
5	Water Body	7.05	0.88	5.65	0.71	0	0.2
6	Agriculture Land	379.26	47.31	375.20	46.81	0	0.5
7	Built-up Area	142.75	17.81	184.83	23.06	5.3	0
	Total	**801.6**	**100**	**801.6**	**100**	**13.4**	**13**

2.7. SWAT Model Results

2.7.1. Hydrological Response Unit (HRU) Definition

The HRUs are the results of the overlay between the generated slope map (Figure 2.3b) and the soil (Figure 2.3c) and land use maps (Figure 2.2). The combination of 12% land use, 15%

soil, and 5% slope threshold were used to create the HRUs. Based on the overlay, 153 HRUs were created by the SWAT simulation. These HRUs were also used as input to calibrate the streamflow using SWATCUP12.

2.7.2. Sensitivity Analysis

Ten parameters were used in the sensitivity analysis (Table 2.5). Parameters highly related to streamflow, such as temperature, precipitation, groundwater, land use, land cover, surface characteristics, and soil, were prioritized in the selection.

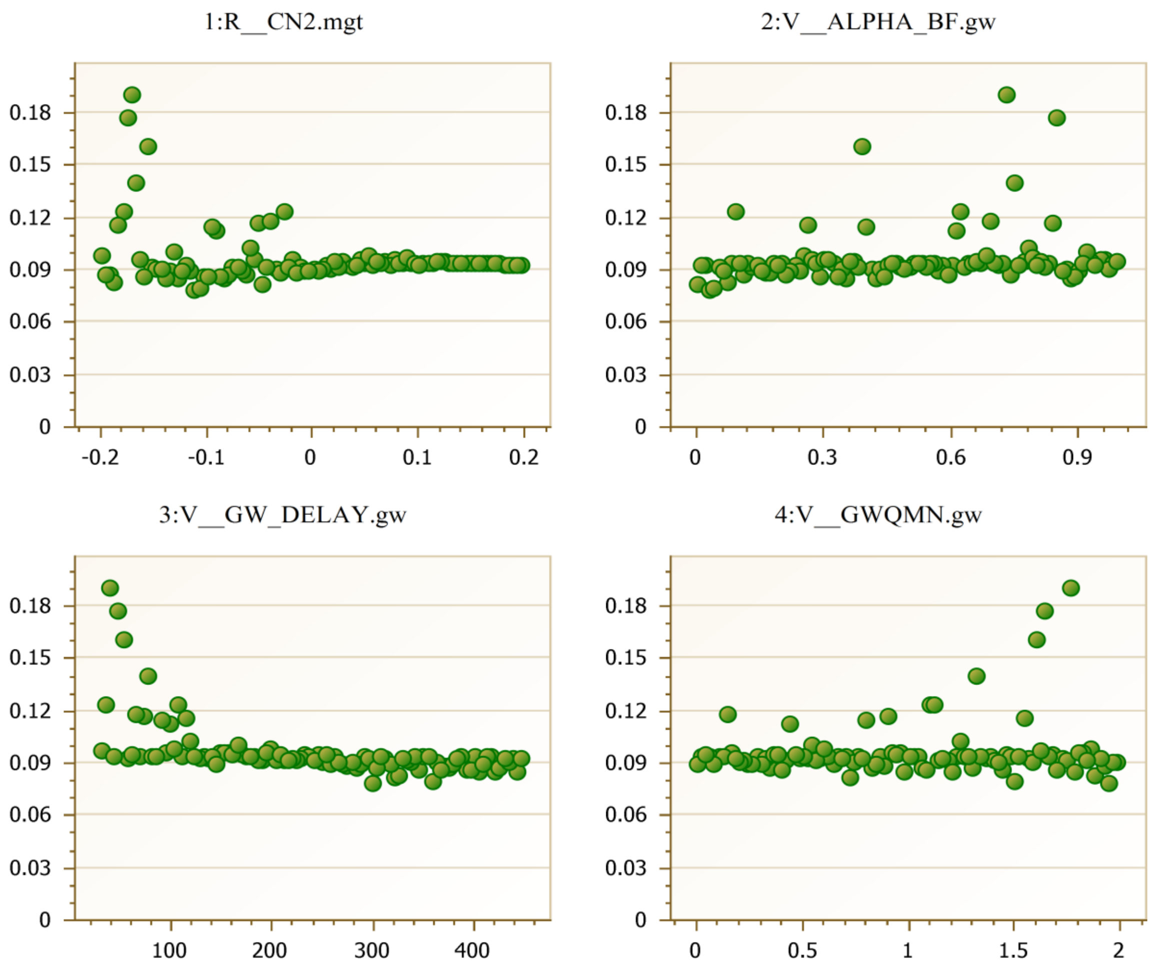


Figure 2.5. Dotty plot showing the best sensitive parameters in the model calibration (Y-axis = p-value, X-axis = t-stat)

After the sensitivity analysis, the top 4 ranked parameters with better sensitivity were used to calibrate the streamflow. The sensitivity analyses for the parameters were conducted for four years in SWAT CUP using SUFI-2 global sensitivity analysis. The parameters' sensitivity was evaluated using *t*-stat and *p*-value. The ratio between the coefficient of parameters and the standard error gives a *t*-stat. The parameter is sensitive when the standard error is less than the coefficient. During the sensitivity analysis of any parameter, the smaller the *p*-value, the more sensitive that parameter is to calibrate the model (Abbaspour, 2015).

Table 2.5. Parameters used in the SWAT model sensitivity analysis.

S.N.	Parameter	Description	Rank
1	r__CN2.mgt	SCS runoff curve number	1
2	v__ALPHA_BF.gw	Baseflow alpha factor	2
3	v__GW_DELAY.gw	Groundwater delay	3
4	v__GW_QMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	4
5	r__TLAPS.sub	Temperature lapse rate	5
6	r__OV_N.hru	Manning's "n" value for overland flow	6
7	r__PLAPS.sub	Precipitation lapse rate	7
8	r__IGRO.mgt	Land cover status code	8
9	r__SOL_Z.sol	Depth from the soil surface to the bottom of the layer	9
10	r__CH_L2.rte	Length of the main channel	10

2.7.3. Model Calibration

As presented in Figure 2.5, based on the statistical model evaluator calibration result, the daily observed and simulated streamflow agreed as predicted by the selected parameters. The SWAT model overestimated the daily high streamflow and underestimated the daily low streamflow. In the medium flow cases, the observed and simulated flows fit better. Abebe & Gebremariam (2019), in their SWAT-based streamflow and sediment yield study in the Kesem watershed of the Awash basin, indicated that SWAT overestimated the streamflow for some months, which had a higher record due to the rainy season. The reason is that SWAT streamflow simulation is highly sensitive to the high streamflow record period during the days of the *Kiremt* season (Spruill *et al.*, 2000). This indicates that the SWAT Cup model best simulated medium flow. Precise parameter adjustments and frequent iterations are needed to simulate high and low flow best. The calibration results suggest that using the SWAT model to simulate streamflow in the Akaki catchment is recommended, with a precise selection of sensitive streamflow parameters.

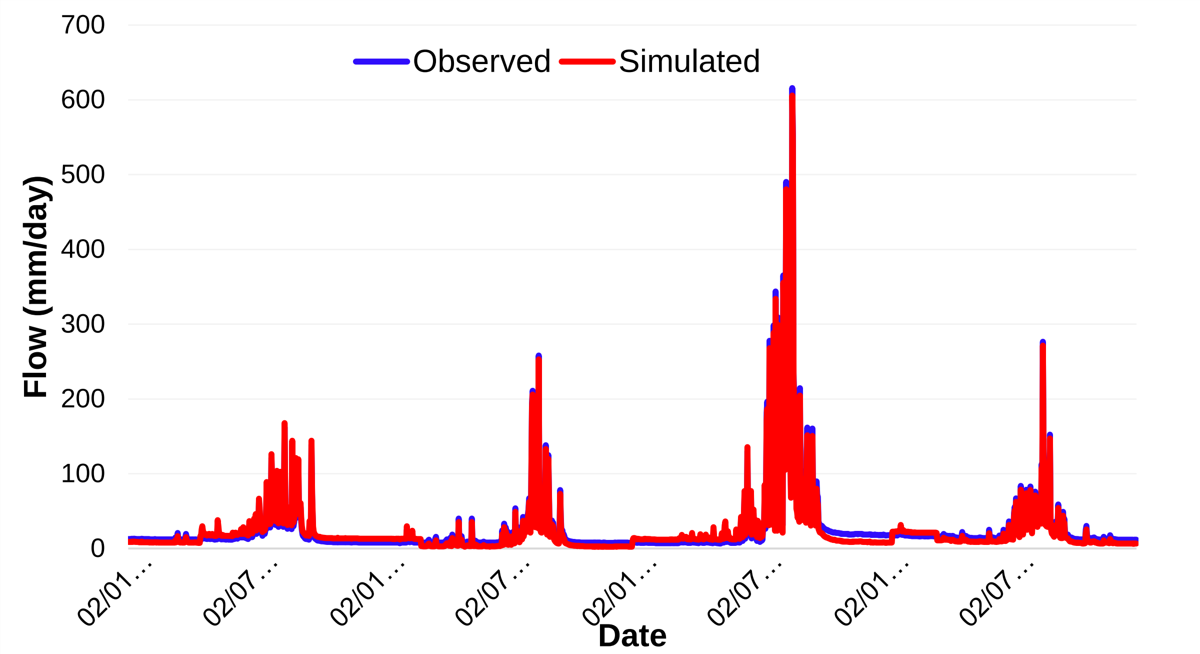


Figure 2.6. Calibrated daily streamflow hydrograph at Akaki gauging station (1993 LULC)

2.7.4. Model Validation

The model validation's R^2, NSE, and PBIAS were 0.80, 0.79, and -0.24, respectively. As shown in Figure 2.7, the observed and simulated daily streamflow of the Akaki catchment depicted a good agreement, though the model overestimated the streamflow during *Kiremt* time. This was due to the high variations in daily streamflow of the catchment during the high rainfall time (June to August).

The daily streamflow simulation between 2012 and 2016 also yielded a peak flow. According to the simulation, the peak flow of the observed and simulated daily streamflow in the Akaki catchment was 469.92 mm and 474.92 mm, respectively. The slight increment of the simulated flow compared to the observed agrees with the previously conducted studies in the Awash basin (Abebe & Gebremariam, 2019; Tessema *et al*., 2021; Abdulahi *et al*., 2022).

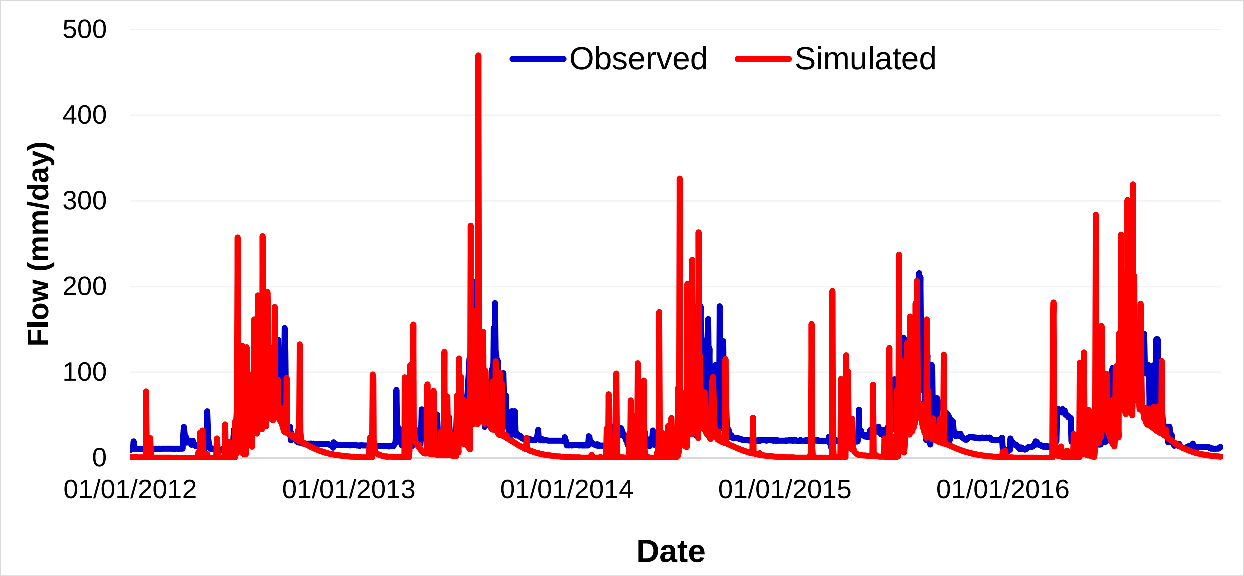


Figure 2.7. Validated daily streamflow hydrograph at Akaki gauging station (2016 LULC)

2.8. Climatic Water Balance Model Results

The seasonal PET of the catchment was computed based on the 27 years (1990 – 2016) time series precipitation and temperature data. The reason behind the computation of the seasonal PET is that the water balance gives direct meaning when it is calculated, which directly correlates with the crop growing season. Hence, the PET was computed for the four seasons, namely, *Tsedey* (Sep-Nov), *Bega* (Dec-Feb), *Belg* (Mar-May), and *Kiremt* (Jun-Aug).

As presented in Figure 2.8, the PET was more than 140 mm/day for most years in the *Belg* season of the Akaki catchment. The highest PET was 176 mm/day observed in the *Belg* season. The *Bega* recorded a relatively higher amount of PET than the *Tsedey* and *Kiremt* seasons. Higher inter-seasonal variabilities of PET results were observed in the *Kiremt* and *Tsedey* seasons. Although increasing streamflow trends were observed in the Akaki catchment, the higher amount of calculated PET has influenced surface water availability. The streamflow at the surface level has shown an increasing trend, which could lead to higher surface water at the catchment. However, the increasing trend of PET has contributed to reducing surface water availability.

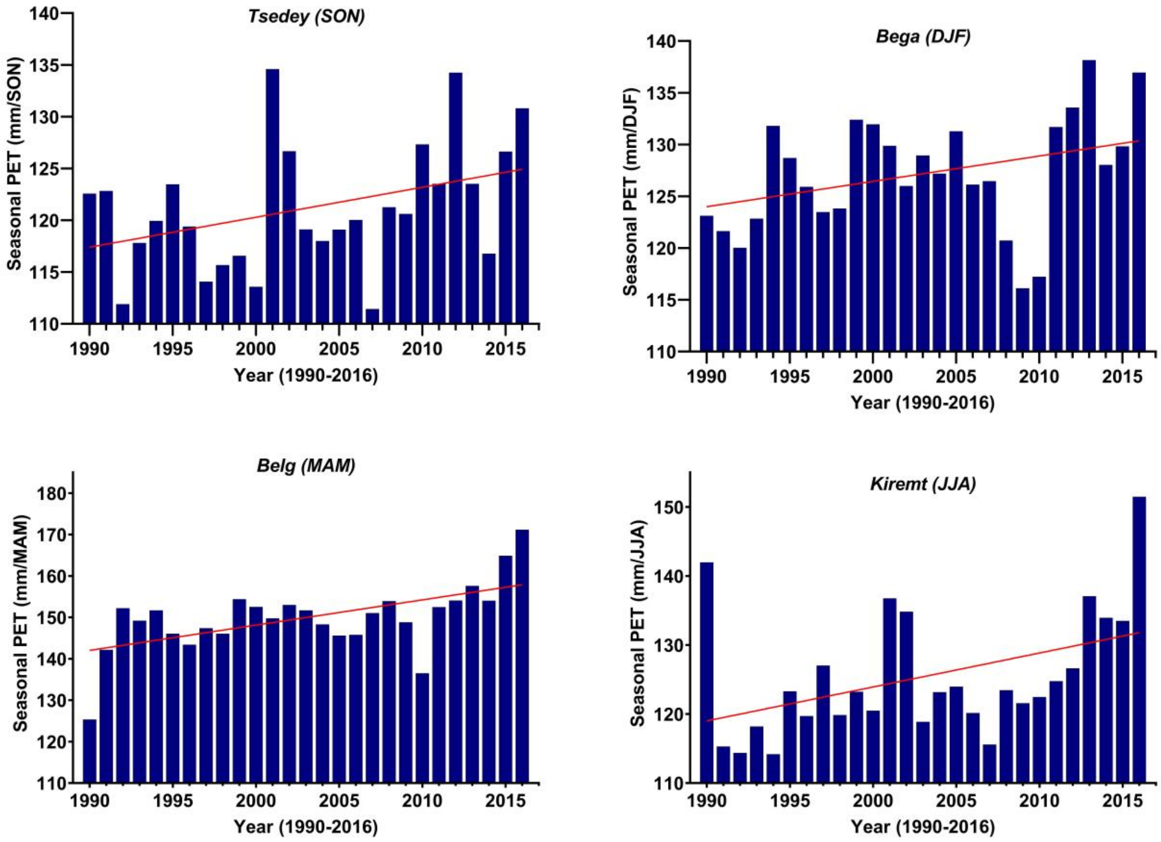


Figure 2.8. Seasonal PET of Akaki catchment (1990 – 2016)

The Mann-Kendall trend analysis results also indicated a significant (95% confidence level) increase in PET trends for the *Belg* and *Kiremt* seasons. The *Bega* season's PET *al*so showed a significant (at a 90% confidence level) increasing trend during the study period (Table 2.6). In the Awash basin, the temperature of *Belg* and *Kiremt* is relatively high (Shawul & Chakma, 2020) due to the movement of the Intertropical Convergence Zone (ITCZ) to the northern hemisphere (Marriner *et al*., 2012). *Belg* and *Kiremt* are the main rainy seasons in the basin and Ethiopia when farmers fully engage in agricultural activities, especially in the rainfed farming system (Behailu *et al*., 2021). The increasing trends of PET during the *Bega* and *Belg* seasons can affect small-scale irrigation agricultural practices. This is in relation to the amount of water evaporated that would have been used for irrigating the crops.

Table 2.6. Mann Kendall and Sen's Slope seasonal trend analysis for PET

Season	P-value	Tau (direction)	Sen's Slope
Tsedey (Sep-Nov)	0.045	0.276	0.319
Bega (Dec-Feb)	0.050^{*}	0.270	0.292
Belg (Mar-May)	0.002^{**}	0.413	0.492
Kiremt (Jun-Aug)	0.005^{**}	0.384	0.492

**Significant at $p < 0.05$; *Significant at $p < 0.1$

As shown in Figure 2.6, the climatic water balance of the *Bega* seasons was negative for 27 years, indicating the season's dryness. Winters are dry in the catchment, so the water balance deficit is high. Positive and negative CWB were observed in the *Tsedey* and *Belg* seasons, with the relative positives dominating. *Tsedey* is the transitional season from cultivation to the harvest of the major crops, while *Belg* is preparing the land for rainfed agriculture in most parts of the catchment.

In most parts of the Akaki catchment, *Kiremt* is the main rainy season. Hence, as shown in Figure 2.9, the CWB is high and positive except for three years compared to the other seasons. The highest CWB, more than 700 mm, was also registered this season. The water availability during this season is crucial for smallholder rainfed farming in the catchment (Gummadi *et al*., 2018).

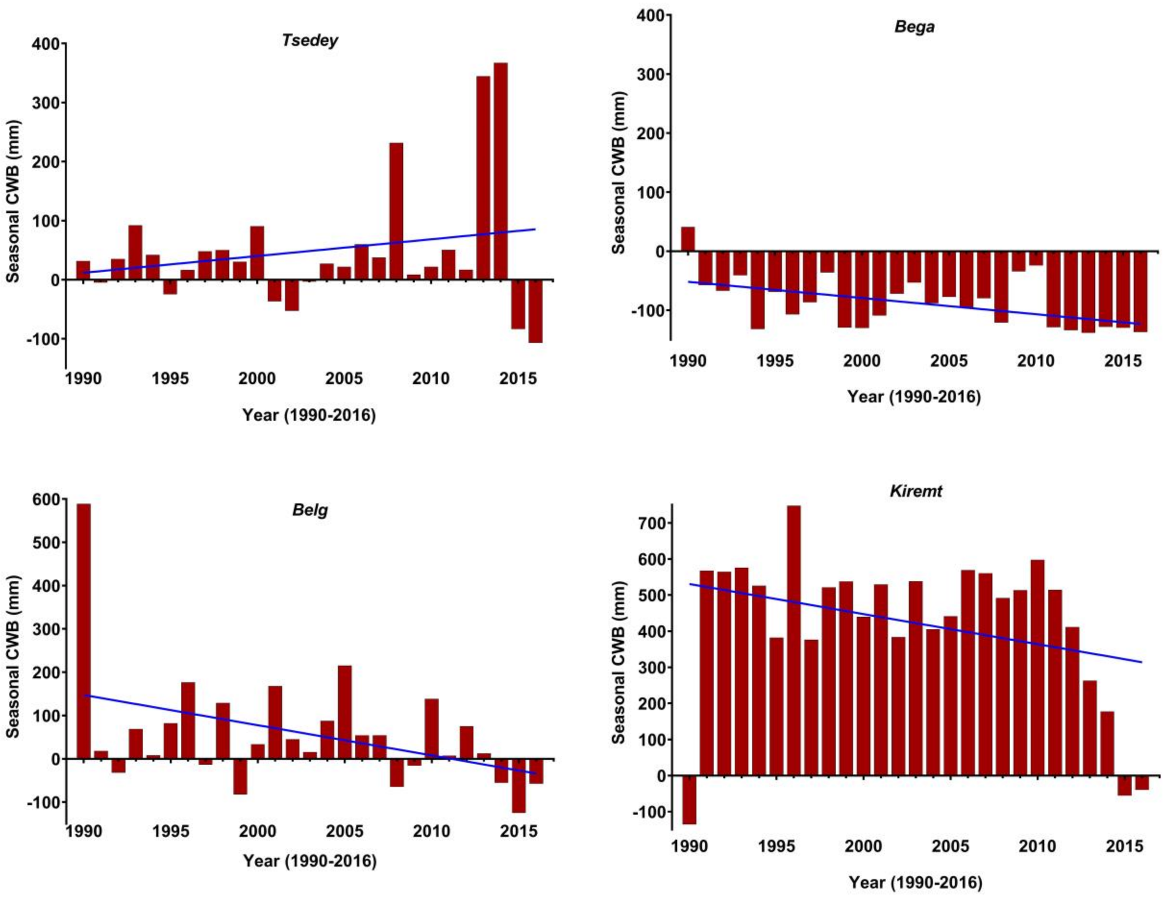


Figure 2.9. Seasonal CWB of Akaki catchment (1990 – 2016)

The seasonal CWB Mann Kendall t-test results supported the above findings. As presented in Table 2.7, except for the *Tsedey* season, statistically significant decreasing trends of CWB were observed in the three seasons. The *Bega* CWB trend was significant at 95%, while the *Belg* and *Kiremt* trends were significant at 90%. The higher PET trends in the *Bega* and *Belg* seasons might have also contributed to the relatively higher decreasing trends in CWB. The results indicate that the seasonal CWB of the Akaki catchment showed a significant decrease in the 27 years. With these results, the water availability in the catchment decreased from 1990 to 2016, implying the meteorological drought dominating the recent years.

Table 2.7. Mann Kendall and Sen's Slope seasonal trend analysis for CWB.

Season	P-value	Tau (direction)	Sen's Slope
Tsedey (Sep-Nov)	0.966	0.008	0.012
Bega (Dec-Feb)	0.009**	-0.351	-2.772
Belg (Mar-May)	0.087*	-0.236	-4.650
Kiremt (Jun-Aug)	0.072*	-0.247	-6.598

**Significant at $p < 0.05$; *Significant at $p < 0.1$

2.9. Implications of LULC Change on Surface Water Availability

One of the capabilities of the SWAT model is it can quantify the surface water using different parameters. Using LULC 1993 and LULC 2016 scenarios, the outputs of the SWAT model for the Akaki catchment were compared based on some parameters. These parameters can estimate the water availability in the catchment. The average surface runoff increased from 236.01 mm to 272.39 mm between 1993 and 2016 (Table 2.8). Between these years, the two major LULC classes included built-up areas and barren land. In the study period, the built-up area and barren land increased by 5.3% and 3.8%, respectively (Table 2.4). Addis Ababa is located in the study area, and its expansion at the expense of the surrounding rural areas is ever-increasing. The expansion of both land uses contributed positively to the lateral water movement on the surface, increasing the runoff. According to Eshtawi *et al*. (2015), built-up and urban expansions yield a rapid lateral surface water flow and increase surface runoff. The increase in surface runoff was attributed mainly to the LULC change because other surface runoff providers, like total aquifer recharge, lateral soil flow, and percolation out of the soil, decreased in the catchment during the study period (Table 2.8).

The total water yield of the catchment also increased during the study period. The difference between the 1993 and 2016 LULC scenarios in total water yield is 15.31 mm (Table 2.8). The combined effect of the increasing surface runoff and total water yield in the catchment can be associated with an extreme climate event – flooding. In recent years, flooding has become one of the extreme climate events in the Akaki catchment (Zeberie *et al*., 2019). For instance, Addis Ababa has expanded from 80.1 km^2 to 287.9 km^2 between 1984 and 2020 (Beshir and Song, 2021), implying an increasing flood risk in the city. According to this study, the long-term rainfall trend of the city was not significant, and the increased surface runoff was the major contributor to the increasing flooding event.

Table 2.8. Water availability parameters with the 1993 and 2016 LULC scenarios in the Akaki catchment.

S.N.	Parameters	LULC Scenario 1993	LULC Scenario 2016
1	Surface Runoff (mm)	236.01	272.59
2	Lateral Soil Flow (mm)	17.06	13.8
3	Groundwater Shallow Aquifer Flow (mm)	107.09	90.01
4	Percolation Out of Soil (mm)	129.93	111.45
5	Evapotranspiration (ET) (mm/s)	428.6	414.2
6	Total Aquifer Recharge (mm)	129.95	111.47
7	Total Water Yield (mm)	366.7	382.01

2.8. Conclusions

The current study analyzed the impacts of LULC change on the streamflow of the Akaki catchment and the availability of surface water in the catchment using SWAT and Climatic Water Balance models. From the study's results, the 27 years of Mann Kendall and Sen's Slope trend analysis indicated that daily streamflow and maximum and minimum temperature increased in the catchment. On the other hand, between 1993 and 2016, the LULC of the catchment showed different changes. The major LULC changes during the study period were the increment of built-up area and barren land and the decrement of grasslands.

The SWAT model results informed that the parameters used to calibrate and validate the daily streamflow in the Akaki catchment revealed an agreement between the daily observed and simulated streamflow. SWAT slightly over-simulated daily peak flows and best simulated the catchment's daily medium and low flows. The over-simulated of the peak flows is related to the high variation in daily streamflow during dry and wet days.

The Mann Kendall and Sen's Slope trend analysis on the seasonal climatic water balance results indicated that the remaining seasons showed a decreasing trend except for the *Tsedey* (Sep-Nov) season. This result indicated the shift of the rainy season in the catchment from *Belg*

(Mar-May) to spring. This means the usually *Belg* rainfall in the catchment starts in *Kiremt* and continues until the *Tsedey* season.

Based on the 1993 and 2016 LULC scenarios, the SWAT has simulated the surface water availability in the catchment. Due to the expansion of built-up areas and barren lands in the catchment, surface runoff and total water yield increased from 1993 to 2016. The major contributor to the increment in runoff and water yield was the LULC change because of the decrement in total aquifer recharge, lateral soil flow, and percolation out of the soil.

One of the impacts of the LULC change on streamflow in the Akaki catchment is that surface water increased from 1993 to 2016. The increase in the surface runoff and total water yield could also lead to a climate extreme event – flooding in the catchment. This was because the major LULC change in the catchment was the expansion of built-up areas that facilitated the surface runoff.

Based on the study's results, since surface water is enhanced, it is recommended that water harvesting techniques could utilize the available water. The harvested water may supplement rainfed agriculture through irrigation. Another consideration could be enhancing the urban drainage and water disposal system to safely dispose of the generated surface flow to the appropriate area. The emerging interest in urban agriculture in terms of hydroponics and hydroponics could have a double benefit in utilizing the extra water surface before it causes the problem and aids urban food production. Unless the surface water is utilized for productive purposes, it could cause flooding, especially in urban areas. In this case, proactive flood management is important to reduce the impacts of flooding on life and property.

CHAPTER THREE

3. Agroecology-Based Analysis of Meteorological Drought and Mapping its Hotspot Areas in Awash Basin, Ethiopia

Abstract

This study analyzes spatiotemporal characteristics of meteorological drought over eight Agroecological Zones (AEZs) of the Awash basin, Ethiopia. The study applied the Standard Precipitation and Evapotranspiration Index (SPEI) and Standard Precipitation Index (SPI) methods to characterize meteorological droughts. The study applied Arc GIS 10.5 to map the drought hotspots. From the result, the value of SPEI and SPI methods was divergent in characterizing drought episodes' magnitude and spatial occurrence. SPEI has more advantages in detecting dry months and a slight advantage in detecting dry seasons compared to the SPI. Temporally, wet and dry years dominated the 1990s and 2010s, respectively. Drought dominated the 1980s, and normal years dominated the 2000s. The spatial context of the drought hotspot showed that AEZs in the upper and lower parts of the Awash basin were hit by severe to extreme drought.

In contrast, the escarpments and middle parts of the basin experienced mild to moderate drought. This contrasts with the common perception that the hot to warm-arid lowlands AEZs are the only hotspot areas for drought. Moreover, previously nonfrequent drought AEZs, such as tepid to cool, humid mid-highlands, were identified as drought hotspots in the basin. This information could help policymakers target AEZs and implement context-specific and informed drought risk management decisions and adaptation measures.

Keywords: Drought risk; Gridded data; Inverse distance weighting; Drought hotspot; Spatial extent of drought

3.1. Introduction

Drought-associated risk is among the most significant global problem of our period. Drought has impacted more people worldwide during the last 50 years, unlike any other catastrophic event, affecting large segments of the population and damaging the foundation of natural resources, livestock, and livelihoods (Rojas, 2020; Singh *et al*., 2020; Sobhani *et al*., 2020). Various droughts depend on their cause (Haile *et al*., 2020a). Hydrological drought is related to streamflow, and agricultural drought is related to soil moisture. Any combination of these three is called drought (Belayneh & Adamowski, 2013; Boudad *et al*., 2018; Guo *et al*., 2020). For example, Mesbahzadeh *et al*. (2020) and Nicolai-Shaw *et al*. (2017) suggest that drought-related precipitation is meteorological.

Drought occurs when a below-average moisture supply spans wider areas for two consecutive years, or aridization occurs in an area due to long-lasting climate change for decades (Guo *et al*., 2020). Fahad and Wang (2020) attribute drought to climate change and claim it is an imminent climate characteristic for almost all climate regimes. Given the trend in global temperatures and the effect on the local environment, climate change would alter the intensity and frequency of meteorological drought (Foguesatto *et al*., 2020; Gyamfi *et al*., 2019). Thus, analyzing the spatiotemporal aspect of meteorological drought episodes due to climate change has gained more attention over recent decades (Danandeh Mehr *et al*., 2020).

Drought is a long-term hydro-meteorological event that affects large regions and significantly impacts different development sectors (Forootan *et al*., 2019). According to Agnew (2000), drought is essentially a meteorological phenomenon. The primary cause of meteorological drought is rainfall deficit (Ma *et al*., 2020; Wichitarapongsakun *et al*., 2016). Its impact is persistent in semiarid and arid areas (Szejner *et al*., 2020). Melese *et al*. (2018) also suggested that drought is more frequent and intense in arid and semi-arid regions with erratic rainfall and high evapotranspiration. Globally, more people are affected by drought than by floods because the drought has broader spatial coverage (Dai, 2013; Shefine, 2018).

Drought is becoming a continuing concern in many countries of Africa (De Pauw & Ramasamy, 2020), sub-Saharan Africa (Ahmed, 2020), and specifically in Ethiopia (Shefine, 2018). This study focuses on meteorological drought, an example of diverse AEZs of the Awash basin, Ethiopia. Edossa *et al*. (2010) reported that drought is among the recurring natural hazards in Ethiopia's Awash basin. Desalegn *et al*. (2006) illustrated that drought happens every two years in the Upper Awash basin. The consequences of drought are catastrophic and have resulted in food scarcity, population displacement, and livestock mortality (Hailu *et al*., 2020; Kogan *et al*., 2013). Depending on the rainfall, this is associated with crop production pastoral and agro-pastoral-based livelihood activities in the basin (Kura & Beyene, 2020). This suggests that analysis of historical meteorological drought gives information for a better understanding of past drought conditions and effective monitoring of future drought events (Spinoni *et al*., 2020).

The current research stems from this perspective and examines the spatiotemporal characteristics of meteorological drought, as it is the most fundamental requirement of any drought investigation (Guo *et al*., 2020). It determines the trend and intensity of other drought types. Meteorological drought is among the most important and fundamental forms of drought to be managed with care and attention (Derdous *et al*., 2020; Raha & Gayen, 2020). Consequently, an accurate rainfall-based model is vital for meteorological drought analysis (Sharafati *et al*., 2020). A skillful method of meteorological analysis of drought can inform better water management decisions and reduce the negative socioeconomic impacts caused by drought (Adisa *et al*., 2020; Shukla *et al*., 2015).

In earlier works, attempts have been made to analyze drought in Africa, Ethiopia, and the Awash basin based on different methodologies, datasets, and periods. Some of these studies were characterized by a desk review and household surveys (Buurman *et al*., 2020; Desalegn *et al*., 2006; Murendo *et al*., 2011; Naumann *et al*., 2014). Others mainly focused on rainfall-dependent meteorological droughts and station-based data (Belayneh *et al*., 2014; Bhunia *et al*., 2020; Edossa *et al*., 2010; Ntale & Gan, 2003). Some of them could not suggest which methods of drought characterization (SPEI and SPI) were better and why (Gebrehiwot *et al*., 2011; Manatsa *et al*., 2010; Tefera *et al*., 2019; Teshome & Zhang, 2019). Regardless of their methods, data sources, and spatial and temporal scales, these studies have contributed to the current understanding of drought occurrence's historical and future probability in their respective focus areas.

This study argues that substantial gaps need to be addressed to inform proactive meteorological drought-related risk management by policymakers and development practitioners. These gaps involve (1) most of these studies using standard precipitation index as a meteorological drought characterization, and the potential impact of evapotranspiration is missing (Abeysingha & Rajapaksha, 2020; Jehan & Waqas, 2020; Kasei *et al*., 2010; Mallenahalli, 2020); (2) and many earlier works were based on the station-based rainfall datasets, which were known for missing values and uneven spatial and temporal coverage (Gebrechorkos *et al*., 2020; Jasim & Awchi, 2020; Yadeta *et al*., 2020b); (3) in-depth understanding of meteorological drought is a key step to manage drought-related risk on the agricultural landscape (Sobhani & Zengir, 2020). This entails that the analysis of meteorological drought needs to disaggregate larger areas, such as basins, into homogeneous AEZs, which is persistently lacking in many previous studies.

Cognizant of these gaps, the objectives of the current study were: (1) to analyze meteorological drought over sub-humid mid-highland, sub-moist mid-highland, moist mid-highland, humid mid-highland, arid mid-highland, moist lowland, arid low land plain, and moist sub-afro alpine AEZs of the Awash basin based on the gridded monthly (4×4 km) climate datasets (precipitation, minimum and maximum temperatures) from 1983 to 2016; (2) to identify hotspot AEZs (for drought vulnerability) and therefore to inform proactive drought risk management decisions; (3) to understand the return period of droughts in the AEZs in time; and (4) to assess the performance of SPEI and SPI approaches in characterizing meteorological drought.

3.2. Materials and Methods

3.2.1. Characterization of the Study Area

Figure 3.1 depicts the location of the Awash basin. In Ethiopia, the Awash basin is among the highly exploited river basins for water use. It covers an 11,200 km^2 area, travels 1250 km (Tadese *et al*., 2020a), and has 21 major tributaries. Awash headwater is from the Dendi district of West Shewa zone, Oromia Region in Ethiopia. Lake Abhe, straddling the Ethiopian–Djibouti border, is Awash River's terminal point (Awash basin Authority, 2018). Administratively, the Awash basin is located across five regional states of Ethiopia (Oromia, Afar, Amhara, Southern Nations, Nationalities and People (SNNP) and Somali, and Dire Dawa Addis Ababa city administrations). It is the fourth-largest basin and seventh in surface water potential (Awash Basin Authority, 2018).

The altitude of the basin ranges between 3000 m above sea level (m.a.s.l) at the headwater and 128 m.a.s.l at the river's terminal point. The annual movements of air currents across the country, such as Atlantic equatorial Westerly and the Southerly and Easterly Indian Ocean currents, are the moisture sources for precipitation of the basin (Hastenrath & Polzin, 2004) that determine the climatic characteristics of the area. The basin's mean annual minimum and maximum temperature are 13 to 20.1 °C, respectively. The annual mean rainfall is 1600 and 160 mm around the highlands and the northern tip lowlands, respectively. Although the middle and lower parts of the Awash are distinguished by bimodal rainfall distribution, uni-modal rainfall characterizes the upper Awash (Edossa *et al*., 2010). Rainfall events are highly unpredictable (Mulugeta *et al*., 2019). The average annual Rainfall also varies significantly year by year. This results in severe droughts occurring in some years and flooding in others in various basin parts (Shawul & Chakma, 2020).

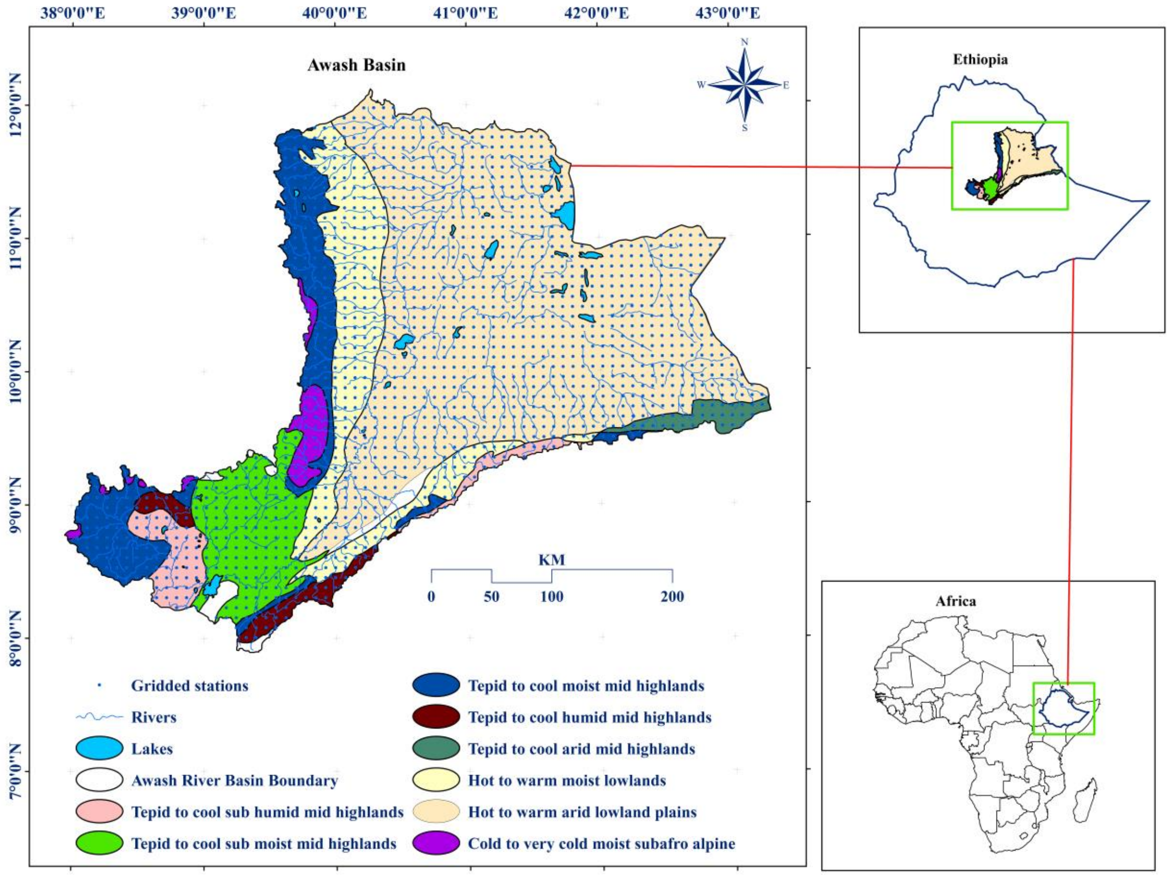


Figure 3.1. Location of Awash basin's major agroecological zones

A recent population estimate indicates that 18.6 million people inhabit the basin and support 34 million heads of livestock population. In different years, the drought had the most damaging consequences and triggered the loss of human life and the livestock population (Tessema *et al*., 2020). The drought in 2015–2016 due to El Niño in different parts of Ethiopia was among the most severe droughts observed in the basin (Awash Basin Authority, 2018). Drought in the basin is primarily a meteorological drought caused by a lack of enough Rainfall, followed by hydrologic drought and manifested as streamflow dwindles. In this regard, the meteorological conditions (precipitation and temperature) significantly influence the occurrence of drought in the basin.

Figure 3.2 shows the study's general approach to analyzing meteorological drought and its hotspot AEZs in Awash Basin. The analysis was based on the steps: data used, methods followed, and outputs generated. The detail of the flow chart is presented in the following subsections independently.

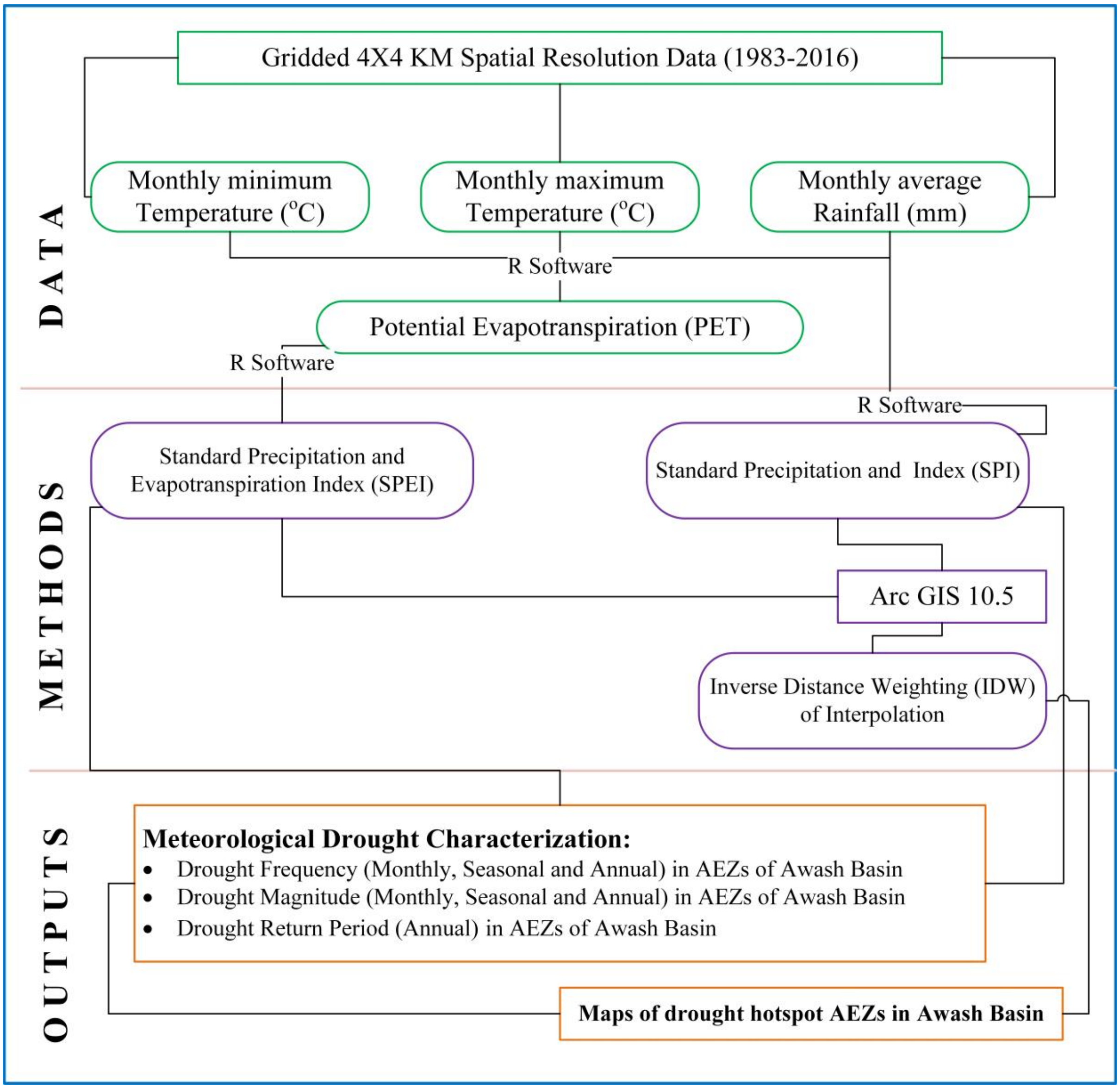


Figure 3.2. Flow chart of the general approach of the study

3.3. Data Sources

Two datasets were used for this study: (1) a gridded dataset (4×4 km spatial resolution) of monthly minimum and maximum temperature and monthly total Rainfall for 34 years (1983–2016). The grid dataset is a hybrid of station data (temperature and rainfall) from the national observer network compiled by the National Meteorological Agency of Ethiopia (NMA) and (2) the European Organization for the Use of Meteorological Satellites (EUMETSAT) and (3) National Aeronautics and Space Administration (NASA) satellite temperature and rainfall forecasts. The data were reconstructed by Ethiopian NMA, collaborating with the International Climate and Society Research Institute at Columbia University, United States of America. In other words, the gridded dataset combined quality-managed station data from the national observer network with locally calibrated satellite data to fill spatiotemporal gaps in Ethiopia's national observations (Esayas *et al*., 2018, 2019). NMA conducted data restoration with the International Climate and Society Research Institute at Columbia University, United States of America. At the same time, Reading University performed the data calibration and validation United Kingdom (Dinku *et al*., 2014).

Compared to the station-based dataset, the gridded dataset is preferred regarding the non-missing value, better temporal and spatial coverages, and easy accessibility from the NMA. Its main limitation is it is simulated data to fill spatiotemporal gaps. However, it is calibrated, validated, and published as knowledge to be used by researchers. NMA of Ethiopia also prefers to provide this dataset than the station-based one. Due to these reasons, we preferred to use the gridded dataset for the current study.

Accordingly, this study relied on 1655 data points for major AEZs in the Awash basin (Figure 3.1; Table 3.1) using the gridded dataset to compare the results across these AEZs over the study period. The 1655 existing data points were identified by their corresponding major AEZ. The areal mean of all points' datasets was taken for each major AEZ to ensure a high level of representation (Table 3.1; Figure 3.1). Unlike representing an AEZ with a single point for climatic data analysis, this study used the area mean of all available points with better representativeness. Put differently, all available points were considered in each major AEZ. The period (1983–2016) was chosen because it is the longest time the gridded datasets are available from Ethiopian NMA. The gridded data can be accessed from NMA on the points located in the AEZs in the Awash basin.

The AEZs were classified based on criteria. These criteria are altitude, major crops grown, cropping pattern and seasons, growing period, rainfall pattern, and temperature (Hurni, 1998). Table 3.1 describes the main climatic characteristics of the AEZ in the basin.

Table 3. 1. Major Agroecological zones, their characters, and the respective number of gridded points in the Awash basin

Standard name of AEZs	No. of Grid points	Elevation (MASL)	Thermal zone (^{o}C)	Annual Rainfall (mm)	Annual AET (mm)	Length of growing (Days)	Traditional name of the AEZs
Hot to warm moist lowlands	220	400-800	21-27.5	250-1500	1300-1600	121-180	Lowlands
Hot to warm arid lowland plains	969	bsl-1400	> 28	100-800	1700-3000	No-45	Lowlands
Tepid to cool arid mid-highlands	27	1200-1600	16-21	500-600	1800-2000	< 45	Midlands
Tepid to cool moist mid-highlands	169	1000-2000	16 -21	700-1100	1400-2200	40 -120	Midlands
Tepid to cool sub-moist mid-highlands	141	1000-2000	16 -21	500-900	1400-1900	61-120	Midlands

Tepid to cool sub-humid mid-highlands	59	1000-2000	16 -21	700-1500	1400-1600	150 -240	Midlands
Tepid to cool humid mid-highlands	35	2000-3000	12.5-18	900 -2000	1300-1500	241-300	Midlands
Cold to very cold moist sub-afro alpines	35	2800-4000	< 7.5-16	1000-1800	1300-1800	150 -210	Highlands
	1,655						

MASL = meter above sea level; PET = Potential Evapotranspiration; LGP = Length of Growing Period

3.4. Indexing and Interpolation of Meteorological Drought

Meteorological data quality control was carried out in ClimPACT2 Software in R (Alexander & Herold, 2016), and potentially wrong values were tested and removed from the datasets. Outliers for monthly maximum and minimum temperatures exceeding ±3 standard deviation were detected and excluded from the dataset. After the quality test, the meteorological drought characterizing indices were computed using R software's SPEI and SPI-installed packages. The monthly minimum, maximum, and monthly total rainfall datasets were the parameters used to calculate both the SPEI and SPI. Arc GIS® 10.5 was employed to map the AEZ hotspots depending on meteorological drought indices' spatial and temporal distribution using the Inverse Distance Weighting (IDW) method. Drought normal, wet, and hotspot AEZs are mapped using this method.

3.4.1. Standard Precipitation Index (SPI)

Different meteorological drought studies used different datasets and approaches. For example, Bhalme and Mooley (1980) used rainfall anomaly to describe long-term meteorological drought, and McKee *et al*. (1993) used the SPI to measure time scale wetness and dryness of regions. In both SPEI and SPI approaches, the probability density function, which describes the long-term series of precipitation data, was determined and used to define the gamma distribution, as illustrated in Equation 3.1 (after Angelidis *et al*., 2012):

$$f(x_i) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} {x_i}^{\alpha-1} e - x_{\frac{i}{\beta}} \qquad (3.1)$$

where α and β are the shape and scale parameters. The larger the shape parameter value is, the closest to the normal distribution curve and x_i(>0) is the rainfall within i consecutive months.

Then, the cumulative likelihood of an observed rainfall amount was computed that required an estimate of corresponding α, β parameters per each timescale of interest (1, 2, … months) for each year. Accordingly, in the selected time scale, the cumulative probability g(x) is given as (Equation 3.2):

$$g(x) = \int_0^{x_i} f(x_i)dx_i = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^{x_i} x_i^{a-1} e - x_{i/\beta} dx_i \text{ for } x \geq 0 \qquad (3\text{-}2)$$

where x is the rainfall amount, (α) is the gamma function, and α and β are the shape and scale parameters described under Equation 3.1.

Maximum likelihood estimation solutions have been used for estimating α and β. The resulting parameters are used to find the cumulative probability of an observed precipitation event for the given month and the timescale in the given station, then to obtain the SPI values.

Finally, the SPI was computed using Equation 3.3 after Agnew (2000):

$$SPI = \frac{X_{ik} - \bar{X}_i}{\dot{O}_i} \qquad (3\text{-}3)$$

where: X_{ik}= i^{th} precipitation and k^{th} observation; $\bar{X}_i$ = mean i^{th} station precipitation; $\dot{O}_i$= standardized i^{th} station deviation.

SPI is a normalized index in time and space. This capability helps comparisons of SPI values between different locations. For rainfall values greater than the annual mean, the SPI values are positive and negative for rainfall values less than average. The divergence from the mean indicates the likelihood of the extent of the wetness or drought that can be used to determine meteorological drought (Agnew, 2000).

3.4.2. Standard Precipitation and Evapotranspiration Index (SPEI)

Failure to consider evapotranspiration is the major limitation of SPI (Wang *et al.*, 2015). Vicente-Serrano et al. (2010) developed the Standardized Precipitation Evapotranspiration Index (SPEI) to measure drought conditions to fill this gap. The SPEI technique is more inclusive of the climatic water balance element, i.e., evapotranspiration, and hence exhibits better monitoring of the drought characteristics. This study performed SPEI measurement on the monthly difference between precipitation and PET at a specific interest-based time, indicating a climatic water balance. For the SPEI calculation, the monthly difference between precipitation (P) and PET (Equation 3.4) has been used.

$$D = P - PET \qquad (3.4)$$

whereas D is a simple calculation of water deficits or aggregated surpluses at various time scales. Later, the values were fitted to multiple parametric statistical probability distributions to transform the original values into standardized units. The PET was calculated using the

Hargreaves & Samani (1982) method by applying the maximum and minimum monthly temperatures in time series data. Therefore, this method requires only temperature data for PET calculation and is the most commonly used method in the region with limited data availability. A limitation on other climatic data (wind speed, relative humidity, and sunshine hour, among others) over the Awash basin was the reason to apply the Hargreaves and Samani method to estimate PET in this study. Hargreaves and Samani's method of PET calculation were done as (Hargreaves & Samani, 1982) (Equation 3.5):

$$PET = 0.0023(T_{mean} + 17.8)\sqrt{(T_{max} - T_{min})R_a} \qquad (5)$$

where PET is the potential evapotranspiration (in millimeters/day); T_{mean}, T_{max} and T_{min} average, maximum, and minimum temperatures (in degrees Celsius), respectively, and R_a is extraterrestrial radiation (in millimeters/day).

To get SPEI series in standard *z* units, it is better to use log-logistic distribution than other methods (Vicente- Serrano *et al*., 2010). According to this distribution method, the probability distribution function of a variable D is given by (Equation 3.6):

$$F(D) = \left[1 + \left(\frac{\alpha}{D-\gamma}\right)^{\beta-1}\right] \qquad (3.6)$$

where α, β, and γ are the scale, shape, and location parameters estimated by sample D.

The L-moment method was discussed by Ahmad *et al*. (1988) as the most stable and most straightforward method for obtaining the log-logistic parameters, alpha, beta, and gamma. On the other side, based on the plotting–position method, the probability-weighted moment technique was used to measure the parameter values (Hosking, 1990). With *F*(*D*), we can easily obtain the SPEI by standardizing the *F*(*D*) values. For example, it is possible to use Abramowitz and Stegun (1965) following the conventional approximation equation. Then, the SPEI was calculated as (Equation 3.7):

$$SPEI = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \qquad (3.7)$$

where W = -2ln(P), P is the probability of exceeding a determined D value, that is P = $1 - F(x)$ for $P \leq 0.5$. The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

If more than one drought assessment technique is used, the methods show reliable meteorological drought characteristics (Homdee *et al*., 2016). Therefore, SPI and SPEI were employed separately to analyze meteorological drought characteristics in this study, comparing the two indices. As to Kebede *et al*. (2020), using more than one accurate and analytical drought index is critical for monitoring and characterizing drought.

Following Li *et al*. (2015), drought levels were classified according to the seven SPI and SPEI values presented in Table 3.2. These drought severity classes were used to compute the time series of drought indices (SPI and SPEI) for each AEZ in the basin and each year at different time scales (1, 3, and 12 months). The SPI and SPEI indices were determined using the loaded SPI and SPEI packages in R® software (R Core Team, 2018).

Table 3.2. The SPI and SPEI drought (or humidity) category (Li *et al*., 2015)

Index values of drought (SPEI and SPI)	Drought severity classes description
+2.0 and above	Extremely wet
+1.5 to +1.99	Very wet
+1.0 to +1.49	Moderately wet
+0.5 to +0.99	Mild wet
-0.49 to +0.49	Normal condition
-0.5 to -0.99	Mild drought
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
-2.0 and below	Extreme drought

3.4.3. Spatiotemporal Interpolation of SPI and SPEI Values

Drought is a regional phenomenon and hence demarcates its spatial extent. The computed SPI and SPEI index values were used to map the spatial extent of meteorological drought severity using Arc GIS® 10.5. SPI and SPEI values over gridded points across major AEZs of the basin were mapped using IDW spatiotemporal interpolation method (Gumus & Algin, 2017). The IDW calculates the cell values of a gridded point in Arc GIS by averaging the value of sample data points near each cell. IDW assumed that the unsampled point attribute value is the weighted average of the measured value within the region. The weights are inversely proportional to the ranges between the expected position and the sampled areas (Lu & Wong, 2008).

IDW method was selected over other spatial interpolation methods because it is easily and readily available (Ikechukwu *et al*., 2017). In addition, according to Azpurua & Ramos (2010), it is intuitive and efficient and works best with evenly distributed points, such as spatially oriented grid-point data. The method was used to characterize an early warning system in Africa (Okpara *et al*., 2017). It was also used for interpolation of rainfall on a broad basin in West Africa (Ruelland *et al*., 2008) and study rainfall variability, drought characterization, and rainfall data reconstruction effectiveness in Kenya (Kisaka *et al*., 2015), and even mapping the spatiotemporal occurrence and patterns of climate variability and its application in Northern Ethiopia (Dawit *et al*., 2019). According to Mishra & Desai (2005), unlike the Thiessen Polygon interpolation method, IDW provides a smooth surface between interpolated areas on the map.

3.5. Results and Discussions

3.5.1. Analysis of Dry, Normal, and Wet Events Using SPEI and SPI

The comparisons of the two drought indices at monthly, seasonal, and annual scales are presented in Figures 3.3 and 3.4. Table 3.3 displays the monthly, seasonal, and annual (dry, wet, and normal) meteorological drought events. Computed SPEI values illustrated that hot to warm humid lowlands experienced the largest monthly meteorological drought events (150 drought months) between 1983 and 2016. The SPEI method recorded the lowest monthly drought events (132) in tepid to cool subhumid mid-highlands. For wet and normal months of meteorological drought events, moist lowlands and warm arid lowland plains were at the top of the list, with a magnitude of 140 and 147, respectively (Table 3.3).

Hot to warm arid lowland plains and tepid to cool sub moist- mid highlands AEZs recorded the highest and lowest amount of observed seasonal drought. Although the highest annual drought (12) occurred in the tepid to cool humid mid-highlands, in the hot to warm arid lowland plains of AEZ, only (8) annual drought years were reported.

Table 3.3 and Figures 3.3 and 3.4 also summarize the SPI index value. The findings indicated that tepid to cool, humid mid-highlands had the largest dry months in 34 years compared to the hot to warm arid lowland plains. Unlike the SPEI approach, for SPI, hot to warm lowland plains were marked by most drought seasons compared with the rest of the AEZs in the basin. Likewise, tepid to cool humid mid-highlands AEZ endured the most droughts over the study period on an annual basis.

Unlike the SPI, the SPEI index provided more monthly and seasonal drought events in the basin. Hence, it is observed that frequent dry months, seasons, and years happened in hot to warm moist lowlands, hot to warm arid lowland plains, and tepid to cool humid mid-highlands

AEZs, respectively. This is irrespective of the number of drought events revealed by SPEI and SPI approaches. However, the SPI has an advantage over the SPEI index in characterizing the largest annual normal events. For example, SPEI characterized most drought years in all AEZs, while SPI gave a larger number of normal months in all AEZs in the study areas.

On the other hand, although the SPEI and SPI values had similar trends, there were cases where SPEI values were higher than SPI values. For example, SPEI values tend to be lower than SPI for dry months. Contrastingly, values of SPI were higher for wet and normal months.

Even though the World Meteorological Organization (WMO) suggested SPI as a universal index, it may not be sufficient to characterize a complicated drought event as a single indicator (Hao & Singh, 2015). In this study's case, the comparison results between the two indices reveal that the SPI reflects only the input side (rainfall). In contrast, the SPEI studies the input and unproductive water depletion evaporative losses. A closer look at the two methods is essential from an agricultural land management perspective. For example, SPEI methods give better prospects in terms of soil moisture balance, thus influencing crop selection because of their comparative advantage in characterizing monthly and seasonal drought conditions. SPEI also gives better results in AEZs where evapotranspiration plays a significant role (e.g., hot to warm arid lowland plains). It should be emphasized that in certain AEZs (e.g., tepid to cool moist and sub-moist mid-highlands), the value of evapotranspiration determines the number of drought events. In contrast, its impact is limited in other AEZs (e.g., cold to very cold moist sub-afro alpines) (Labudová et al., 2017).

The differences in values of the two approaches depend on the time scale. Homdee et al. (2016) reported that the association between the SPI and the SPEI was reasonably strong at shorter timescales (1–6 months) and decreased significantly at longer time scales (9–24 months). This indicates that SPEI and SPI methods clearly understand the drought condition, especially on monthly and seasonal scales, in distinct AEZs (Liu et al., 2018).

SPEI has more advantages in detecting dry months and a slight advantage in detecting dry seasons than the SPI approach. Annually, the trend showed SPEI is better in some AEZ, for example, in hot to warm arid lowlands, tepid to cool sub-humid mid-highlands, and tepid to cool arid mid-highlands. In hot to warm moist lowlands, SPI detected more dry years. The same output in tepid to cool humid mid-highlands has been observed. To this end, the meteorological drought characterization capacity of the SPI and SPEI methods depend on the specific AEZ: in the AEZs where potential evapotranspiration is higher, SPEI is better. SPI is advantageous over SPEI in giving more wet and drought normal episodes regarding the type of drought.

Figure 3.5 shows the distribution of annual dry, normal, and wet events over major AEZs for the study area. The SPEI characterized the dry events better than SPI, while SPI values for the normal events were superior to SPEI, which aligns with Homdee *et al*. (2016). The SPEI characterized the dry events better than SPI, while SPI valued normal events (2016). Accordingly, in Figure 3.5(a–c, Left), on the loading of SPEI, seven years have been identified as drought years in five major AEZs of the basin, and the number of wet and normal years for the last three decades was nine in the major AEZs. On the other hand, Figure 3.5(a–c, Right) specifies the number of dry, wet, and normal years in the study AEZs based on the SPI indices. Six dry, 16-normal, and 9-wet years were identified in this case. Although the number of dry years based on the SPI value is less than the SPEI, the number of normal years for SPI increases by seven. The number of wet years remained the same for SPEI and SPI values.

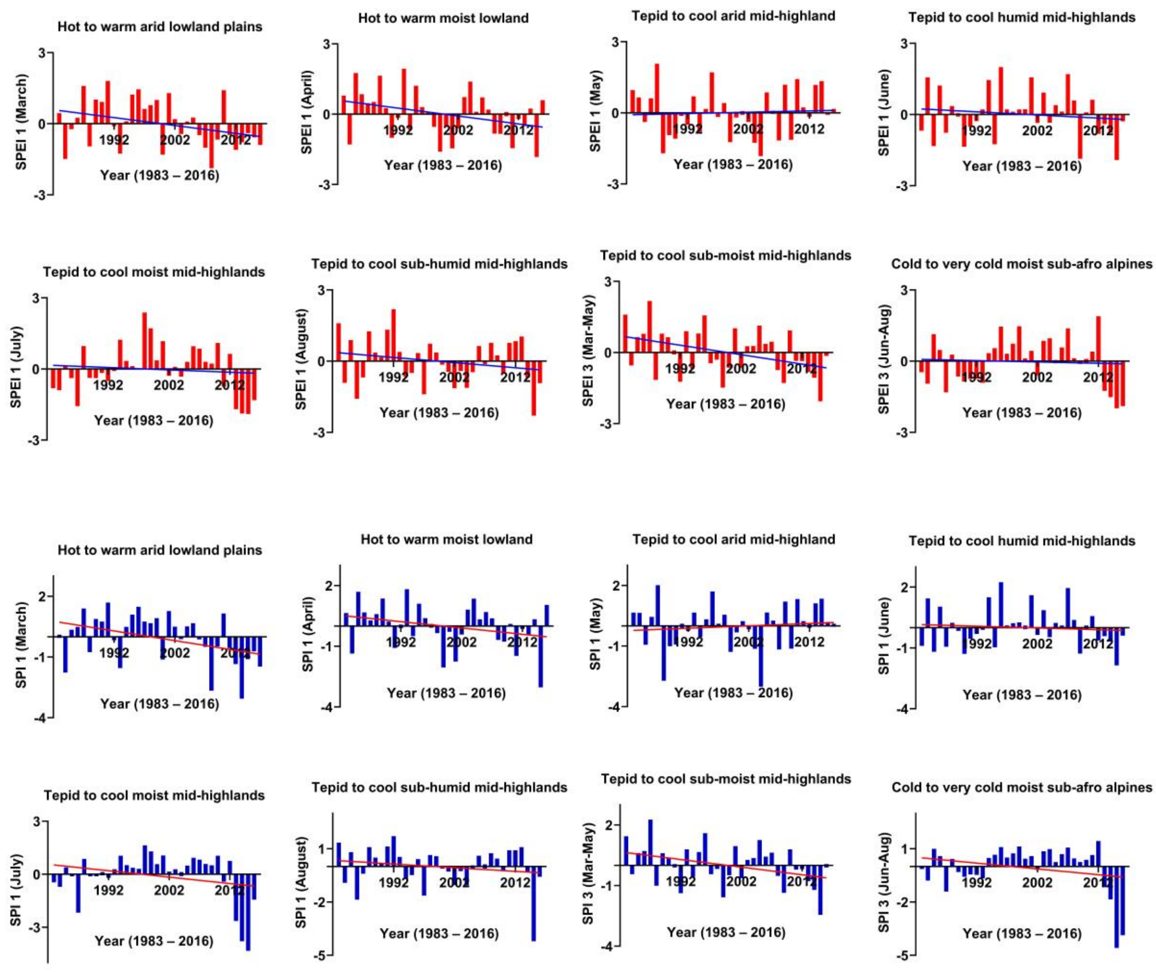


Figure 3.3. Monthly and seasonal SPEI (Above) and SPI (Below) of the eight AEZs in the Awash basin (1983–2016)

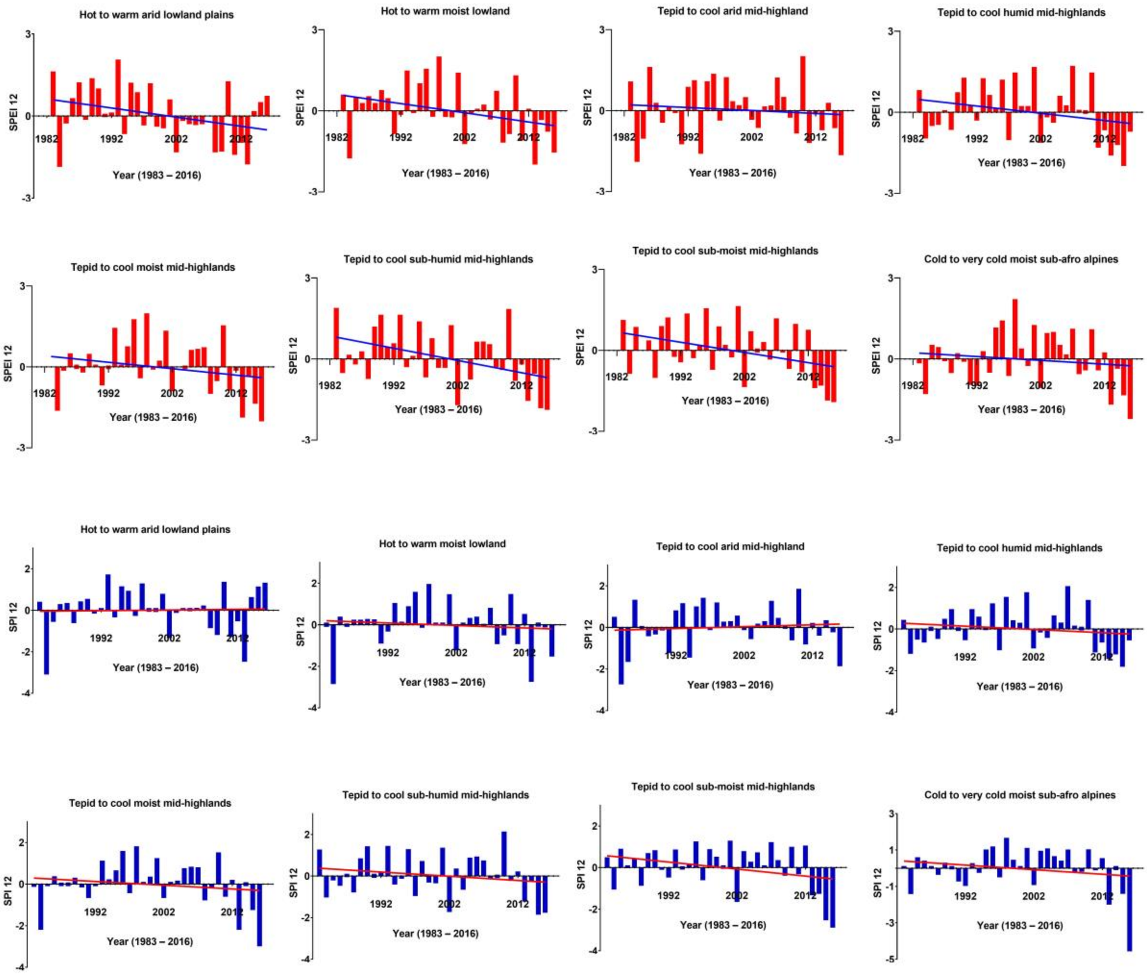


Figure 3.4. Annual SPEI (Above) and SPI (Below) of the eight AEZs in the Awash basin (1983–2016)

Figures 3.3 and 3.5 show that dry and wet years dominated during the 2010s and 1990s, respectively, signifying the occurrence of climate extremes. The 1980s and 2000s were normal years in most AEZs of the basin. Studies by Tefera *et al*. (2019) and Yisehak & Zenebe (2020) reported that the 2010s were known for drought events signifying 2012 as the worst drought year; 2015 was identified as the year with extreme drought events in Northern Ethiopia (Ademe *et al*., 2020); Teshome & Zhang (2019) confirmed the 1990s as wet years in Ethiopia. The abovementioned years were the drought at its worst in the Awash basin, with more than half of the total basin region under drought, along with the previous fatal drought periods in the country when most people were exposed to severe famine and large livestock resources died out of it (Tolera & Senbeta, 2020).

Using the two indices, characterizing wet, normal, and dry events tells the normal conditions of rainfall for wet and normal events. Arguably, this is a critical value in informing decision-makers about interventions. For example, SPI does not reflect evapotranspiration and could overestimate the number of normal years. Soil moisture is deficient during these "normal" years. Related studies confirmed that SPEI performed well in capturing the drought years at all timescales (Tefera *et al*., 2019). Still, when the additional temperature is considered in the case of SPEI (Tirivarombo *et al*., 2018), dry events are better detected than when using the SPI (Tan *et al*., 2015). SPI may be considered in the humid and moist AEZs that experience high rainfall. However, SPEI can be used in arid and semi-arid areas characterized by high PET to capture the drought characteristics effectively.

In summary, the similar performance between SPEI and SPI has implications for farmers' adaptation measures, particularly in selecting sawing dates and crop selection and inadequate preparedness for future drought risks. SPI in the sub-humid (humid) region and SPEI in the semi-arid (arid) region is necessary to monitor drought impacts effectively.

Table 3.3. Overview of SPEI and SPI based number of monthly, seasonal, and annual dry, wet, and normal events across AEZs of the Awash

	Drought characterization indices																	
SPEI										**SPI**								
Major Agroecological Zones (AEZs)	Dry months	Wet months	Normal months	Dry seasons	Wet seasons	Normal seasons	Dry years	Wet years	Normal years	Dry months	Wet months	Normal months	Dry seasons	Wet seasons	Normal seasons	Dry years	Wet years	Normal years
HM Lowlands	150	140	118	44	45	47	10	10	14	126	133	149	43	45	48	7	8	19
HA Lowlands	134	127	147	49	47	40	8	13	13	117	132	159	45	46	45	9	10	15
TM Midlands	143	128	137	42	46	48	9	10	15	124	133	151	38	43	55	8	9	17
TSM Midlands	140	134	134	39	43	54	10	12	12	122	147	139	39	41	56	8	13	13
TSH Midlands	132	131	145	43	46	47	10	12	12	120	145	143	39	45	52	8	11	15
TH Midlands	143	128	137	45	43	48	12	11	11	126	136	146	37	44	55	12	9	13
TA Midlands	135	136	137	42	45	49	10	11	13	94	136	178	42	37	57	8	11	15
CMSA Alpine	149	134	125	45	40	51	10	10	14	123	140	145	36	43	57	8	11	15
Total	**1,126**	**1058**	**1080**	**349**	**355**	**384**	**79**	**89**	**104**	**952**	**1102**	**1210**	**319**	**344**	**425**	**68**	**82**	**122**

basin (1983 to 2016)

HM Lowlands = Hot to warm moist lowlands; HA Lowlands = Hot to warm arid lowland plains; TM Midlands = Tepid to cool moist mid-highlands; TSM Midlands = Tepid to cool sub-moist mid-highlands; TSH Midlands = Tepid to cool sub-humid mid-highlands; TH Midlands = Tepid to cool humid mid-highlands; TA Midlands = Tepid to cool arid mid-highlands; CMSA Alpine = Cold to very cold moist sub-afro-alpine

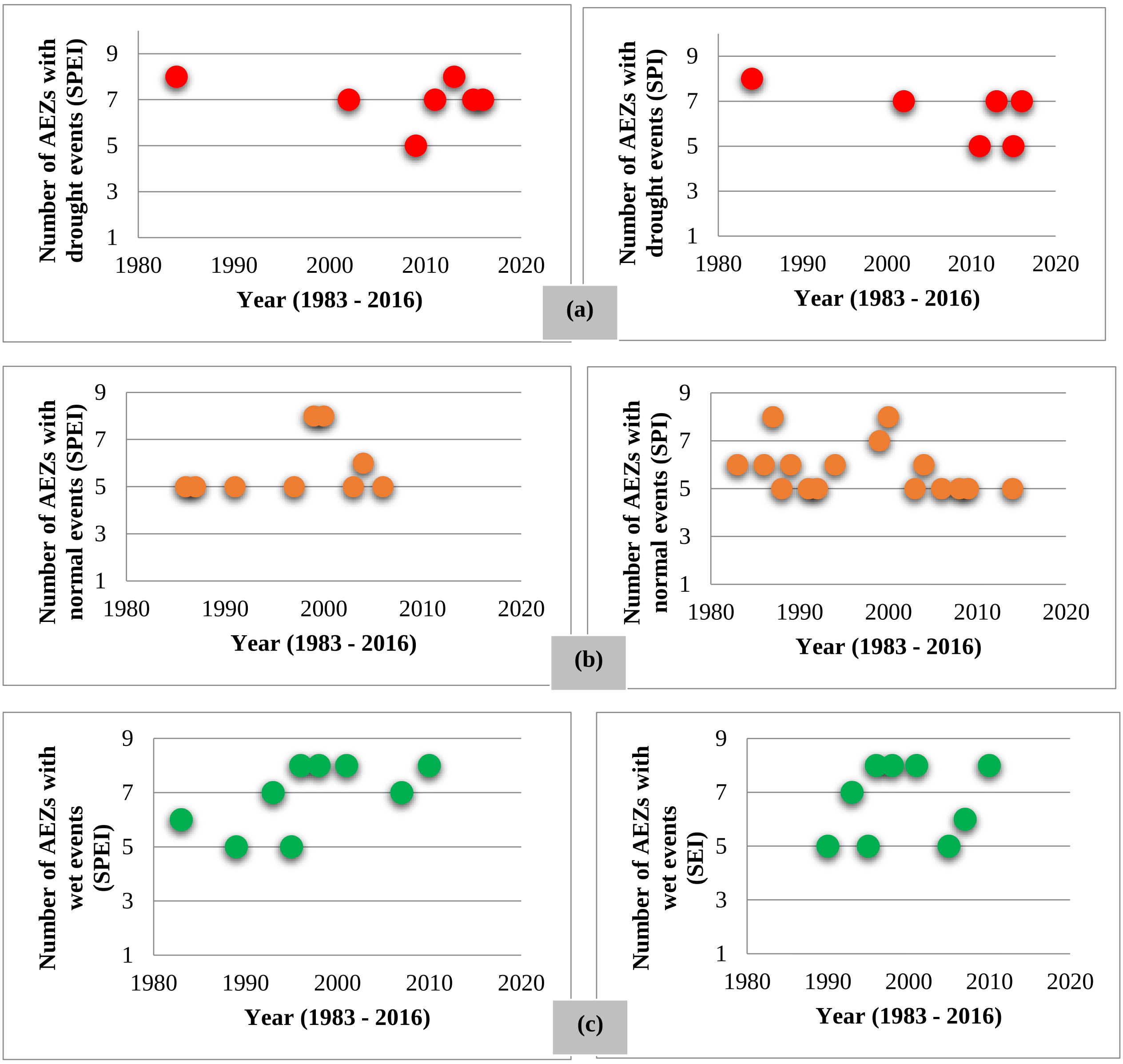


Figure 3.5. Temporal distribution of annual dry years (a), normal years (b), and wet years (c) based on SPEI (Left) and SPI (Right) indices.

3.5.2. Magnitudes of the Drought

Table 3.4 indicates the magnitude of seasonal and annual dry, normal, and wet events in the Awash basin by AEZ for the study period (1983–2016). In all cases, the magnitude of drought experienced in the basin varies by AEZ and ranges from extremely dry to extremely wet. Table 3.4 shows the most extreme dry seasonal event observed in tepid to cool arid mid-highlands. At the same time, annually, it occurred in tepid to cool moist mid-highlands and cold to very cold moist sub-afro alpines. The stronger value for normal events was observed in the hot to warm moist lowlands and tepid to cool sub-moist mid-highlands seasonally and annually. The largest number of the extreme wet seasonal event was recorded in tepid to cool sub-moist mid-highlands.

Table 3.4 also shows severe and mild dry seasons dominated by hot to warm arid lowland plains. In contrast, most moderate dry events were experienced in the hot to warm moist lowlands. This infers that in addition to the hot to warm lowland AEZs, tepid to cool sub-moist mid-highlands are more prone to frequent annual and seasonal drought occurrence, demanding proactive drought management that suits the biophysical and socioeconomic contexts of the agroecology. The study result agrees with studies reported by Edossa *et al*. (2010), Esayas *et al*. (2019), and Mengistu *et al*. (2014), which confirmed that most drought events dominate the lowland AEZ in the Awash basin, Blue Nile basin, and Wolaita zone, respectively. The study demonstrates that tepid-to-cool sub-moist mid-highlands are among the newly drought-prone areas in the basin. The ever-decreasing rainfall amount causes it due to the expansion of aridization of the climatic condition is expressed in an increase in the number of days with abnormally high temperatures in this AEZ. A recent study by Gebrehiwot *et al*. (2020) noted that this AEZ had shown a significant decrease in recent years, currently as low as 401 mm annually, from its average annual rainfall of 700 mm.

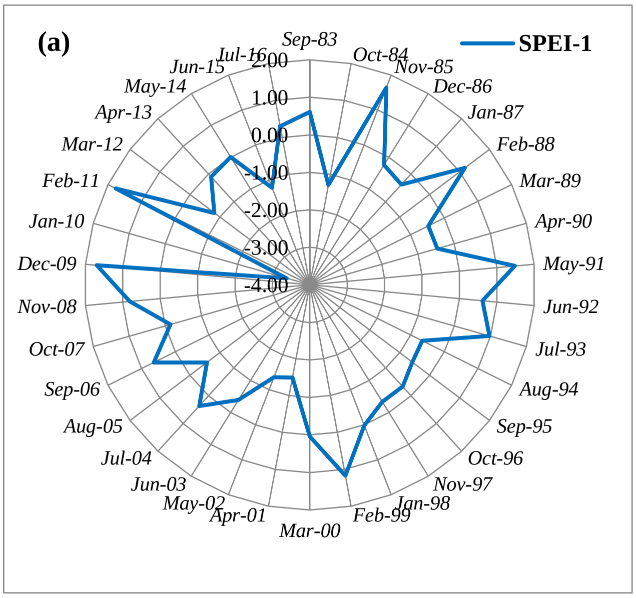
Table 3.4. Magnitude of seasonal and annual dry, normal, and wet events in Awash basin by agroecology (1983 to 2016)

Agroecological Zones (AEZs)	**Extreme dry**		**Severe dry**		**Moderate dry**		**Mild dry**		**Normal**		**Mild wet**		**Moderate wet**		**Very wet**		**Extreme wet**	
	S3	S12	S3	S12	S3	S12	S3	S12	S3	S12	S3	S12	S3	S12	S3	S12	S3	S12
HM Lowlands	1	0	5	3	19	3	19	3	47	15	16	4	20	4	5	1	3	1
HA Lowlands	1	0	6	2	15	4	27	2	40	13	19	5	21	6	3	1	4	1
TM Midlands	1	1	7	2	15	2	19	4	48	15	20	5	18	2	4	3	4	1
TSM Midlands	3	0	5	2	14	4	18	4	54	12	20	6	14	4	4	2	5	0
TSH Midlands	3	0	4	4	16	0	20	6	47	12	27	5	11	3	4	4	4	0
TH Midlands	2	0	4	2	16	4	23	5	48	12	18	4	15	5	8	2	2	0
TA Midlands	4	0	4	3	17	3	17	4	49	13	20	3	14	6	9	1	2	1
CMSA Alpine	2	1	6	1	12	3	25	6	51	13	12	3	22	6	4	0	2	1

3.5.3. Monthly and Seasonal Drought

Figures 3.6a and b present the study period's monthly and seasonal drought conditions in the hot to warm arid lowland plains and cold to very cold moist sub-afro alpines AEZs. The 1-month and 3-month SPEI/SPI values reflect the short and medium-term moisture and temperature conditions, provide a monthly and seasonal estimation of precipitation and/or temperature, and can effectively show the rainfall and temperature over distinct months and seasons. Based on the monthly SPEI values for randomly selected months and years, January, April, May, June, and October are dry months. February, November, and December could be considered wet in hot, warm, arid lowland plains. Normal condition events were observed in September, March, July, and August (Figure 3.6**a**).

As revealed in Figure 3.6**b** on randomly selected years and seasons, for cold to very cold moist sub-afro alpines, dry events frequently happened in *Bega* (December, January, February) and *Tsedey* (September, October, November) seasons, whereas *Kiremt* (June, July August) was wet. Though variations depend on the year difference, *Belg* (March, April, May) was known as a regular condition season[1]. In Ethiopia, *Bega* and *Tsedey* are known as dry seasons. The temperature of these seasons has also shown a warming trend in the last four decades (Mengistu *et al.*, 2014), contributing to dry events in the study area.



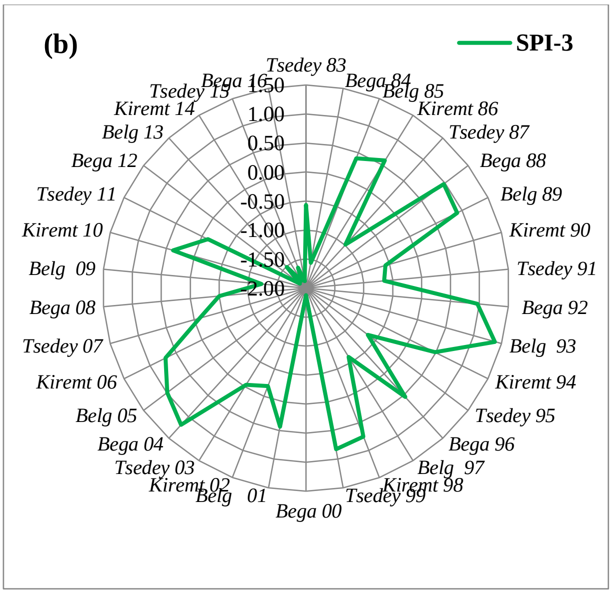


Figure 3.6a. Selected monthly SPEI of Hot to warm arid lowland plains and **b** selected seasonal SPI of Cold to very cold moist sub-afro alpines.

Drought can affect seasonal crop failure and soil moisture at smaller time scales, such as 1 and 3 months (Masud *et al*., 2020). For instance, the above results indicate that June is among the rainy months in Ethiopia when major crops are planted in rainfed agriculture. Due to this, June's rain shortage leaves farmers vulnerable to failure of farm crops and, thus, famine in the community unless time and space-specific management occur. In sum, methods for reducing

[1] Ethiopia has four different seasons, including *Kiremt*, *Tsedey*, *Bega* and *Belg*. The rainy seasons are two: The *Kiremt* or *Meher* (main rainy) and the *Belg* (short rainy). The dry seasons are *Tsedey* and *Bega* (Mekonen & Berlie, 2020).

drought should focus on the particular month and season (Haile *et al*., 2020b) and AEZs of interest as agricultural practices in Ethiopia depend on time and space.

3.5.4. Annual Drought Frequency

The occurrence of annual drought for each AEZ was counted, taking the first drought incidence as a reference. The objective was to determine the return of drought occurrences in specific AEZs in time. As illustrated in Figure 3.7a, based on the SPEI values, the most frequent annual drought happened in the tepid to cool the humid mid-highlands. In this AEZ, a drought occurred on average every three years from 1983 to 2016. The least frequent drought was observed in the hot to warm arid lowland plains, where drought occurred on average every 4.1 years. Like the SPEI-based index, the SPI index predicted the most frequent droughts for the tepid to cool humid mid-highlands; accordingly, drought events occurred every 2.9 years. The smallest drought frequency happened in the tepid to cool sub-moist mid-highlands, where it took an average of 6 years for the drought to return between 1983 and 2016 (Figure 3.7b). These results inform that frequent practical drought management practices must be implemented for rainfed and agro-pastoral communities in tepid to cool humid mid-highlands where annual drought events have frequently occurred.

From the temporal variation point of annual droughts, all major AEZs of the basin have been hit by drought events almost every year since 2011. This indicates that the basin has been highly prone to recurrent drought every year for the last five years since 2011 (Figure 3.7a, b). As of 2011, recurrent droughts have significantly affected populations and economic growth in the Awash basin (Taye *et al*., 2018). Murendo *et al*. (2011) reported that severe droughts in the basin have led to a significant depression in crop yields and livestock death, resulting in increased food insecurity. Due to climate shocks and a national humanitarian response affecting more than 10 million people, humanitarian aid demands are frequent, with several priority districts in the Awash basin. Studies conducted in various locations in Ethiopia have also revealed that recent years have been characterized by more frequent drought (Bayissa *et al*., 2015; Esayas *et al*., 2018; Gidey *et al*., 2018; Shefine, 2018) substantiate the findings of this study. With the effect of persistent drought on activities relating to irrigation, and pastoral and agro-pastoral livelihood, it is imperative to understand the frequency of drought occurrence better and devise proactive adaptation and mitigation measures under diverse agroecology settings.

On the other hand, given the frequency, magnitude, and temporal extent of the Awash basin's monthly, seasonal, and annual drought conditions, some agroecological zones are identified as hotspot areas of drought. Hot to warm moist and humid lowlands, hot to warm arid lowland plains, and tepid to cool moist mid-highlands reveal more frequent dry events from 1983 to 2016 (Figure 3.9). Hot to warm moist lowlands and dry to warm arid lowland plains are noted for their high temperatures and potential evapotranspiration (Figure 3.8). Therefore, these areas' agricultural, pastoral, and agro-pastoral livelihood conditions are highly vulnerable unless proactive drought risk management measures are taken based on the evidence.

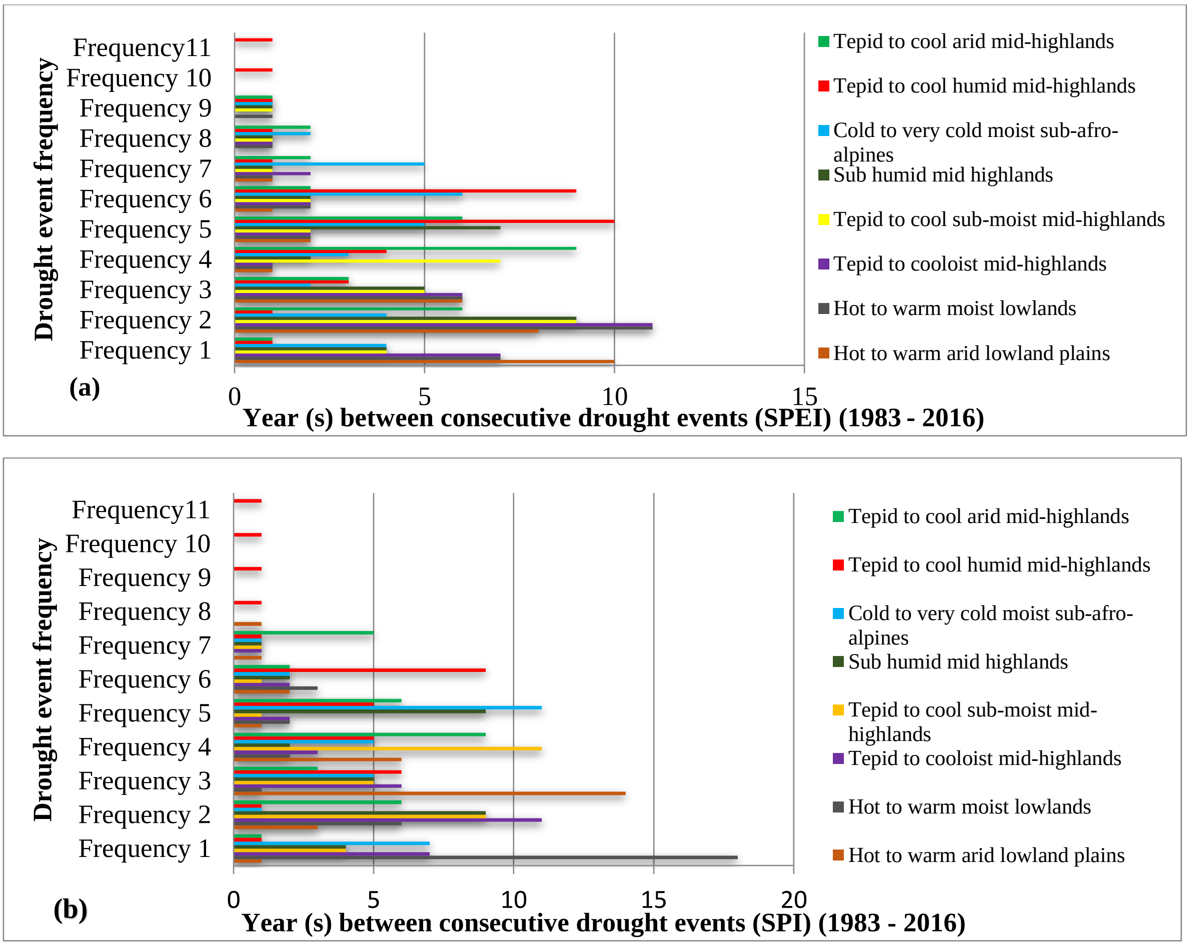


Figure 3.7. The gap between consecutive drought years (starting from the first drought event) in major AEZs in SPEI (**a**) and SPI (**b**)

3.5.5. Mapping Agroecological Drought Hotspots

All AEZs experienced annual drought, normal, and wet events in different years. Considering the severity of drought characteristics, drought hotspot, normal spot, and wet spot maps were prepared for 1984–2016 based on the annual SPI and SPEI values. Figures 3.9, 3.10, and 3.11 show the spatial distribution of dry, wet, and normal spots for the selected period. The maps were produced in three categories: drought hotspots (Figure 3.9a1–a6), drought normal spots (Figure 3.10b1–b6), and non-drought (wet spots) (Figure 3.11c1–c6).

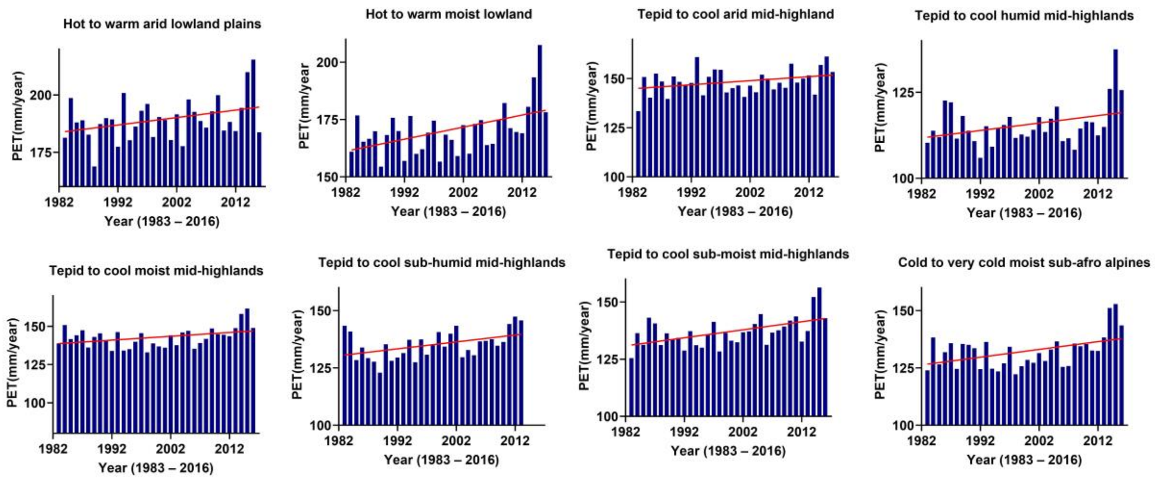


Figure 3.8. Potential evapotranspiration (PET) of agroecological zones in the Awash basin (1983–2016)

The spatial distribution of drought hotspots shows large variations between AEZs. As shown in Figure 3.9a1 1984, a drought occurred in almost all AEZs. Dry spells also dominated the hot to warm arid lowlands in 2002, 2009, and 2011. In 2013 and 2015, the upper parts of the basin were tepid to cool moist, and humid mid-highland AEZs were hit by drought episodes (Figure 3.9: a2–a6). Unlike the lower lowlands, drought events in recent years affected the upper high and midlands (2013–2016). The potential evapotranspiration of these agroecological zones has shown a significant increase, especially in recent years (Figure 3.9). The results indicate the rapid expansion of drought events in previously non-drought AEZs of the basin-like tepid to cool sub-moist mid-highlands. For example, tepid-to-cool sub-moist mid-highlands are one of the AEZs having increasing temperature and decreasing rainfall trends and hence relatively higher evapotranspiration (Figure 3.8). Future drought management is better considered in the tepid to cool sub-moist mid-highland AEZs, where meteorological drought is becoming a new and expanding phenomenon.

Drought normal spots were also mapped and are presented in Figure 3.10b1–b6. Figure 3.10: b1–b6 illustrates that normal drought spots dominated the middle and lower parts of the basin in the 1980s and 1990s. However, in the 2000s, normal events dominated the basin's upper, north-eastern, and south-eastern escarpments. For instance, in 2004, most parts of the escarpments of the basin had a normal drought situation.

Figure 3.11: c1–c6 shows the spatial extent of wet spots. In 1986, 1991, and 1995, part of the basin's upper and lower lowlands was relatively wet. Except for the middle of the basin, all other areas encountered wet spells in 1997 and 1998. Almost all AEZs and locations experienced wet situations in 2010.

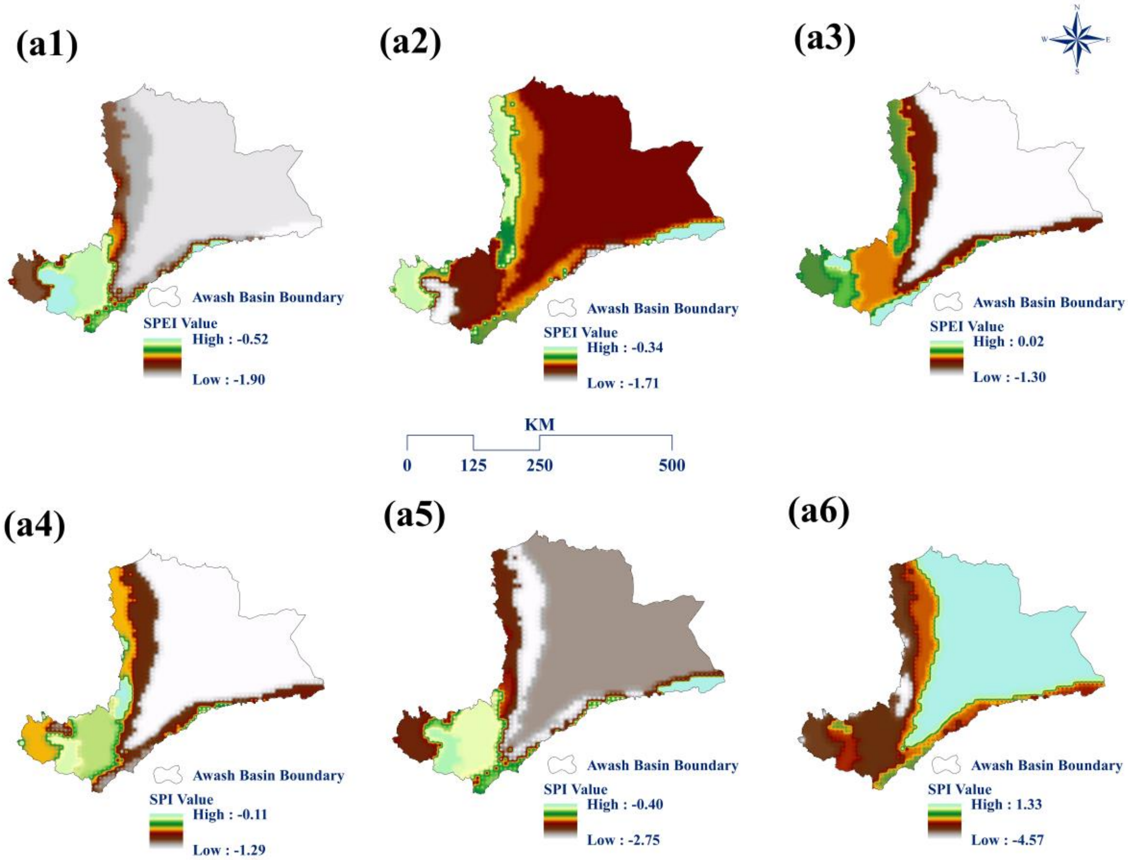


Figure 3.9. Spatial extents of drought hotspots in Awash basin [1984 (**a1**); 2002 (**a2**); 2009 (**a3**); 2011 (**a4**); 2013 (**a5**); and 2016 (**a6**)]

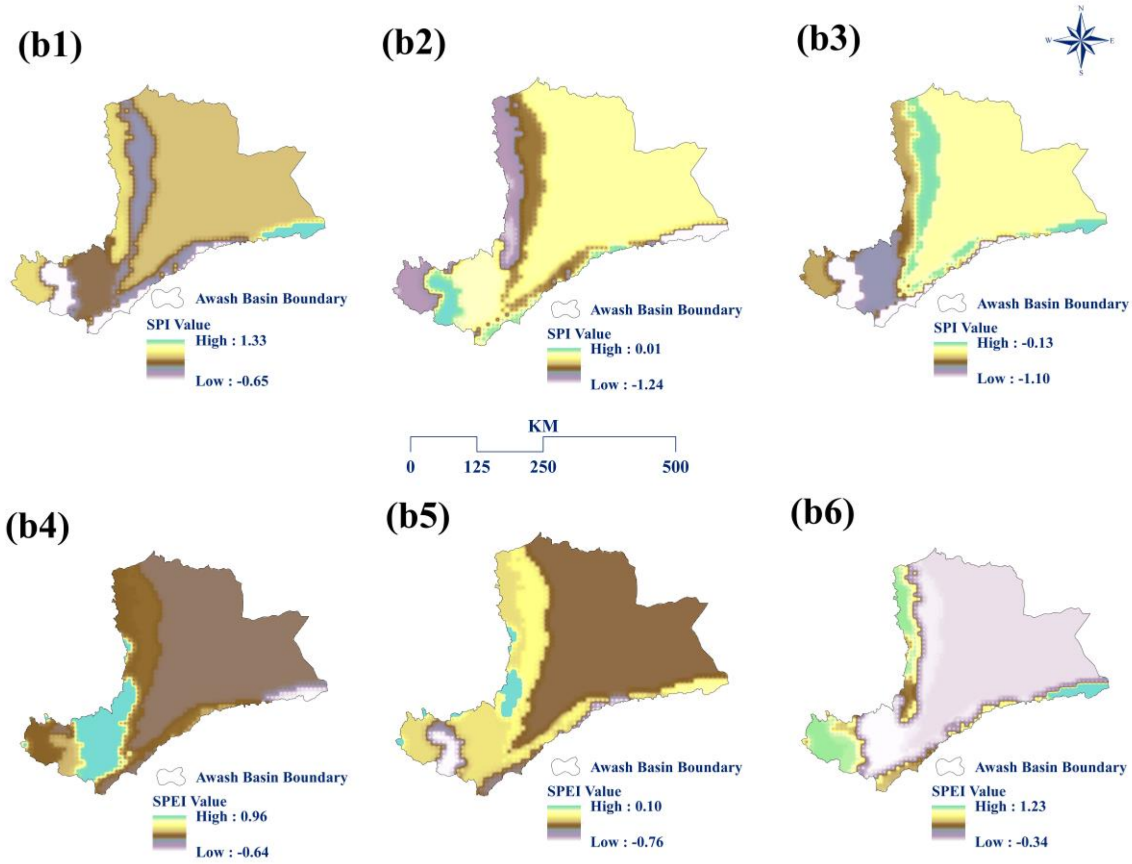


Figure 3.10. Spatial extents of normal spots in Awash basin [1986 (**b1**); 1991 (**b2**); 1997 (**b3**); 2003 (**b4**); 2004 (**b5**); and 2006 (**b6**)

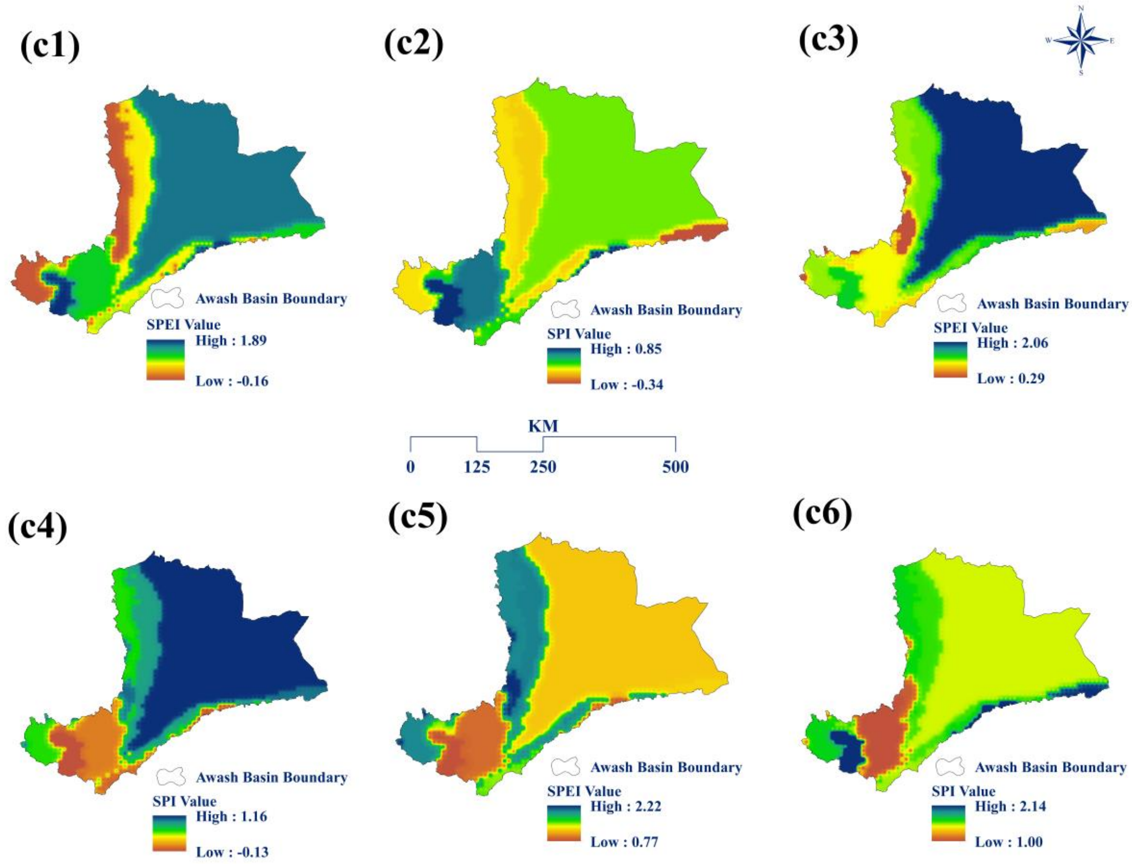


Figure 3.11. Spatial extents of wet spots in Awash basin [1983 (**c1**); 1989 (**c2**); 1993 (**c3**); 1995 (**c4**); 1998(**c5**); and 2010 (**c6**)

3.6. Conclusions

The current study analyzed the SPEI and SPI-based meteorological drought and mapped drought hotspot agroecological zones in the Awash Basin using meteorological gridded time-series data for 1983–2016. A comparison of the SPEI and SPI-based meteorological drought characterization was made on monthly, seasonal, and annual timescales, taking the eight distinct AEZs in the basin.

Based on the SPEI, hot-to-warm-moist lowlands, hot-to-warm arid lowland plains, and tepid-to-cool humid mid-highlands had the driest months, seasons, and years, respectively. SPEI's capacity for characterizing drought is higher in AEZs, where the impact of potential evapotranspiration is relatively strong. Moreover, while the dry drought events have higher values in the SPEI method, the wet and normal drought conditions are better detected by the SPI method. The difference observed in the two methods has implications for farmers' adaptation measures, particularly in sawing data and crop selection in an agricultural system.

Hot to warm arid and moist lowlands were found to have frequent dry and wet events, suggesting intensive extreme climate events in the lowlands. Temporally, dry and wet years dominated the 2010s and 1990s, respectively. The 1980s and the 2000s were drought-normal years in most AEZs of the basin.

In terms of drought magnitude, events ranging from extremely dry to extremely wet were observed in the AEZs of the basin. Frequent extreme seasonal and annual droughts occurred in arid and tepid to cool moist mid-highlands, while the most frequent extreme wet events happened in tepid to cool sub-moist mid-highlands. The SPEI and SPI results showed that annual drought had occurred almost every year since 2011, with the earlier predicted drought in recent years. Spatially, drought events were concentrated in various parts of the basin. Concerning drought hotspot AEZs, the upper and lower parts of the Awash basin have been hit by severe to extreme drought. In contrast, the escarpments and middle parts have experienced mild to moderate drought, with recent years remaining drought in nearly every part of the basin. Likewise, hot-to-warm moist and humid lowlands, hot-to-warm arid lowland plains, and tepid-to-cool moist mid-highlands are the basin's drought hotspot AEZs where future proactive drought risk management practices should be focused.

The study inferred the following based on those findings. (1) The results of SPEI and SPI differ for dry, wet, and normal components of the meteorological drought analysis. The SPEI method has an advantage over the SPI method in detecting meteorological drought in arid AEZs with relatively higher evapotranspiration. To accurately track the effects of drought, it is important to consider SPI in the sub-humid (humid) region and SPEI in the semi-arid (arid) region. However, as meteorological drought combines all the different drought events, combined SPI and SPEI would provide better insight; (2) the study AEZs experienced different frequencies and magnitude of droughts. Although understanding context-specific management options is important, it should also be underlined that the highlands are sources of water/flood for the dry lowlands, and therefore, AEZ in highland and lowland areas is interdependent, and an integrated management strategy could give better risk management option; (3) hot to warm arid lowland plains, hot to warm moist lowlands as well as tepid to cool humid mid-highlands are identified as drought hotspot AEZs in the basin. Unlike the lower lowland AEZs, upper high and midlands were affected by drought events in recent years (2013–2016).

The results for meteorological drought situations in different AEZ settings and mapping meteorological drought hotspots suggest important information for planning and implementing agroecological drought mitigation and adaptation actions. On the other hand, the results also inform the rapid expansion of drought events in previously non-drought AEZs of the basin. Therefore, providing local adaptation and drought preparedness mechanisms and establishing early warning systems could be a potential policy direction.

CHAPTER FOUR

4. Analysis of Smallholders' Livelihood Vulnerability to Drought Across Agroecology and Farm Typology in the Upper Awash Sub-Basin, Ethiopia

Abstract

Assessing the magnitude of smallholder farmers' livelihood vulnerability to drought is an initial step in identifying the causal factors and proposing interventions that mitigate drought impacts. This study aimed to assess smallholders' livelihood vulnerability to the drought in the upper Awash sub-basin, Ethiopia. Household (HH) and climate data were used for sensitivity, exposure, and adaptive capacity indicators that define vulnerability to drought. The vulnerability of farmers' livelihoods to drought was compared among the agroecological zone (AEZ) studies and farm typologies. The result illustrated a diverse vulnerability index (VI) magnitude ranging from -1.956 to -4.253 for AEZ. The highest magnitude of VI was estimated for livelihood in the lowland AEZ, while the lowest magnitude of VI was in the midland AEZ. This could be accounted for by the fact that lowland farmers showed the highest exposure (0.432) and sensitivity (0.420) and the lowest adaptive capacity (0.288). A closer look at farmers' livelihood typology in each AEZ showed substantial diversity of farmers' vulnerability to drought, implying potential aggregations at AEZ. Accordingly, the vulnerability index for livestock and on-farm-income-based livelihood and marginal and off-farm-income-based livelihood typologies were higher than the intensive-irrigation-farming-based smallholders' livelihood typology. Based on the result, we concluded that smallholders' livelihood resilience-building efforts should better target AEZ to prioritize the focus region and farmers' livelihood typology to tailor technologies to farms. Although the result emphasizes the importance of an irrigation-based livelihood strategy, the overall enhancement of farmers' adaptive capacity needs to focus on action areas such as reducing the sensitivity and exposure of the households, improving farmers' usage of technologies, diversifying farmers' livelihood options, and, hence, long-term wealth accumulation to strengthen farmers' adaptive capacity toward drought impacts.

Keywords: Vulnerability to drought; Exposure; Sensitivity; Adaptive capacity; Farm typology; Resilience

4.1. Introduction

Climate change is a phenomenon that constantly affects livelihoods, especially in developing countries where the livelihoods of smallholder farmers depend on subsistence agriculture (Farid *et al*., 2019; Balaganesh *et al*., 2020; GebreMichael, 2020). Smallholder farmers' livelihood vulnerability to climate change (particularly drought) stems from their geographic location in tropical regions and the difference in socioeconomic and policy trends that limit their adaptive capacity to the changing climate (Jamshidi *et al*., 2019). Farmers who depend solely on the naturally available rainfall for crop and livestock production are among the most vulnerable to the impacts of climate change (Tibesigwa *et al*., 2015). A household-level drought vulnerability analysis will help understand livelihood challenges and alternative mitigation and adaptation measures (Aribi & Sghaier, 2021).

The main livelihood activities in many developing countries are mixed crop-livestock production systems, agropastoralism, and pastoralism (Ndung'u *et al*., 2019; Ahmad & Ma, 2020). In this regard, Ghosh and Ghosal (2020) and Jellason *et al*. (2021) indicated that farmers relying on these livelihood activities are severely impacted by climate change. One of the factors affecting livelihoods is the increasing occurrence of frequent and severe drought (Shiferaw *et al*., 2014; Lennox *et al*., 2019). Drought has become frequent in Africa, especially in countries in the Horn of Africa (e.g., Ethiopia (Dutra *et al*., 2013; Nicholson, 2014; Agutu *et al*., 2020)).

In Ethiopia, drought has been understood as the most severe long-term climatic shock and cause of concern for farm households (Abid *et al*., 2020; Epstein *et al*., 2020; Gebrehiwot & van der Veen, 2020; Lottering *et al*., 2020). Climate variability and extreme weather are two of the most serious threats to agricultural productivity and smallholder livelihoods (Tessema & Simane, 2019; Singh *et al*., 2020). Sam *et al*. (2020) indicated that drought strengthens over time, unlike other natural disasters, gradually destroying the affected area. Therefore, drought's spatial distribution and persistence for a long period are significant threats to rural livelihoods, putting many smallholders in a poverty trap (Kumar *et al*., 2020; Chavez *et al*., 2020).

According to the International Rescue Committee (IRC) report (2022), drought relief in Ethiopia will cost $1.66 billion. Only 42% of this was funded by the end of 2022. Only 12% of people in drought-affected areas have received health services, and less than 30% have received water, sanitation, and hygiene assistance. Despite the response mechanisms made by the government and non-governmental organizations, the impact of drought on livelihood persisted due to the recurrent nature of the drought incidents and the low capacity to respond.

Abeje et al. (2019) state that more than ten major drought episodes have occurred in Ethiopia since the 1970s. Awash basin, where this study focuses, experienced more than nine drought events on average in the last three decades (Maru *et al*., 2022). More specifically, the upper parts of the Awash Basin are known as smallholders with mixed crop-livestock, agropastoralism, and pastoralism livelihood systems, which are highly vulnerable to climate-related disasters such as drought (Auci & Coromaldi, 2020). This is mainly because of environmental sensitivity and exposure to climate shocks due to aridity and natural resource degradation (Borromeo *et al*., 2018). The historical period of land use transformation in the upper Awash sub-basin indicates a significant expansion of croplands and urban areas (Shawul & Chakma, 2019; Adane *et al*., 2020a). It is a highly populated part of the basin compared to the lower Awash. In Ethiopia, two major cities—Addis Ababa and Adama—are in the upper Awash sub-basin (Hailu *et al*., 2018). In addition to other natural factors, these stressors made smallholders extremely vulnerable to drought in this part of the country.

Though livelihood is a complex and comprehensive concept (De Haan & Zoomers, 2003), it is a means of living for individuals and households (Ellis, 1998). The most cited understanding of livelihood includes the skills, resources (including both social and material resources), and activities that generate the means of household survival (Ndlela & Worth, 2020). The subsistence-mixed crop-livestock production, agropastoralism, and pastoralism ways of living rely heavily on ecosystem services and are more vulnerable to drought-related climatic shocks. In sustainable development, vulnerability assessment is important because it accurately explains how vulnerable a system is to climate change impacts (Liu *et al*., 2013).

According to the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2007), vulnerability to the changing climate is the extent to which the system is exposed to and incapable of dealing with the noticeable impact of climate change, including climate instability and extremes. Vulnerability is a state of sensitivity to disaster due to exposure to environmental and societal change stress and a lack of adaptive capacity. Within the framework of this study, vulnerability is conceptualized as the occurrence, magnitude, rate, and variability of climate change shock (particularly drought) to which the system is exposed and the system's sensitivity and adaptive capacity.

The IPCC definition was applied to identify the vulnerability of farming communities to drought at the household level. Accordingly, the vulnerability of households was derived as a function of the three elements—adaptive capacity, sensitivity, and exposure (Denton *et al*., 2014). Adaptive capacity explains rural households' ability to adapt to drought stress (Choden *et al*., 2020; Mukasa *et al*., 2020) and can be characterized by capital, livelihood diversification, wealth, and access to infrastructure. Exposure can be referred to as climate change shock and describes the pressure drought shocks put on rural households (Balaganesh *et al*., 2020; Gessler *et al*., 2020), which the intensity, frequency, and duration of drought can explain. Sensitivity is understood as the extent of environmental factors' impact on households (Adzawla & Baumüller, 2021; Sharafi *et al*., 2020) and expressed by various subcomponents, such as the prevalence of crop failure, environment-related diseases, and different crises.

Smallholder farmers' responses to climate-induced livelihood vulnerabilities are not uniform but diverse, as response strategies are embedded in the heterogeneous sociodemographic, economic, livelihood type, and adaptation mechanisms. Since the variation in vulnerability to drought cannot be detailed at the AEZ level, we used farm typology. Farm typology is a method for categorizing farmers into classes with similar characteristics (Shukla *et al*., 2019). We conducted a cluster analysis to understand these variations to group farmers into farm typologies. Farm typologies are a valuable tool for unpacking and recognizing the large variety of smallholder farms to target better adaptation strategies (Haileslassie *et al*., 2016; Chikowo *et al*., 2014). Musafiri *et al*. (2020) recommended using farm typology to investigate the actual characteristics of individual smallholder farmers in determining the vulnerability to climate change impacts. The timely information on the occurrence of drought and the analysis of the level of farmers' vulnerability is an element of the drought response mechanism. Nasir *et al*. (2021a) indicated that drought often returns once it ends. Due to this nature, the government will again be misinformed about the next severe drought episode occurrence. Hence, investigating the vulnerability of farmers' livelihood to this nature of recurrent drought helps devise the response mechanisms.

Various studies have been conducted in the upper Awash sub-basin and elsewhere; (i) some have focused on livelihood vulnerability to the entire climate change impacts (Abeje *et al*., 2019; Koech *et al*., 2020; Asmamaw *et al*., 2020; Das *et al*., 2020; Gupta *et al*., 2020; Poudel *et al*., 2020a). These studies only used household survey data to understand the level of livelihood vulnerability (Ahmad & Ma, 2020; Nyairo *et al*., 2020; Singh, 2020; Endalew & Sen, 2020); (ii) some vulnerability studies (e.g., (Dechassa & Simane, 2020; Wabwire *et al*., 2020)) considered only basin-wide livelihood vulnerability analyses that overlooked the local and farmers' specific contexts; (iii) some studies completed livelihood vulnerability analysis using few numbers of indicator variables (e.g., (Huong *et al*., 2019; Rudiarto & Pamungkas, 2020; Zhu *et al*., 2020)). Though these studies have significantly contributed to our current level of knowledge and understanding of livelihood vulnerability to climate change, there are likely gaps that must be filled. Here, we argue that these gaps can be filled by analyzing smallholders' livelihood vulnerability to climate-induced shocks, especially drought, by incorporating real-time climate data into the vulnerability assessment, relying on local contexts in the analysis to understand the problem at a household level (by clustering farms based on their livelihood and activity profile to overcome the vulnerability), and including as many indicators as possible to make the vulnerability analysis multidimensional and robust.

The core aim of the current study is to analyze the smallholders' livelihood vulnerability to drought using AEZs and farm typologies as units of analysis. The study hypothesized that the vulnerability of farmers' livelihoods to drought varies in agroecology and farm typology. However, the level of vulnerability at the agroecology scale is more general and necessitates inspecting at the farm typology scale. The drought management mechanism should consider these variations, and entry points have to depend on the actual level of farmers' vulnerability to drought.

To analyze smallholders' livelihood vulnerability to drought at a household level in upper Awash, this study is designed in a way that can address the research mentioned above gaps. According to Singh (2020), model-based vulnerability analysis can provide a long-term view of macro-scale climate scenarios' physical aspects but fails to accurately interpret the human dimensions of microscale climate uncertainty and hazards (Müller-Mahn *et al*., 2020). Hence, this micro-scale (household-level) study of smallholder farmers' vulnerability to drought considered indicators' human and natural dimensions by integrating climate and household (HH) survey data to characterize a household's vulnerability to drought. The procedures developed, and the information generated would help experts and policymakers enhance farmers' resilience to drought impacts by identifying farmers' highly vulnerable livelihood capabilities.

4.2. Materials and Methods

4.2.1. The Study Area–Location and Characterization

Location

Awash is one of the 12 River Basins of Ethiopia. The basin is divided into the lower, middle, and upper- based on physical, climatological, agricultural, socioeconomic, and water resources (Taye *et al*., 2020). This research has been carried out in the upper part of the basin (Figure 4.1). Addis Ababa, the capital of Ethiopia, is situated at the northern end of the basin. The sub-basin is limited to the 37°54′35″ E–40°16′53″ E longitude and 7°53′15″ N–9°25′15″ N latitude boundaries, and the area is 24,545 square kilometers.

The climatic condition of the upper Awash is classified as humid to afro-alpines, with a mean annual temperature varying from 15 to 20 degrees Celsius. Based on the elevation difference, the mean annual precipitation in the sub-basins ranges from 800 to 1400 mm (Tolera *et al*., 2018). The altitude varies from 4055 to 742 m above sea level (m.a.s.l. (Figure 4.1)), which suggests a greater altitude range within the sub-basin (Shawul & Chakma, 2020), influencing climatic variables and associated biophysical settings. The precipitation during the year occurs in different seasons. The major rainy season in Ethiopia is called *Kiremt*, which typically occurs between June and September.

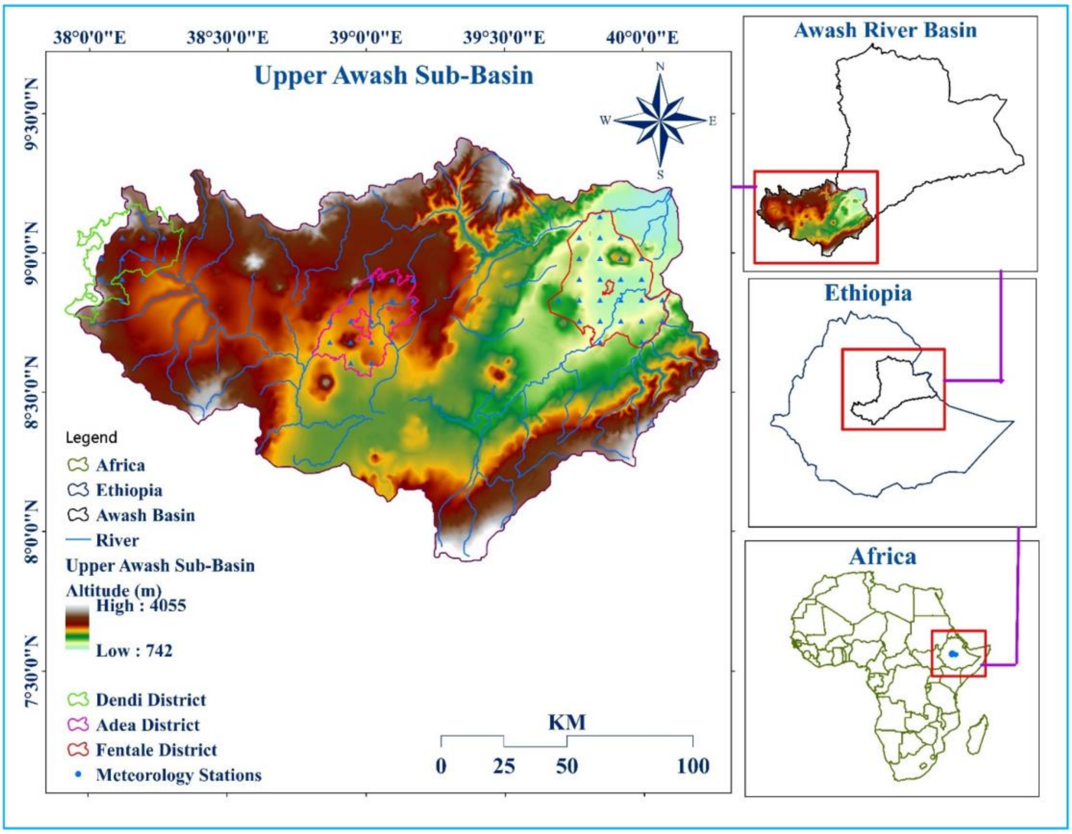


Figure 4.1. Location map of the study area

4.2.2. Livelihood Characterization

Farmers' livelihoods in the highland and midland of the basin are dependent on crop-livestock mixed farming systems that seek naturally available rainfall for farming. Tajebe *et al*. (2013) stated that major highland crops (e.g., Dendi District) include teff, wheat, barley, beans, peas, maize, potato, and *enset*. Dominant crops in the Adea District (midland) are teff, wheat, maize, and other cereals (Table 4.1). Livestock is integrated into crop production in midland and highland areas, serves as wealth accumulation, and enables crop production. The two systems' components, crop and livestock, complement each other through livestock supporting crop production and crop residues used to feed animals (Haileslassie *et al*., 2009a, 2009b). Lowlanders are known mainly for agropastoralism and pastoralism way of life in which limited crop production and livestock and their products are the main assets of the households. Camels, goats, and cattle are the dominant livestock assets in Fentale. Off-farm pursuits and livestock ventures may help farm households supplement their income depending on their farm structure and objectives. The contribution of these income-generating activities to farm income varies by season and farmer (Haileslassie *et al*., 2016). Whether in the case of a mixed system or agropastoral/pastoralist livelihood, naturally available moisture has a great role. Moreover, the potential evapotranspiration rates are high as the area is known for longer sunshine hours (Yadeta *et al*., 2020a). Those are the reasons for the severe to extreme drought episodes in this part of the basin, particularly in recent years (Maru *et al*., 2022).

Table 4.1. Characteristics of districts and the distribution of sample respondents

Agroecological zones	Sample districts	Altitude (m)	Major livelihood	Major crop type	Major livestock	Number of respondents
Highland	Dendi	2300 - 3600	Mixed farming	Wheat, Barley, Teff	Sheep, Cattle, Equines	132
Midland	Adea	1500 - 2300	Mixed farming	Teff, Wheat, Maize	Cattle, Sheep	132
Lowland	Fentale	500 - 1500	Agro-pastoralism and Pastoralism	Sorghum, Maize	Camels, Goats, Chickens	132

Although recurrent drought is a common phenomenon, its impact on the livelihood of smallholder farming households could not be the same. There are variations based on the farmers' exposure to drought, the sensitivity of the environment they live in, and the adaptive capacity of the farmers to the shock of drought (Zhu *et al*., 2020). The characteristics of individual farmers to withstand the drought stress and absorb the shock are the other distinguishing factors. These could lead farmers to have a different level of vulnerability to the impact of the drought.

Even though most of the farmers in the study area practice mixed farming and pastoralism, they do not share the same characteristics. Some farmers have agricultural, agropastoral, and pastoral livelihoods. They have different farm systems, even within similar livelihood systems (Simane *et al*., 2016). For example, some use irrigation to produce crops in the dry season. Others are predominantly herders who own cattle. Due to these characteristics, Upper Awash is part of the basin with diverse livelihoods. Rainfed crop farming is the most important activity for households in agricultural and agropastoral areas. Rainfall is inadequate in these areas, including an uneven distribution and a short growing season. The pastoral group's livelihood is based on livestock raising, heavily influenced by the area's harsh environment and climatic shocks. Pastoralists rely on grazing and water, heavily reliant on naturally available rainfall.

4.2.3. Indicators and Their Relationship with the Sub- and Major Components of the IPCC–Drought Vulnerability Index (IPCC–DVI)

Researchers in the area of vulnerability analysis use different models to compute vulnerability. One of the models is the generalized additive model, which is usually applied in modeling natural hazards, particularly flood susceptibility, landslide vulnerability, and gully erosion hazard (Talukdar *et al*., 2021). Random subspace models are applied to measure vulnerability to environmental challenges and natural hazards (Singha *et al*., 2020). The other model is the IPCC-DVI, which can be best applied to analyze the vulnerability of households' livelihoods to drought.

Figure 4.2 depicts the indicators' workflow for each IPCC–DVI sub-component and their interaction. Ten indicators were recategorized into 3 subcomponents, 8 were regrouped into 3 sub-components, and 38 were reclassified into 6 sub-indicators that made the exposure, sensitivity, and adaptive capacity major components of the IPCC–DVI. As illustrated in Figure 4.2 and Table 4.2, if the indicator contributes to the increment of the sub-component, the relation is positive, plus marks were put in the workflow line. If the indicator influenced the sub-component negatively, the relationship is negative; hence, the minus sign was used to show this correlation (Uddin *et al*., 2019).

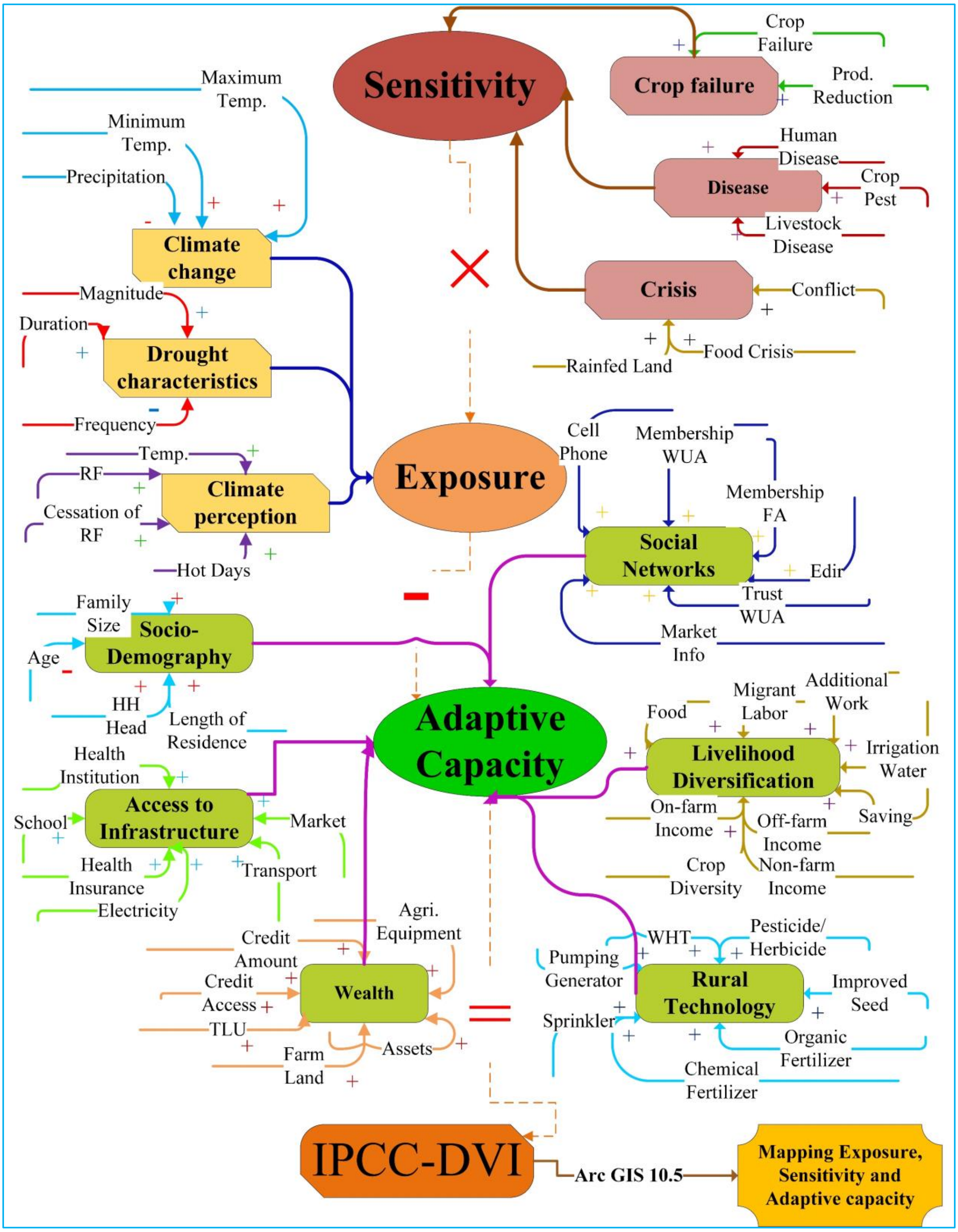


Figure 4.2. Workflow of the study, the indicators, and their relationship with the sub- and major components of the IPCC– DVI (dot lines represent mathematical relationships). Temp. = temperature; RF = rainfall HH = household; TLU = tropical livestock unit; Agri.— agricultural; Prod. = production; WUA = water users' association; WHT = water harvesting technologies; FA = farmers' association; IPCC–DVI = Intergovernmental Panel on Climate Change–drought vulnerability index.

4.2.4. Sampling and Data Sources

The HH survey data were collected from sample households in three districts covering the three AEZ in the upper Awash sub-basin. A three-stage sampling technique was used to select target respondents in the study area. The moist highlands and midlands are AEZs vulnerable to annual and seasonal droughts (Maru *et al.*, 2022). This entails the inclusion of all three AEZs in the vulnerability assessment using the climate and HH survey data. Firstly, Dendi for a highland, Adea for midland, and Fenatle for a lowland were selected purposely to represent the three dominant AEZ. Secondly, the sample size was determined using Equation (4.1) as follows (Kadam & Bhalerao, 2010):

$$n = \frac{2(Z_\alpha + Z_{1-\beta})2\sigma^2}{\Delta^2} \tag{4.1}$$

where

$n =$ Required sample size for the HH survey

$Z_\alpha =$ Constant (1.96) at 5% margin of error

$Z_{1-\beta} =$ Constant (1.6449) at 5% margin of error

σ = the standard deviation (estimated)

$\Delta =$ estimated effect size

Accordingly, the Equation yields a sample size of 360 HHs. Adding a 10% (36 in Number) non-response rate makes the total sample size 396. Thirdly, respondent household heads were randomly selected using a lottery method. Experienced survey enumerators who could speak the local language and with relevant backgrounds were recruited and trained to fill out the survey questionnaire. The questionnaire was tested before implementation, and ambiguous questions were corrected. The HH survey was carried out from November 2018 to February 2019. Table 4.1 presents the districts' characteristics and the distribution of sample respondents.

Data and sources: This study is based on two datasets — (1) the meteorological monthly total precipitation (mm), as well as monthly minimum and maximum temperature (°C) accessed from the Ethiopian Meteorological Institute (EMI), and (2) household survey data collected from sample smallholders in the three sample districts illustrated earlier. The meteorological data (rainfall and temperatures) are 4×4 km gridded data and were used to characterize rainfall and temperature and calculate the exposure of smallholders to drought (intensity, frequency, and length) shock. This was integrated into the household survey data as a proxy to characterize households within the agroecological zone. The HH survey data were used to characterize smallholders in their adaptive capacity, sensitivity, and exposure, which are elements in the computation of the livelihood vulnerability of smallholders to drought. Key informant interviews (KII) were conducted to triangulate information from the HH survey.

Thus, the combination of meteorological data and household survey data was used in this study. We used the meteorological data to characterize the drought exposure profile of households in their respective AEZs. Similarly, we used the household survey data to characterize the household's exposure, sensitivity, and adaptive capacity. There were, however, some limitations associated with this approach. For example, the data used for the climate analysis and drought magnitude, frequency, and intensity were in time series. They did not represent the latest details as the data from the questionnaire. The two datasets had a temporal variation (e.g., lacking meteorological data for the latest years). Thus, the meteorological data were proxy data from the household survey.

4.2.5. Approach to the Measurement of Vulnerability to Drought

The three vulnerability components (exposure, sensitivity, and adaptive capacity) must be understood and distinguished to derive indicators. The indicators selected were designated to represent farmers' adaptive capacity, sensitivity, and exposure to drought in the sub-basin. Each indicator used in the vulnerability assessment was normalized before use (see Table 4.2).

Normalization of the Indicators

Normalization is important for multivariate statistical analysis since some variables have a wide range and others have a small variance range. The difference in unit of measurement for certain socioeconomic factors must also be normalized. The technique of normalization that requires the transformation of the dataset to a particular range (0–1) is therefore important (Uddin *et al*., 2019). We followed the suggestion made by Quackenbush (2002) that recommended the normalization of data using transformation methods to create a more robust dataset. The dataset was normalized to avoid the effect of one variable on other variables. Normalization of the indicators was performed using the formula presented as Equations (4.2) and (4.3) below (Hahn *et al*., 2009; Pandey & Jha, 2012).

Table 4.2. Indicators and their definitions are used to analyze vulnerability to drought and relationships (Figure 4.2).

Attributes	Indicator	Measures and Explanations	Relationship (− or +) to Attribute	Sources
Exposure	[E1] Precipitation	SD Ave. monthly precipitation (mm) (1983–2016)	−	(Neset *et al*., 2009)
	[E2] Minimum temperature	SD Ave. monthly minimum temperature (°C) (1983–2016)	+	(Neset *et al*., 2009)
	[E3] Maximum temperature	SD Ave. monthly maximum temperature (°C) (1983–2016)	+	(Neset *et al*., 2009)
	[E4] Drought magnitude	SD Drought magnitude (SPEI) (1983–2016)	+	(Zhu *et al*., 2020)
	[E5] Drought duration	SD Drought duration (SPEI) (1983–2016)	+	(Zhu *et al*., 2020)
	[E6] Drought frequency	SD Drought frequency (SPEI) (1983–2016)	−	(Zhu *et al*., 2020)
	[E7] Temperature increase	% of HHs that did not perceive temperature increase	+	(Marlon *et al*., 2021)
	[E8] Number of hot days	% of HHs that did not perceive hot days in a year increase	+	(Marlon *et al*., 2021)
	[E6] Rainfall decrease	% of HHs that did not perceive rainfall decrease	+	(Marlon *et al*., 2021)
	[E9] Cessation of rainfall	% of HHs that did not perceive early cessation of rainfall	+	(Marlon *et al*., 2021)
	[E10] Rainfall decrease	SD Ave. monthly precipitation (mm) (1983–2016)	+	(Marlon *et al*., 2021)
Sensitivity	[S1] Crop failure	% of HHs reporting crop failure over the last 10 years	+	(Ghosh & Ghosal., 2021)
	[S2] Production reduction	% of HHs reporting crop production reduction in 10 years	+	(Neset *et al*., 2009)
	[S3] Crop disease	Number of crop pests/diseases in 10 years	+	(Ahmad & Ma, 2020)
	[S4] Livestock disease	Number of livestock diseases in 10 years	+	(Ahmad & Ma, 2020)
	[S5] Human disease	Number of human diseases in 10 years	+	(Ahmad & Ma, 2020)
	[S6] Local conflict	% of HHs reporting local conflicts in 10 years	+	(Asmamaw *et al*., 2020)
	[S7] Food crisis	Number of food crises occurred in 10 years	+	(Poudel *et al*., 2020a)
	[S8] Rainfed land	Size of rainfed agriculture land per household/*Hectare*	+	(Zhu *et al*., 2020)
Adaptive Capacity	[A1] HH head	% of male-headed households	+	(Tesema & Haile, 2021)
	[A2] Age	Age of the HH head (year)	−	Tesema & Haile, 2021)
	[A3] Family size	Family size of the household	+	Tesema & Haile, 2021)
	[A4] Residence length	Length of residence of the HH head (year)	+	Tesema & Haile, 2021)
	[A5] Health	Ave. time to reach health institution (walking minutes)	−	Tesema & Haile, 2021)
	[A6] Education	Ave. time to reach school (walking minutes)	−	(Poudel *et al*., 2020a)
	[A7] Market	Ave. time to reach marketplace (walking minutes)	−	(Ghosh & Ghosal., 2021)
	[A8] Transport	% HHs having access to transport services	+	(Ghosh & Ghosal., 2021)
	[A9] Electricity	% HHs having access to electricity utility at home	+	(Singh, 2020)
	[A10] Health insurance	% HHs having access to health insurance	+	Rudiarto & Pamungkas, (2020)
	[A11] Livestock	Livestock in Total Livestock Unit (TLU)	+	Tesema & Haile, 2021)
	[A12] Land	Size of cultivated farmland (ha)	+	Tesema & Haile, 2021)
	[A13] Assets	Monetary value of productive assets (Birr)	+	(Asmamaw *et al*., 2020)
	[A14] Credit access	% HHs reporting availability of credit access	+	(Dechassa *et al*., 2020)
	[A15] Credit amount	Amount of accessed credit for productive works	+	(Asmamaw *et al*., 2020)
	[A16] Equipment	% of HHs having full agricultural equipment	+	(Williams *et al*., 2019)
	[A17] Sprinkler	% of HHs having irrigation sprinkler	+	(Anandhi *et al*., 2020)
	[A18] Water pumping	% of HHs have irrigation water pumping generator	+	(Anandhi *et al*., 2020)
	[A19] WHT	% of HHs using water harvesting technologies	+	(Anandhi *et al*., 2020)
	[A20] Chemical fertilizer	Amount of farm chemical fertilizers used (kg)	+	(Asfaw *et al*., 2016)
	[A21] Organic fertilizer	Amount of farm organic fertilizers used (kg)	+	(Asfaw *et al*., 2016)
	[A22] Pesticide/herbicide	Amount of farm pesticides/herbicides used (Liter)	+	(Asfaw *et al*., 2016)
	[A23] Improved seed	Amount of farm improved seeds used (kg)	+	(Asfaw *et al*., 2016)
	[A24] Crop variety	Crop diversity score	+	(Singh, 2020)
	[A25] On-farm income	Annual on-farm income (Birr)	+	(Dechassa *et al*., 2020)
	[A26] Non-farm income	Annual non-farm income (Birr)	+	(Dechassa *et al*., 2020)
	[A27] Off-farm income	Annual off-farm income (Birr)	+	(Dechassa *et al*., 2020)
	[A28] Saving	Amount of cash saved (Birr)	+	Rudiarto & Pamungkas, (2020)
	[A29] Additional work	% of HHs engaged in additional works besides farming	+	(Singh, 2020)
	[A30] Irrigation water	% of HHs having access to irrigation water	+	(Asmamaw *et al*., 2020)
	[A31] Migrant labor	% of HHs working as a migrant labor	+	(Huong *et al*., 2019)
	[A32] Food	Variety of food consumed in the HH per 24 h	+	(Huong *et al*., 2019)
	[A33] Farmers association	% of HHs have membership in the Farmers Association	+	Rudiarto & Pamungkas, (2020)
	[A34] WUA	% of HHs have membership in the Water Users Association	+	(Wabwire et a., 2020)
	[A35] *Edir*	Number of "*edir*" a household has	+	(Asmamaw *et al*., 2020)
	[A36] Trust WUA	% of HHs trust the Water Users Association	+	(Villamayor-Tomas *et al*., 2017)
	[A37] Market information	% of HHs having access to market information	+	(Poudel *et al*., 2020a)

[A38] Cell phone	Number of cellphones in the household	+	(Wright *et al*., 2012)

For the indicators having a positive relationship with the major component, this is

$$\mathrm{X}d = \frac{X_i - X_{imin}}{X_{imax - X_{imin}}} \tag{4.2}$$

For the indicators having a negative relationship with the major component, this is

$$Xd = \frac{X_{imax} - X_i}{X_{imax} - X_{imin}} \tag{4.8}$$

where, X_i is the observed value (mean) of the original subcomponent; X_{imin} and X_{imax} are the lowest and the highest value in the same collection, respectively, and Xd is a standardized value of X_i. For rendering variables equivalent to each other, this normalization allows for data with values varying from 0 to 1.

Principal Component Analysis (PCA)

Wold *et al*. (1987) introduced the principal component analysis, forming the foundation for multivariate analysis data in many ways. PCA is a statistical method that applies an orthogonal transformation to turn a series of observations that might be correlated variables into linearly uncorrelated variables known as principal components (Uddin *et al*., 2019). This transformation is performed so that the first main component has the greatest possible variance. After the restriction is orthogonal to the previous components, each of the next main components has the greatest variance possible. Finally, an uncorrelated orthogonal basis set is the resulting vectors generated by PCA (Li *et al*., 2018). PCA helps build uncorrelated components where each component's initial variables are a linear weighted combination. The two-step PCA was performed based on Equation (4.4) (Adzawla & Baumüller, 2021) as follows:

$$\left.\begin{aligned} PC1 &= a_{11}X_1 + a_{12}X_2 + \cdots a_{1n}X_n \\ &\;. \\ &\;. \\ &\;. \\ &\;. \\ &\;. \\ PC_m &= a_{m1}X_1 + a_{m2}X_2 + \cdots + a_{mn}X_n \end{aligned}\right\} \tag{4.4}$$

The first component is selecting variables that describe the greatest difference in the initial dataset; thus, optimal values summarize all input variables. The results of the first PCA components were maintained as weight in the first step and multiplied by their respective normalized values. Hence,

$$M_j = \sum_{i=1}^{N} a_m X_i \tag{4.5}$$

where, a_m is the weight and X_i is the normalized value. In the second step, XM_j was analyzed using PCA to determine the contribution of minor components to the major component. Again, the weights from the first principal component were preserved, and Equation (4.5) was applied as follows:

$$MC_j = \frac{\sum_{i=1}^{N} a_m X_i}{n} \tag{4.6}$$

where MC_j is the j^{th} major component (adaptive capacity, exposure, and sensitivity). These values were then consolidated and used to measure the drought vulnerability scores using Equation (4.7).

$$DVI = s * (e - a) \tag{4.7}$$

where DVI is the drought vulnerability index, s and e are the sensitivity and exposure to drought, respectively, and a is adaptive capacity at the household level.

The current study's analysis unit was agroecological zones and farm typologies to understand the differences within agroecological zones. Even in the same agroecology, there could be variations depending on the characteristics of the households. Hence, we applied cluster analysis to categorize smallholders into farm livelihood typologies based on similar livelihood activity characteristics. Therefore, the level of the drought vulnerability of households was compared and presented in their respective agroecology as highland, midland, and lowland, and among *livestock and on-farm-income-based*, *marginal off-farm-income-based*, and *intensive-irrigation-farming-based* farm livelihood typologies (Haileslassie *et al.*, 2016).

Farm Typology with Cluster Analysis

Using PCA, nineteen continuous variables that characterize smallholders were used to classify farmers into typologies. Variables generated an Eigen's value of ≥1 (6 in number) by the PCA were selected and used in the cluster analysis to classify farmers (i.e., size of rainfed land, the monetary value of productive assets, annual off-farm and non-farm income, variety of crops produced, and amount of chemical fertilizer used). Then, using Ward's method and the Euclidean distance matrix, we used hierarchical clustering on principal components to perform hierarchical, agglomerative clustering. The minimum and maximum number of necessary clusters were given as input. Ward method was applied to calculate the cluster number retained and the subjective inspection of the dendrogram, which was accompanied by statistics of inertia gain. Ward's method is the sole among the agglomerative clustering approaches based on a sum-of-squares criterion, producing groups that minimize within-group differences at each agroecological zone (Murtagh & Legendre, 2014). After identifying farmer types, their characteristics were described and compared for each type to understand the differences in the major components of vulnerability.

Finally, the values of drought sensitivity, exposure, and adaptive capacity were used as input to map and spatially demonstrate the sensitivity, exposure, and level of adaptive capacity of the households in the sub-basin using the Aeronautical Reconnaissance Coverage Map (ArcMap) extension of the Arc Geographic Information System (ArcGIS) 10.5®. This farm-level VI was also superimposed on the farm typologies to understand the farm typology level of vulnerability for overall systems and in each study AEZ. Hoque *et al*. (2020) suggested that a spatial mapping system for drought vulnerability that incorporates all drought categories using an acceptable weighting scheme should be developed to generate comprehensive vulnerability information to formulate drought mitigation and adaptation strategies.

4.3. Results and Discussions

4.3.1. Farm Typologies

Based on the earlier methods, this study identified three distinct farm typologies and named them depending on their major asset and livelihood characteristics (Tables 4.4, 4.6, and 4.8). Many farmers (68 percent) are livestock and on-farm-income-based. Smallholders in this typology receive most of their income from on-farm activities, with minimal off-farm and non-farm activities, and they have the highest livestock holdings. The second farm typology, which accounts for 23% of all smallholders, is the marginal and off-farm-income-based category. The income for those in this group depends on non-farm activities, and farm practices are uncommon. The smallest portion of the farm typology (only 9%) is the third farm typology, which is named the intensive-irrigation-farming-based group. Irrigators in this typology have larger irrigation land holdings, use a higher input rate of chemical fertilizer, and have the highest overall profits.

4.3.2. Exposure: Climate Change, Perception, and Drought Characteristics

The exposure profile of the smallholders in this study consists of three sub-components, including climate change and perception, as well as drought characteristics, which, in turn, merge the ten indicators presented in Table 4.3. In terms of the change and variability of the climate, the midland showed the largest exposure with a 0.439 index value, followed by lowland and highland AEZs. This indicates that temperature is increasing, and precipitation is decreasing in the midlands compared to the remaining AEZs. When the selected variable's index value increases, the magnitude of exposure of a region to drought vulnerability increases (Balaganesh *et al*., 2020).

This contradicts a generally held idea that the climate in arid lowland areas is rapidly changing. However, recent trends in climate change show that temperature and precipitation have increased and decreased trends in midlands, respectively (Esayas *et al*., 2018). Hence, focusing on adapting and mitigating climate change impacts, particularly drought, has to target areas where the actual change is observed (Altieri *et al*., 2015).

Table 4.3. Exposure drought vulnerability index along with indexed major and sub-components.

Sub-Component (Indicators)	HL	ML	LL	Component	HL	ML	LL
PRCP	0.249	0.227	0.242				
MINT	0.443	0.636	0.629	Climate change	0.376	0.439	0.436
MAXT	0.437	0.455	0.439				
DRM	0.462	0.499	0.443				
DRD	0.625	0.785	0.800	Drought risk	0.609	0.461	0.610
DRF	0.739	0.438	0.588				
TI-HH	0.111	0.262	0.312				
HD-HH	0.227	0.361	0.175	Climate perception	0.205	0.441	0.250
RFD-HH	0.318	0.425	0.231				
ECR-HH	0.164	0.714	0.283				
Exposure					**0.396**	**0.447**	**0.432**

SPEI = standard precipitation and evapotranspiration index; PRCP = standardized average monthly precipitation (mm) (1983–2016); MINT = standardized average monthly minimum temperature (°C) (1983–2016); MAXT = standardized average monthly maximum temperature (°C) (1983–2016); DRM = standardized drought magnitude (SPEI) (1983–2016); DRD = standardized drought duration (SPEI) (1983–2016); DRF = standardized drought frequency (SPEI) (1983–2016); TI-HH = % of HHs that did not perceive temperature increase; HD-HH = % of HHs that did not perceive hot days in a year increase; RFD-HH = % of HHs that did not perceive rainfall decrease; ECR-HH = % of HHs that did not perceive early cessation of rainfall.

The other exposure component is the drought risk aggregating drought magnitude, duration, and frequency. The score of drought risk was the highest (0.61) in the lowland (Figure 4.3 and Table 4.3). The overall influence of the risk is the highest in describing the exposure profile of the farm households in the upper Awash sub-basin. The above assertion is supported by qualitative evidence from an interviewed farmer in the Fentale District of lowland agroecology. According to this respondent, "*Getting two days of rainfall in a year is a surprise for us in this area since we lived in drought for decades and most of our ages pass searching for water and fodder for our cattle. Our main demand in this arid land as pastoralists is water for ourselves and our cattle*". This explains the drought adaptation mechanism from the perspective of a household. To reduce their exposure, pastoral and agropastoral communities should be reinforced by tackling pressing issues they are currently facing, such as the changing nature of drought threats and the underlying vulnerability of the socioecological setting in which they live (Leal Filho *et al*., 2020). This entails livestock production, land management, biodiversity conservation, and coping with natural, social, and economic consequences.

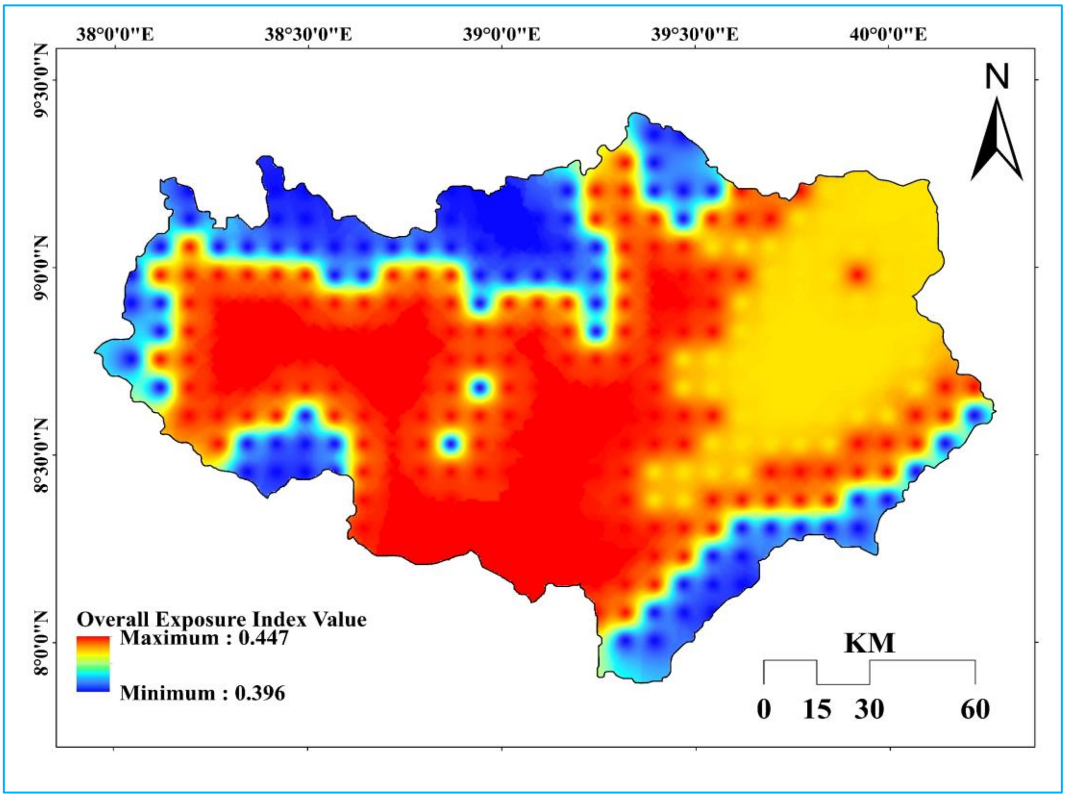


Figure 4.3. The spatial distribution of exposure to drought in the upper Awash sub-basin.

More than 44 percent of households in the midland AEZ did not perceive that the climate was changing (Table 4.3). As a result, they are the worst in the perception of climate change and, therefore, the most vulnerable to drought shock. Table 4.4 shows differences between the three typologies are noticed based on the farm typology. For example, only 16.4% and 18.3% of the *livestock and the on-farm-income-based* group did not perceive the number of hot days in a year, and the temperature has increased. Early cessation of rainfall and rainfall decrement was not perceived by *intensive-irrigation-farming-based* farm typology, with percentage values of 57.9 and 42.9, respectively. Those in the *livestock and on-farm-income-based* group most perceived the changing climate and were less exposed to drought. Smallholders in this typology are more connected to the climate for their crop and livestock production and perceive it as more likely than in other typologies. The less perception of climate change by *intensive-irrigation-farming-based* livelihood could be due to their engagement in irrigation activities irrespective of the naturally available moisture. Climate perception of communities plays a remarkable role in managing the impacts (Poudel *et al*., 2020b). The community's exposure rises because of its inability to understand that the environment is changing. At the same time, Altieri *et al*. (2015) argued that in the areas where the observation of drought is less (such as highlands and midlands), it is unlikely for farmers to perceive it as an occurrence. Sanderson & Curtis (2016) confirmed that climate change was more likely to be discussed as less perceived by irrigators who cited it as a natural phenomenon.

Being a drought-prone part of the Awash Basin, the upper Awash is characterized by different magnitudes of overall exposure to drought. This variation results from the diversity in agroecology, livelihood condition, and the socioeconomic profile of the farmers. For instance, the changing climate and drought risks are the core determinants of exposure in the upper Awash sub-basin (Table 4.3). Regarding the overall exposure profile of the midland, lowland, and highland households, AEZs are exposed with an indexed value of 0.447, 0.432, and 0.396, respectively (Table 4.3). This provides information on where to emphasize intervention in managing drought exposure in agricultural, agropastoral, and pastoral livelihood environments. A closer look at farm typology results dementated the variability of degree of exposure. For indicators considered in estimating the exposure index, marginal and off-farm-income-based smallholders and intensive-irrigation-farming-based smallholders showed stronger values, implying the need for raising awareness of climate change among these livelihood typologies (Table 4.4). Such efforts to change the farmers' behavior will impact, for example, the irrigation water use and water productivity positively and create opportunities for the saved water for other ecosystem services.

Table 4.4. Farm typologies with exposure indicators (frequency percentages for dummy variables).

Indicators	HL				ML				LL				Total		
	1 (N = 94)	2 (N = 30)	3 (N = 8)	Sub-Total (N = 132)	1 (N = 63)	2 (N = 51)	3 (N = 18)	Sub-Total (N = 132)	1 (N = 112)	2 (N = 11)	3 (N = 9)	Sub-Total (N = 132)	1 (N = 269)	2 (N = 92)	3 (N = 35)
TI-HH	8.4	10.3	0	8.3	18.8	28	44.5	25.8	35.8	0	11.1	30.3	22	18.3	25.7
HD-HH	16.8	41.4	12.5	22	29.7	36	61.1	36.4	8.3	0	0	6.8	16.4	32.3	34.3
RFD-HH	29.5	34.5	37.5	31.1	34.4	44	66.7	42.4	7.3	28.6	0	9.1	21.6	38.7	42.9
ECR-HH	13.7	24.1	12.5	15.9	64.1	78	77.8	71.2	22.9	42.9	27.3	29.5	29.5	55.9	57.1

1 = livestock and on-farm-income based; 2 = marginal and off-farm-income based; 3 = intensive irrigation-farming based.

4.3.3. Sensitivity: Crop Failure, Diseases, and Crisis

Since the economy of the farmers in the upper Awash sub-basin depends on a small-scale, mixed crop-livestock farming system, the environmental sensitivity to the ecosystem services has a crucial role. Table 4.6 summarizes the eight indicators defining smallholders' sensitivity to drought in the study area. In arid and semi-arid regions such as the study site, crop failure and hence reduction in crop production are common problems. The erratic rainfall during the main growing season with spatially fragmented appearance has negatively affected crop production. For example, with a crop failure indexed value of 0.735, the lowlands are the highest victim, followed by the highlands with a crop failure weight of 0.568 (Table 4.5).

Moreover, more than 90 percent of pastoral and agropastoral households in the lowland reported that the average production of major crops reduced in the last decade. Table 4.6 indicates that the largest crop failure (59.1%) was reported by marginal and off-farm-income-based livelihood typology, and 86.9% of livestock and on-farm-income-based livelihood typology reported production reduction in the last ten years. This reveals that in terms of crop failure and productivity reduction, lowland farmers are more sensitive, while those farmers who live in midlands are less sensitive to drought. *Livestock and on-farm-income-based* and *marginal and off-farm-income-based* farm typologies are more sensitive to drought than their *intensive-irrigation-farming-based* counterparts. The rainfall variability in space and time in the Awash Basin makes it difficult to predict where it falls. This spatiotemporal variation in rainfall distribution causes serious problems such as crop failure (Yadeta *et al*., 2020b).

Table 4.5. Sensitivity DVI along with indexed major and sub-components.

Sub-Component (Indicators)	HL	ML	LL	Component	HL	ML	LL
CFL-HH	0.568	0.168	0.735	Crop failure	0.675	0.520	0.821
CPR-HH	0.781	0.871	0.907				
NPD	0.148	0.208	0.224				
NLD	0.091	0.061	0.288	Diseases	0.133	0.176	0.216
NHD	0.160	0.260	0.137				
LCF-HH	0.106	0.136	0.144				
NFC	0.113	0.370	0.154	Crisis	0.234	0.336	0.222
RFL	0.482	0.502	0.367				
Sensitivity					**0.347**	**0.344**	**0.420**

CFL-HH = % of HHs reporting crop failure over the last ten years; CPR-HH = % of HHs reporting crop production reduction in 10 years; NPD = Number of crop pests/diseases in 10 years; NLD = Number of livestock diseases in 10 years; NHD = number of human diseases in 10 years; LCF-HH = % of HHs reporting local conflicts in 10 years; NFC = Number of food crises occurred in 10 years; RFL = size of rainfed agriculture land per household/hectare.

Regarding crop, animal, and human diseases, lowland AEZs are highly sensitive, with a weighted index of 0.216, followed by midlands, with an index value of 0.176. Invasive crop pests are highly expanding in the lowlands (Table 4.5). Especially the spreading plant pest locally named *shola* or *woyane* (*Prosopis Juliflora*) is alarmingly in the lowlands of the sub-basin, particularly around the Fentale District. An interviewed farmer described the pest: "*This shola or woyane is something we have not seen in our generation. When we cut it, it coppices in a more number. It depletes nutrients and soil moisture and competes with crops and animal feed. It even kills our animals when its thorn stabs them. It is causing a multidimensional challenge to our livelihood.*" Rangelands are core livelihood resources for pastoralists (Liao *et al*., 2020), and the expansion of these pests exposes the smallholders to the impact of drought risks. Table 4.6 depicts the occurrence of the crop, livestock, and human infectious diseases in the upper Awash sub-basin based on farm typology. Farmers in the livestock and on-farm-income-based livelihood typology were most sensitive to crop and livestock diseases. The crop and livestock occurrence mean ± standard deviations of smallholders in this farm typology were 1.33 ± 1.4 and 1.03 ± 1.1, respectively, making them more susceptible to diseases than the rest of the farm typologies.

Local conflicts, food crises, and the proportion of rainfed land made the ingredients of the crisis sub-component. As seen in Table 4.6, lowlands, with a 0.144 index value, lead the conflict, and the proportion of rainfed land is 0.502 in the midland AEZ, which makes it more sensitive than other AEZs. In sum, with aggregate crisis score values, the midland AEZ was more sensitive to the crisis than the other agroecological zones, while the lowland AEZ was least sensitive.

Analyzing the sensitivity of the households reveals the options for tackling the impacts of drought on the livelihood of farmers AEZ. For instance, the overall sub-components of sensitivity to drought impacts, crop failure, and production reduction score highest in the upper Awash sub-basin (Table 4.5). This could be highly related to the moisture stress and overexploitation of the farmlands in the basin. Hence, while management options that enhance the moisture, such as irrigation schemes and soil and water conservation practices, could be possible, it is also advisable to introduce crop insurance schemes for the smallholders, especially for rainfed crops in highland and lowland AEZs. Adane *et al*. (2020b) have suggested agricultural insurance to mitigate damage to rainfed farmers in the upper Awash sub-basin on the occasion of delayed onset or early cessation of rainfall.

As presented in Figure 4.4, the sensitivity of smallholder farmers to the drought risk is dominating the lowland AEZ. The midland AEZ is the least sensitive. Therefore, the response mechanisms should consider the degree of sensitivity of the household against each indicator and sub-component with spatial information to apply sound adjustment mechanisms.

Table 4.6. Farm typologies with sensitivity indicators (mean and standard deviations for continuous variables and frequency percentages for dummy variables).

Indicators	HL				ML				LL				Total (N = 396)		
	1 (N = 94)	2 (N = 30)	3 (N = 8)	Sub-Total (N = 132)	1 (N = 63)	2 (N = 51)	3 (N = 18)	Sub-Total (N = 132)	1 (N = 112)	2 (N = 11)	3 (N = 9)	Sub-Total (N = 132)	1 (N = 269)	2 (N = 92)	3 (N = 35)
CFL-HH	51.6	24.1	12.5	43.2	93.8	94	88.9	93.2	30.3	7.1	11.1	26.5	53	59.1	51.4
CPR-HH	78.6	76.7	65.6	73.6	93	89.5	86	89.5	90.6	69.7	72.2	77.4	86.9	82.5	77.8
NPD	1.33 ± 1.6	2.21 ± 3.6	0.88 ± 1.3	1.49 ± 2.2	0.84 ± 1.9	0.7 ± 0.7	0.56 ± 0.7	0.75 ± 1.4	1.61 ± 0.9	1.79 ± 1	1.44 ± 0.5	1.62 ± 0.9	1.33 ± 1.4	1.33 ± 2.2	0.86 ± 0.9
NLD	0.83 ± 1.2	0.48 ± 0.8	0.38 ± 0.7	0.73 ± 1.1	0.63 ± 1.3	0.72 ± 0.7	0.28 ± 0.4	0.61 ± 1	1.43 ± 0.9	1.57 ± 1	1.33 ± 0.5	1.44 ± 0.9	1.03 ± 1.1	0.77 ± 0.8	0.57 ± 0.6
NHD	0.48 ± 0.6	0.59 ± 0.6	0.13 ± 0.3	0.48 ± 0.6	0.5 ± 0.5	0.66 ± 0.5	0.22 ± 0.4	0.52 ± 0.5	1.31 ± 0.9	1.93 ± 2.3	1.22 ± 0.4	1.37 ± 1.1	0.82 ± 0.8	0.83 ± 1.1	0.46 ± 0.6
LCF-HH	21.9	33.3	50	27.5	18.8	66.7	50	35.3	59.4	0	0	37.3	11.9	16.1	11.4
NFC	0.44 ± 0.6	0.52 ± 0.5	0.38 ± 0.5	0.45 ± 0.6	0.77 ± 0.4	0.78 ± 0.5	0.56 ± 0.5	0.74 ± 0.5	1.56 ± 1.4	1.5 ± 0.7	1.33 ± 0.5	1.54 ± 1.3	0.97 ± 1.1	0.81 ± 0.6	0.91 ± 1
RFL	1.2 ± 1.1	0.62 ± 0.7	0.96 ± 1.6	1.1 ± 1.1	0.92 ± 0.8	1 ± 0.8	1.5 ± 1.1	1 ± 0.9	0.82 ± 0.8	0.47 ± 0.3	0.42 ± 0.3	0.75 ± 0.8	1 ± 0.9	0.82 ± 0.7	1.1 ± 1.2

1 = livestock and on-farm-income based; 2 = marginal and off-farm-income based; 3 = intensive-irrigation-farming based.

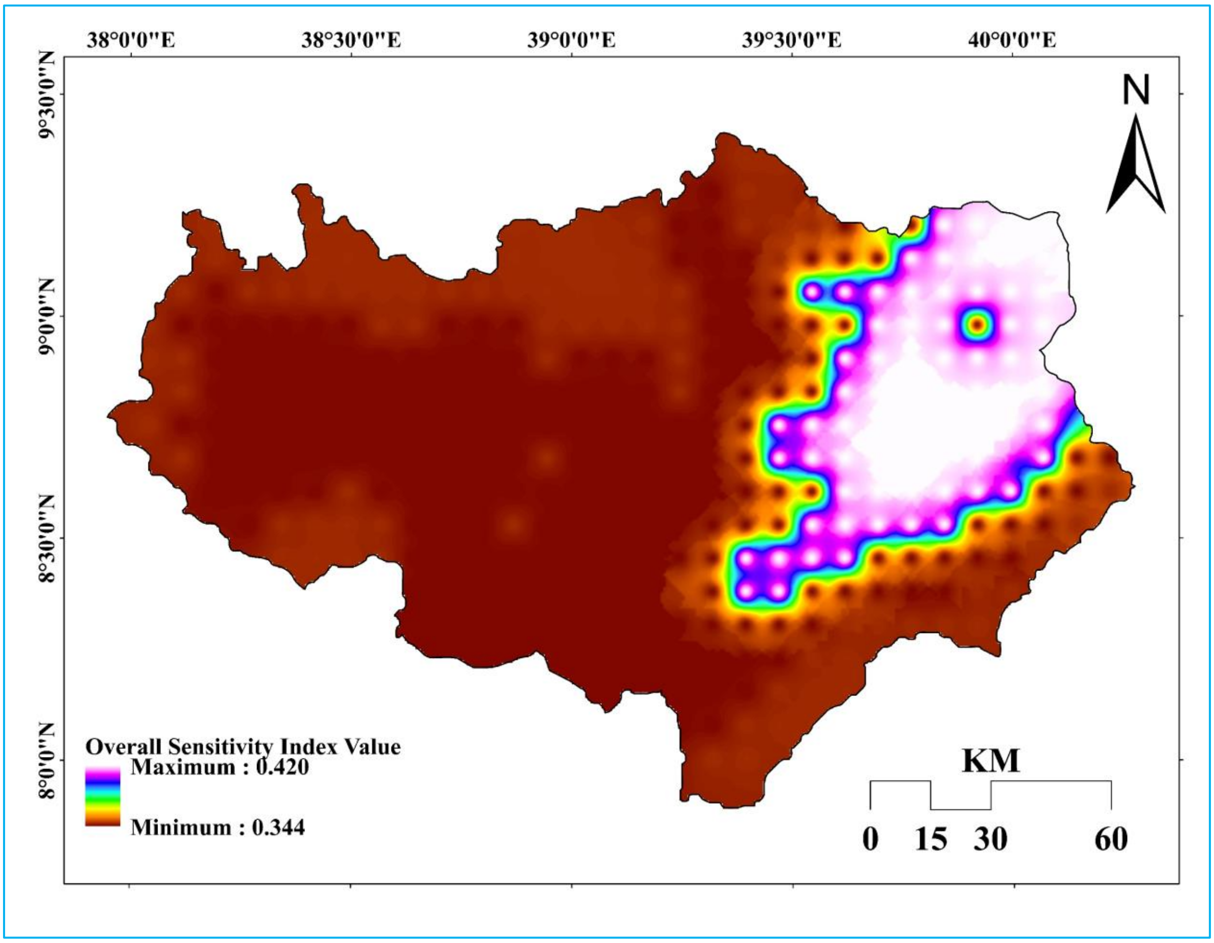


Figure 4.4. The spatial distribution of sensitivity to drought in the upper Awash sub-basin.

4.3.4. Adaptive Capacity: Accesses, Wealth, Technology, and Livelihood Diversification

In this study, 38 indicators were regrouped into six sub-components to characterize households' livelihood adaptive capacity to drought (Table 4.7). Increasing the Number of indicators allows for understanding each farmer's livelihood factor and its contribution to their capacity to withstand drought shock from a multidimensional perspective.

Table 4.7. Adaptive capacity DVI along with indexed major and sub-components.

Sub-Component (Indicators)	HL	ML	LL	Component	HL	ML	LL
M-HH	0.803	0.833	0.909	Socio-demographics	0.590	0.603	0.593
Age HH	0.641	0669	0.674				
FS-HH	0.391	0.478	0.312				
LR-HH	0.524	0.433	0.478				
D-HI	0.211	0.374	0.242	Access to Infrastructure	0.293	0.507	0.284
D-Sc	0.123	0.267	0.170				
D-MP	0.117	0.401	0.202				
AT-HH	0.939	0.879	0.992				
AE-HH	0.280	0.652	0.100				
AHI-HH	0.091	0.470	0.000				
TLU	0.148	0.237	0.221	Wealth	0.252	0.293	0.212
Farmland	0.182	0.240	0.176				
MV-PA	0.122	0.156	0.188				
AC-HH	0.515	0.258	0.068				
CA-HH	0.029	0.032	0.021				
AFE-HH	0.515	0.833	0.598				
EE-HH	0.091	0.030	0.015	Rural Technology	0.126	0.091	0.119
PG-HH	0.053	0.083	0.008				
WHT-HH	0.409	0.045	0.152				
CF	0.153	0.181	0.297				
OF	0.090	0.212	0.260				
FPH	0.047	0.012	0.093				
FIS	0.040	0.073	0.012				
CDS	0.525	0.576	0.402	Livelihood Diversification	0.229	0.278	0.175
ONFI	0.127	0.164	0.118				
NFI	0.078	0.163	0.075				
OFFI	0.027	0.067	0.036				
ACS	0.165	0.040	0.072				
AW-HH	0.167	0.326	0.098				
IW-HH	0.508	0.568	0.598				
ML-HH	0.061	0.288	0.008				
VF-HH	0.400	0.308	0.172				
FA-HH	0.129	0.417	0.189	Social Networks	0.357	0.506	0.333
WUA-HH	0.121	0.098	0.015				
NE-HH	0.466	0.566	0.216				
TWUA-HH	0.205	0.364	0.144				
MRI-HH	0.932	0.773	0.758				
NCP-HH	0.288	0.818	0.674				
Adaptive Capacity					**0.308**	**0.380**	**0.288**

M-HH = % of male-headed households; Age HH = age of the HH head (year); FS-HH = family size of the household; LR-HH = length of residence of the HH head (year); D-HI = A= average time to reach health institution (walking minutes); D-Sc = average time to reach school (walking minutes); D-MP = average time to reach marketplace (walking minutes); AT-HH = % HHs having access to transport services; AE-HH = % HHs having access to electricity utility at home; AHI-HH = % HHs having access to health insurance; TLU = livestock in total livestock unit; Farmland = size of cultivated farmland (ha); MV-PA = monetary value of productive assets (Birr); AC-HH = % HHs reporting availability of credit access; CA-HH = amount of accessed credit for productive works; AFE-HH = % of HHs having full agricultural equipment; EE-HH = % of HHs having irrigation sprinkler; PG-HH = % of HHs having irrigation water pumping generator; WHT-HH = % of HHs using water harvesting technologies; CF = amount of farm chemical fertilizers used (kg); OF = amount of farm organic fertilizers used (kg); FPH = amount of farm pesticides/herbicides used (liter); FIS = amount of farm improved seeds used (kg); CDS = Crop diversity score; ONFI = annual on-farm income (Birr); NFI = annual non-farm income (Birr); OFFI = annual on-farm income (Birr); ACS = amount of cash saved (Birr); AW-HH = % of HHs engaged in additional works besides farming; IW-HH = % of HHs having access to irrigation water; ML-HH = % of HHs working as a migrant labor; VF-HH = variety of food consumed in the HH per 24 h; FA-HH = % of HHs having membership in a farmers' association; WUA-HH = % of HHs having membership in a water users association; NE-HH = number of "*edir*" a household has; TWUA-HH = % of HHs trusting a water users association; MRI-HH = % of HHs having access to market information; NCP-HH = number of cellphones in the household.

Empirically, the adaptive capacity scores of the major components ranged from 0.091 to 0.603, as shown in Table 4.8. The socio-demographic characteristics of households in the midland AEZ showed the highest adaptive capacity compared to the highland and lowland AEZs. Farm households with comparatively young and working-age, greater family sizes, and male household heads who had lived in the area for a long time were more resilient to the effects of drought shocks. Table 4.8 shows that male-headed households dominated *intensive and irrigation-farming-based* livelihood typologies (88.8%) and were older, with a mean age of 42 ± 12 standard deviations. With a mean age of 40 ±12 standard deviations, those in the *livestock and on-farm-income-based* livelihood category were the youngest. A similar trend was observed for family size, with the *livestock and on-farm-income-based* livelihood typology having the highest mean (4.2 ± 1.7 standard deviations). This suggests that those in the *livestock and on-farm-income-based* livelihood typology had better values in terms of sociodemographic adaptive capacity than the other typologies.

Similarly, the midland AEZ had the highest access to infrastructures such as health and education institutions, transport, markets, electricity utility, and health insurance, with an average weight of 0.507. In contrast, the lowland had the lowest value (0.284). *Intensive-irrigation-farming-based* livelihood typology showed greater adaptive capacity regarding distances to health facilities and markets, with average walking minutes of 26.21 and 23.26 standard deviations. Regarding transportation access, 97.8% of those in the *livestock and on-farm-income-based* livelihood typology had better access to transportation. In comparison, 45% of smallholders in the *marginal and off-farm-income-based* livelihood typology had electricity service at home (Table 4.8). Whether agroecology or farm typology disaggregation, access to the infrastructures mentioned above is directly related to the quality of life, and the productivity of the farm households is an important point to consider. For example, electricity access could diversify households' income through petty trading. As Phoumin & Kimura (2019) indicated, adequate lighting and electricity can enable rural children to read and do more homework for longer. At the same time, families can listen to the radio, watch television, access weather and market information, or earn extra money out of the linked service provision.

From all the six sub-components, the score for using rural technology was the lowest (0.091). Sample farmers had little experience practicing irrigation technologies (sprinklers, pumping generators, and water harvesting) and utilizing agricultural inputs (fertilizers, pesticides/herbicides, and improved seed). Differences were observed in the usage of chemical fertilizer between the three farm typologies. *Livestock and on-farm-income-based* farmers, who account for 68% of the total farmers in the study area, were the lowest in using chemical fertilizer during the study period, with a mean of 183 kg ± 234 standard deviations (Table 4.8). This could also influence the overall productivity and hence income of the households. Adaptive capacity enhancement programs by the government and the projects could target the improved access and adoption of rural technologies in the study area, especially for livestock and on-farm-income-based farmers.

Regarding wealth, 0.293 highest score was computed in the midland AEZ, followed by highland and lowland AEZs, with values of 0.252 and 0.212, respectively (Table 4.8). Wealth is very important for a society that depends mainly on agriculture for its livelihood (Krishnaiah, 2019). For instance, it is difficult to meet livelihood expectations for a farmer who does not have cattle and cropland, which are the constituents of wealth. The same is true for agricultural equipment. As presented in Table 4.8, marginal and off-farm-income-based livelihood typologies had the lowest number of farmers possessing livestock (6 ± nine standard deviations in total livestock unit), indicating they are highly vulnerable to drought impacts. Livestock resources are food sources (milk, butter, and meat), means of production for agricultural smallholders, and wealth indicators for all farmers. In addition to determining the household's current capability level, wealth can determine the future prosperity of smallholders and holds the core element in assessing the adaptive capacity in absorbing drought impact (Tinch *et al*., 2015).

Livelihood diversification is the other determining component of the adaptive capacity of the smallholders. Livelihood diversification, considering its positive contribution to the adaptive capacity, was analyzed using annual income (on-farm, off-farm, and non-farm), saving, engagement of household members in additional works besides farming, access to irrigation water, and hence engagement of farmers in irrigation activities, as well as the involvement of family members in seasonal migrant labor and food consumption diversification (Table 4.7).

Table 4.8. Farm typologies with adaptive capacity indicators (mean and standard deviation for continuous variables and frequency percentages for dummy variables).

Indicators	HL				ML				LL				Total		
	1 (N = 94)	2 (N = 30)	3 (N = 8)	Sub-total (N = 132)	1 (N = 63)	2 (N = 51)	3 (N = 18)	Sub-total (N = 132)	1 (N = 112)	2 (N = 11)	3 (N = 9)	Sub-total (N = 132)	1 (N = 269)	2 (N = 92)	3 (N = 35)
M-HH	82.1	75.9	75	80.3	73.4	90	100	83.3	91.7	92.9	77.8	90.9	84	86	88.8
Age HH	42 ± 12	37 ± 11	48 ± 13	41 ± 12	41 ± 14	44 ± 13.1	42 ± 12	42 ± 13	39 ± 12	38 ± 7	35 ± 7	39 ± 11	40 ± 12	41 ± 12	42 ± 12
FS-HH	3.8 ± 1.4	3.5 ± 1.5	3.9 ± 2	3.7 ± 1.6	3.7 ± 1.8	4.2 ± 1.7	3.9 ± 1.7	4.6 ± 1.7	5.9 ± 1.8	5 ± 1	4.8 ± 2	4 ± 1.8	4.2 ± 1.7	4.1 ± 1.7	4.1 ± 1.9
LR-HH	40 ± 13	31 ± 12	48 ± 13	39 ± 13	39 ± 16	42 ± 15	38 ± 14	40 ± 15	38 ± 13	38 ± 7	35 ± 7	38 ± 13	39 ± 14	38 ± 14	40 ± 13
D-HI	26 ± 19	23 ± 15	22 ± 8	25 ± 18	24 ± 27	48 ± 35	27 ± 28	34 ± 32	30 ± 20	27 ± 21	28 ± 16	30 ± 20	27 ± 22	37 ± 30	26 ± 21
D-Sc	21 ± 23	22 ± 12	36 ± 13	22 ± 21	15 ± 9	17 ± 14	18 ± 14	16 ± 12	21 ± 15	22 ± 10	21 ± 7	21 ± 14	19 ± 18	19 ± 13	23 ± 14
D-MP	26 ± 23	23 ± 12	26 ± 12	25 ± 20	39 ± 30	40 ± 32	15 ± 13	36 ± 30	37 ± 25	33 ± 13	35 ± 7	36 ± 10	33 ± 23	34 ± 26	23 ± 26
AT-HH	100	100	100	100	92.2	90	66.7	87.9	99.1	100	100	99.2	97.8	94.6	82.9
AE-HH	29.5	27	12.5	28	70.3	64	50	65.2	9.2	14.3	11.1	9.8	31	45	31.4
AHI-HH	8.4	13.8	0	9.1	42.2	48	61.1	47	0	0	0	0	13.1.	30.1	31.4
TLU	6.3 ± 6	6 ± 9	12.8 ± 8	6.6 ± 7	2.9 ± 3	3 ± 2	5.3 ± 4	3.3 ± 3	11.3 ± 11	16.6 ± 16	14.8 ± 14	12 ± 12	7.5 ± 7	6 ± 9	9.5 ± 9
Farmland	1.3 ± 1	0.9 ± 0.8	1.4 ± 2.1	1.2 ± 1.1	1 ± 1.2	1.3 ± 0.9	2.4 ± 1.9	1.3 ± 1.3	1.2 ± 1	0.7 ± 0.3	0.8 ± 1	1.1 ± 1	1.2 ± 1	1 ± 0.8	1.8 ± 1.9
MV-PA	1289 ± 1284	927 ± 667	1007 ± 709	1193 ± 1153	2824 ± 3112	3148 ± 2984	4831 ± 3666	3220 ± 3189	1248 ± 982	1997 ± 1681	1729 ± 1418	1360 ± 1123	1639 ± 1923	2282 ± 2505	3159 ± 3226
AC-HH	43.2	69	87.5	51.5	17.2	28	50	25.8	4.6	14.3	22.2	6.8	21.3	38.7	51.4
CA-HH	3415 ± 12,696	3472 ± 6266	4043 ± 5204	3465 ± 11,204	721 ± 2734	1052 ± 2598	3972 ± 9709	1289 ± 4418	155 ± 1039	357 ± 907	2222 ± 5068	318 ± 1677	1446 ± 7819	1702 ± 4141	3538 ± 7705
AFE-HH	52.6	44.8	62.5	51.5	82.8	88	72.2	83.3	60.6	64.3	44.4	59.8	63.1	71	62.9
EE-HH	9.5	0	0	6.8	3.1	0	5.6	2.3	1.8	0	0	1.5	4.9	0	2.9
PG-HH	5.3	3.4	12.5	5.3	6.3	4	27.8	8.3	1	0	0	1	3.7	3.2	17.1
WHT-HH	33.7	58.6	62.5	40.9	6.3	0	11.1	4.5	7.3	50	55.6	15.2	16.4	25.8	34.3
CF	146 ± 124	98 ± 49	173 ± 191	137 ± 118	405 ± 356	567 ± 594	1097 ± 639	561 ± 545	81 ± 89	136 ± 80	102 ± 88	88 ± 89	182 ± 234	356 ± 492	630 ± 672
OF	54 ± 121	39 ± 97	93 ± 174	54 ± 119	47 ± 68	45 ± 57	15 ± 32	42 ± 61	31 ± 164	2.5 ± 5	1.5 ± 4	25 ± 150	43 ± 131	37 ± 70	29 ± 89
FPH	31 ± 78	19 ± 38	19 ± 23	28 ± 68	2.5 ± 2	3.5 ± 3	45 ± 163	8.5 ± 60	1.5 ± 3.5	6 ± 6	1.5 ± 3	2 ± 4	12 ± 48	9 ± 22	28 ± 117

FIS	20 ± 56	14 ± 23	40 ± 56	20 ± 51	17 ± 40	16 ± 29	3 ± 11	14 ± 34	2 ± 5	6 ± 6	3 ± 5	2 ± 5	12 ± 40	14 ± 25	11 ± 31
CDS	3.06 ± 1	3.07 ± 1	3.63 ± 1	3.10 ± 1	2.49 ± 1	3.12 ± 1	3.56 ± 1	2.88 ± 11	1.89 ± 1	2.73 ±	2.56 ± 1	2.01 ± 1	2.44 ± 1	3.05 ± 1	3.31 ± 1
ONFI	7826 ± 10156	6998 ± 5280	7737 ± 5647	7639 ± 9044	18,035 ± 15,658	20,750 ± 25,329	16,172 ± 21,103	18,809 ± 20,454	15,907 ± 20,032	24,075 ± 24,560	29,555 ± 47,796	17,704 ± 23,386	13,551 ± 16,590	16,962 ± 21,959	17,685 ± 28,785
NFI	2710 ± 5808	7236 ± 6766	31,593 ± 23,694	5455 ± 10,577	7528 ± 13,679	11,294 ± 16,709	25,627 ± 24,843	11,422 ± 17,597	1638 ± 7776	13,135 ± 14,788	20,444 ± 20,845	4140 ± 11,410	3424 ± 9274	10,306 ± 14,080	25,658 ± 23,279
OFFI	555 ± 3432	2103 ± 4558	5950 ± 16,036	1222 ± 5338	1425 ± 3311	2842 ± 5965	10,255 ± 13,468	3165 ± 7109	308 ± 1643	4035 ± 6368	11,888 ± 18,428	1493 ± 6022	662 ± 2832	2791 ± 5603	9691 ± 15,109
ACS	6593 ± 7980	7686 ± 7573	16,357 ± 13,191	7425 ± 8523	5184 ± 7970	6869 ± 21,699	6083 ± 9229	5945 ± 14,776	4957 ± 14,305	17,690 ± 22,007	17,444 ± 22,051	7159 ± 16,420	5591 ± 10,988	8753 ± 18,738	11,353 ± 14,941
AW-HH	11.6	31	25	16.7	23.4	36	55.6	32.6	4.6	35.7	33.3	9.8	11.6	34.4	42.9
IW-HH	48.4	55.2	62.5	50.8	53.1	56	72.2	56.8	58.7	71.4	55.6	59.8	53.7	58.1	65.7
ML-HH	6.3	3.4	12.5	6.1	28.1	38	5.6	28.8	11.9	21.4	33.3	14.4	13.8	24.7	14.3
VF-HH	2.61 ± 0.8	2.5 ± 0.6	2.75 ± 0.8	2.6 ± 0.8	2.58 ± 0.8	2.52 ± 0.7	2.44 ± 0.9	2.54 ± 0.8	1.97 ± 1	1.29 ± 0.4	1.44 ± 0.7	1.86 ± 0.9	2.34 ± 0.9	2.33 ± 0.7	2.26 ± 0.9
FA-HH	11.6	13.8	25	12.9	43.8	48	16.7	41.7	20.2	14.3	11.1	18.9	22.8	32.3	17.1
WUA-HH	11.6	10.3	25	12.1	9.4	12	5.6	9.8	2	0	0	1.5	7.1	9.7	8.6
NE-HH	2.3 ± 1	2.2 ± 0.7	2.25 ± 0.4	2.3 ± 0.9	2.7 ± 1	3 ± 1	2.8 ± 1	2.8 ± 1	1 ± 0.8	1 ± 1	1 ± 1.5	1 ± 0.9	1.9 ± 1	2.5 ± 1	2.2 ± 1
TWUA-HH	17.9	27.6	25	20.5	29.7	42	44.4	36.4	16.5	7.1	0	14.4	20.1	32.3	28.6
MRI-HH	95.8	89.7	75	93.2	87.5	70	61.1	77.3	77.1	64.3	77.8	75.8	86.2	77.3	68.6
NCP-HH	0.4 ± 0.7	0.3 ± 0.7	0.1 ± 0.3	0.3 ± 0.7	1.4 ± 1	1.7 ± 1	1.5 ± 1	1.5 ± 1	0.7 ± 0.6	0.9 ± 0.4	1.7 ± 1.3	0.8 ± 0.7	0.8 ± 0.9	1.1 ± 1	1.2 ± 1.3

1 = livestock and on-farm-income based; 2 = marginal and off-farm-income based; 3 = intensive-irrigation-farming based.

The aggregate value of all the computed indicators informed that midland AEZ farmers were less vulnerable to livelihood diversification (with an average indexed value of 0.278) than those in the AEZs. Farmers in the lowland AEZ were identified as the most vulnerable in their livelihood diversification, with an average weight of 0.175, compared to other households in the studied AEZ (Table 4.7). The data analysis on livelihood diversification revealed that most households were not engaged in on-farm and off-farm livelihood activities in this AEZ. The overall level of annual income from farm-related activities in the midland and lowland AEZs were 7.5% and 3.6%, respectively, which are much lower than the national average, at 57% in 2014, as Kassegn & Endris (2021) reported. Similarly, the cash saving and migrant labor values during off-farming seasons are very low, indicating the lowest livelihood diversification. The above factors have limited farmers' livelihood options and weakened their adaptive capacity to drought impacts. As shown in Table 4.8, farmers engaged in non-farm livelihood activities and irrigation (typology 2 and 3) were better in their annual on-farm, non-farm, and off-farm income. Hence, they had a better adaptive capacity to drought impacts than crop- and livestock-dependent farmers. This reflects that income diversification and, therefore, more livelihood opportunities are crucial for rural smallholders to create resilience to the impact of drought. Increased livelihood diversification means more opportunities to move from one activity to another, allowing for greater response to the threats presented by climate change and associated shocks and increased livelihood resilience (Mesfin *et al*., 2020).

At a household level, access to information can significantly impact adaptive capacity (Matewos, 2020). In rural areas, information can be accessed mainly through social networks. The social network was aggregated by household members' membership in the farmers' association and water users' association, the number of locally monthly gatherings called "*edir*", the farmers' trust in the water users committee, access to market information, and the cell phones number possessed by a farm household. Accordingly, lowland farmers were the lowest in social networks compared to the other farmers, with an index value of 0.333 (Table 4.7), informing that their social network adaptive capacity is the lowest. It is evident that the arid lowland AEZs are fragmented in the settlement and are usually mobile in search of water. This might have contributed to reducing their social capital score in adaptive capacity. Table 4.8 depicts that 86.2% of those in the livestock and on-farm-income-based livelihood typology had better access to market information, which makes them better than their counterparts in the marginal and *off-farm-income- based* and intensive irrigation-farming-based livelihood typologies, who reported 77.3% and 68.6% of market information access, respectively. This contradicts the number of cell phones in a household, which was better in typologies 2 and 3 (non-farm and irrigation-based). The key informant irrigator farmer in the Adea district described this situation: "*The issue is not about having market information in selling our irrigation products. It is the role of brokers who misinform producer farmers and force us to sell vegetables at a lower price. We hear that the price of vegetables in Addis Ababa is high, but since our products are perishable, we are forced to sell them at a price that brokers and buyers fix*." Therefore, to build the resilience of smallholders, especially irrigators, the market system has to be improved, the role of local brokers must be inspected, and corrective measures must be taken.

As presented in Table 4.7, households had better values in their socio-demographics, infrastructure access, and adaptive capacity's social network dimensions. Differences were observed in the magnitude of the components of adaptive capacity based on the profile of the households. There were differences in the components of adaptive capacity based on the farm typology. Livestock and on-farm-income-based typology's sociodemographic adaptive capacity was better. However, the farmers' adaptive capacity, in terms of usage of rural technology, livelihood diversification, and wealth, was comparably low.

In contrast, intensive-irrigation-farming-based farmers' adaptive capacity was higher regarding access to infrastructure, wealth, access and usage of rural technologies, and livelihood diversification. However, the intensive-irrigation-farming-based typologies are only 9% of the total smallholders in the study area (Table 4.8). The remaining 91%, occupied by livestock and on-farm-income-based and marginal and off-farm-income-based smallholders, showed less adaptive capacity, signifying their low level of resisting drought impacts.

The ability to adapt is often fluid and subject to various influences. As overall adaptive capacity is influenced by the proper functioning of all the components as a system rather than each component as a separate unit, there is a need to make concerted efforts to consider the high-scoring components in future drought-tackling mechanisms. It is essential to devise a proper balance between the various components. In building the livelihood resilience of smallholders, the focus should also be on the livestock and on-farm-income-based and marginal and off-farm-income-based farmers, as their adaptive capacities, are lower than their intensive-irrigation-farming-based counterparts. Finally, the focus should be on continuously enhancing the system's overall performance to cope with the effects of drought risk and capitalize on the opportunities it presents.

As shown in Figure 4.5, low adaptive capacity situations dominated the sub-basins of lowland AEZ, where pastoralism's livelihood conditions prevailed. This could inform that future adaptive capacity improvement schemes need to prioritize these arid AEZs, especially focusing on improving the farmers' rural technology usage, livelihood strategy diversification, and boosting their wealth status to overcome the negative impacts of the recurrent drought.

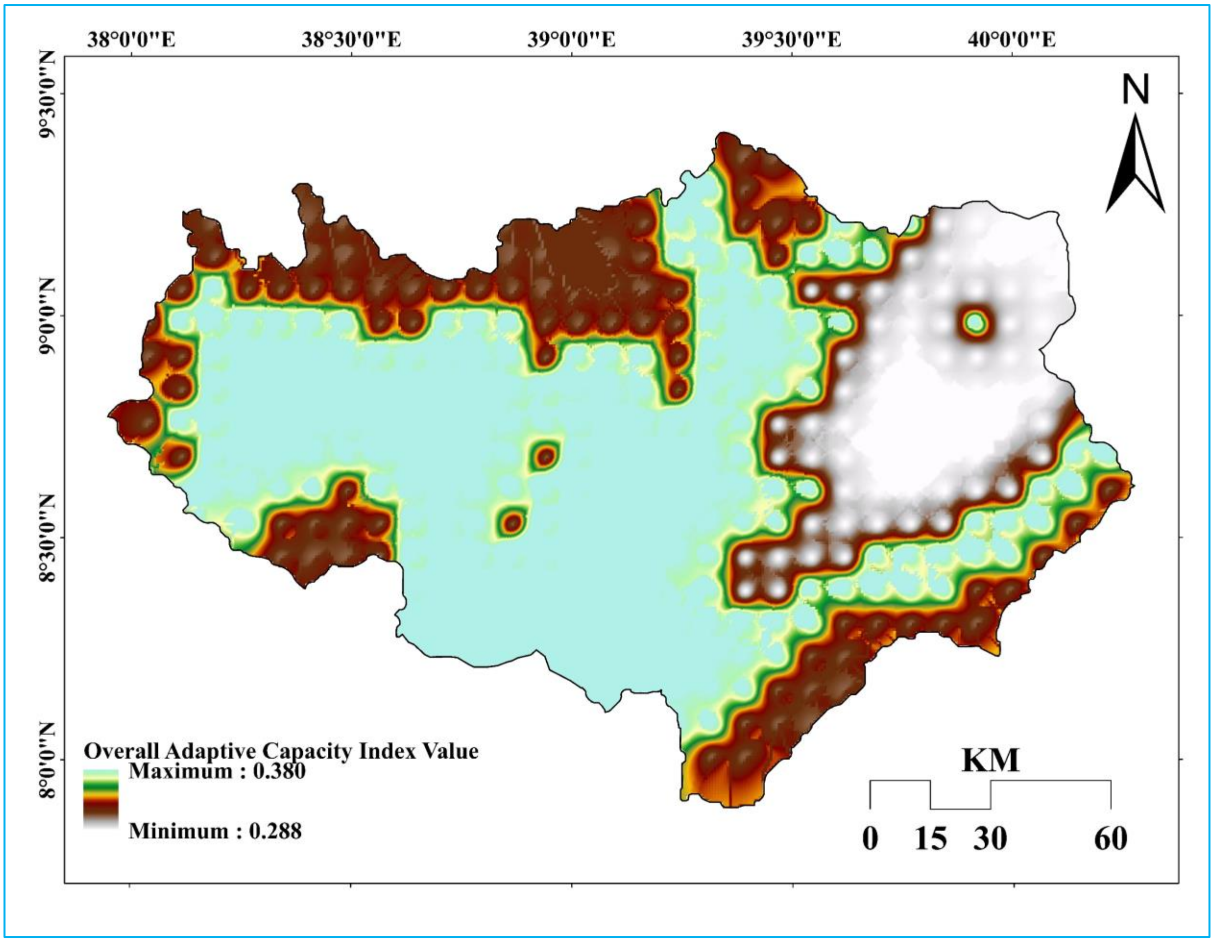


Figure 4.5. The spatial distribution of adaptive capacity to drought in the upper Awash sub-basin.

4.3.5. The Overall Drought Vulnerability: Sensitivity, Exposure, and Adaptive Capacity

The three major components of vulnerability—adaptive capacity, exposure, and sensitivity to drought—were examined following the IPCC–DVI. Compared to adaptive capacity, high exposure values result in positive vulnerability ratings, while low exposure values concerning adaptive capacity have negative vulnerability ratings. High sensitivity results in high vulnerability (large positive score) when exposure exceeds the adaptive capacity with its multiplier impact. In contrast, high sensitivity exceeds exposure, which results in lower susceptibility when adaptative capacity exceeds exposure (large negative score). In the current study, in all the AEZs, exposure exceeds adaptive capacity, though the rate of change has disparities. The rate of change is the largest (0.144) in the lowland and the smallest (0.088) in the highland. Tessema & Simane (2019) have also confirmed that lowlands have the highest exposure profile than the other agroecological zones and are more vulnerable to exposure vulnerability factors. In this principle, the relative exposure was found to be higher (0.447) in the midland, while adaptive capacity was lower (0.288) in the lowland (Table 4.9). Coupled with the relatively higher sensitivity (0.420) in the lowland (compared to the rest of the agroecological zones), this resulted in a larger negative vulnerability score (-1.956), implying relatively higher livelihood vulnerability to the drought of lowlanders compared to farmers in the highland (-3.045) and the midland (-4.257) (Table 4.9). Conversely, the lower exposure (0.396) in the plateau and the higher adaptive capacity (0.380) of the midland, compared to the rest (Table 4.9), resulted in a relatively small negative vulnerability score (-4.257) in the midland, showing that the overall vulnerability is estimated to be low in the midland, compared to the lowland and highland. Comparably, lowlands were highly vulnerable to the impacts of drought (-1.956), highlands (-3.045) were moderately vulnerable, and midlands were least vulnerable, with an overall score value of -4.257 (Table 4.9).

Table 4.9. Indexed major components, DVI contributing factors, and the overall DVI.

Component	HL	ML	LL	Component	HL	ML	LL
Climate change	0.590	0.603	0.593				
Drought Risk	0.609	0.461	0.610	Exposure	0.396	0.447	0.432
Climate perception	0.205	0.441	0.250				
Crop failure	0.675	0.520	0.821				
Disease	0.133	0.176	0.216	Sensitivity	0.347	0.344	0.420
Crisis	0.234	0.336	0.222				
Socio-demographics	0.590	0.603	0.593				
Access to infrastructure	0.293	0.507	0.284				
Wealth	0.252	0.293	0.212	Adaptive capacity	0.308	0.380	0.288
Rural technology	0.126	0.091	0.119				
Livelihood diversification	0.229	0.278	0.175				
Social networks	0.357	0.506	0.333				
Overall DVI					**0.350**	**0.390**	**0.380**
DVI = Sensitivity × (Exposure − Adaptive capacity)					**−3.045**	**−4.257**	**−1.956**

4.4. Conclusions

The farmers in highland AEZs were more exposed than those in midland and lowland AEZs. The core components contributing to the high exposure score were drought risks and long-term climate change impacts. In terms of the sensitivity of the households to drought, farms in all AEZs were sensitive. At the scale of farm typology, most households in the sub-basin in livestock and on-farm-income-based livelihood typology were more sensitive to drought than the intensive-irrigation-farming-based farmers. Adaptive capacity, which makes farmers cope with the impacts of exposure and sensitivity, was better for farmers in midland than those in highland and lowland AEZs. Comparably, farm households in the lowland AEZ were highly vulnerable in the overall IPCC- DVI score. On the other hand, those who live in highland and midland AEZ were medium and low, respectively.

The farm typology level analysis results informed that intensive-irrigation-farming-based livelihood typology had higher adaptive capacity. In contrast, the components of the livestock and on-farm-income-based adaptive capacity and marginal and off-farm-income-based livelihood typologies were low, informing that they are more vulnerable to drought impacts.

To reduce the exposure and sensitivity of smallholder farmers' livelihood to drought impacts and increase their adaptive capacity, crop varieties that can tolerate moisture stress need to be identified and integrated into the farm system. The environment's sensitivity that causes crop and livestock diseases and pests must be managed. Considering the time and amount needed could be a better option for supplying pesticides and herbicides to smallholders. Since the vulnerability to drought impacts is a function of all the indicators used in this study, interventions in the weak index points (sensitivity, adaptive capacity, exposure) observed in the study's agroecological zones and farm typologies are important entry points to consider. For example, interventions could include weather-indexed crop and livestock insurance, expansion of rural technologies and improved inputs, and creating awareness among farmers to be engaged in livelihood diversification strategies such as trading agricultural products, especially during off-farm periods, improving their adaptive capacity.

On the other hand, improved access to and managing water for irrigation is a potential entry point to reduce vulnerability to drought risk. In the long run, with the increasing exposure and sensitivity to water sources, it could be challenging to sustain irrigation because the water supplies may be affected due to the impacts of drought. Hence, interventions related to water demand management could be better solutions to overcome this situation. Existing rainfed-dependent farming systems must be supported through supplementary or full irrigation, agroecology, and farm typology-specific natural resources conservation practices. Finally, to build smallholders' resilience to drought, efforts should better target AEZs to prioritize the focus region and farmers' livelihood typology to tailor technologies to farms.

CHAPTER FIVE

5. Impacts of Small-Scale Irrigation on Framers' Livelihood: Evidence from the Drought-Prone Areas of Upper Awash Sub-Basin, Ethiopia

Abstract

Irrigation is an important mechanism to mitigate risks associated with the variability in rainfall for the smallholder subsistence farming system. This study analyzed how practicing small-scale irrigation (SSI) impacts the key livelihood assets on farm households' human, physical, natural, financial, and social capitals in Ethiopia's upper Awash sub-basin. The household-level survey data collected from the 396 sample households were used for the current study. A Propensity Score Matching (PSM) analytical model was applied to match the SSI user and non-user groups. The difference between the five livelihood capital assets was estimated using the PSM's Nearest Neighbor, Radius, Kernel Mahalanobis, and Stratification matching criteria. The results indicated that farmers' participation in SSI has enhanced the capital assets of the farm households. Compared to the non-users, the irrigation users were better off in the number variety of food consumed (0.28±0.13 Standard Error [SE]), types of crops produced (0.60±0.17 SE), expenditures on land renting, and agricultural inputs (3118±877 SE) measured in Ethiopian Birr (ETB), as well as on-farm (9024±2267 SE ETB) and non-farm (3766±1466 SE ETB) incomes. Challenges such as the involvement of local brokers in the market value chain and the absence of farmers' marketing cooperatives have reduced the benefit of irrigated agriculture. Hence, the expansion of SSI schemes for non-user farmers should consider improving the water usage mechanism and productivity, establishing proper water allocation institutions between up and down streams, and limiting the role of brokers in the irrigation product marketing chain be future policy directions.

Keywords: Small-Scale Irrigation; Livelihood capital assets; Propensity Score Matching; Drought-prone areas; Upper Awash sub-basin; Ethiopia

5.1. Introduction

Small-scale irrigation has enhanced agricultural production by increasing cropping frequencies and production, though the magnitude of this effect varies significantly across the globe (Bjornlund *et al*., 2017; Rufin *et al*., 2018). The livelihood of farmers using irrigation is more resilient than that of rainfed-dependent farmers globally (Ahmed & Sarma, 2021; Asante *et al*., 2021). This is because, compared to rainfed agriculture, irrigation has proven to be a better alternative for increasing the availability and quality of water resources for farming (López-Felices *et al*., 2020), contributing to agricultural sustainability and livelihood improvements.

In Africa, irrigation has a more significant potential to supplement the rainfed agricultural production system and improve the life of smallholder farmers (Biazin *et al*., 2012; Darko *et al*., 2020). Expanding irrigation in Africa, especially in Sub-Saharan Africa, is important to support farmers' fragile livelihood and support their endeavors out of poverty (Bjornlund *et al*., 2020; Higginbottom *et al*., 2021). However, the expansion of irrigation needs a timely inspection of its role in improving the farmers' livelihood (Chilundo *et al*., 2020).

Agriculture continued to be Ethiopia's most important economic sector, as its development heavily depended on it (Kebede, 2020; Mekuyie and Mulu, 2021; Yigezu, 2021). However, agricultural activities in Ethiopia are predominantly dependent on rainfall (Lankford and Grasham, 2021; Degife *et al*., 2021), which is dominantly practiced by smallholders, making the country's food production system very vulnerable to climatic variability and extreme events like drought (Yang *et al*., 2020; Lala *et al*., 2021). Variations in rainfall amount, distribution, trends, and rising temperatures directly impacted rainfed agriculture productivity and farmers' livelihoods who rely heavily on agriculture (Elzopy *et al*., 2020; Moges and Bhat, 2021; Nasir *et al*., 2021a). In drought-prone parts of Ethiopia, production from rainfed agriculture is highly variable (Debela *et al*., 2020; Minale, 2020; Nasir *et al*., 2021b), corresponding to the amount, the duration, and the spatial distribution of rainfall (Asfaw *et al*., 2018). To tackle the impact of rainfall variability in areas of abundant surface water, supplementing rainfed agriculture with small-scale irrigation-based schemes is encouraged by the government of Ethiopia (Gedefaw *et al*., 2018a). Maru *et al*. (2021a) and (2021b) also proved that irrigation is essential for building farmers' resilience to drought.

Small-scale irrigation scheme takes place on plots of land (5 to 200 hectares) (Smith *et al*., 2014), where individual farmers have the bulk of control and use technologies that they can run and maintain (Mosissa & Bezabih, 2017; Bjornlund *et al*., 2019). The individual farmer's plot of land varies between 0.25 ha and 0.5 ha (Awulachew *et al*., 2010). According to Passarelli *et al*. (2018), more focus should be on Ethiopia's small-scale irrigation. This is because the dominant farmers in the country are smallholders with limited farmland size. Smallholder farmers can plan and manage it in the community (farmer-led irrigation). Moreover, small-scale water supply schemes need only involve the *Kebele* administration and the local community (Dawit *et al*., 2020). Thus, decentralizing water resources development means local authorities, the *Kebele,* and community administrations, should play a more active role in planning and implementation (Hailu *et al*., 2018).

The current study was conducted in the upper Awash sub-basin (UASB). Awash Basin is Ethiopia's most utilized river basin (Gedefaw *et al*., 2018b**;** Tadese *et al*., 2019). Awash Basin households are known for their livelihood activities' subsistence mixed-crop-livestock production system (Maru *et al*., 2021). Most rely on the rainfed system and naturally available moisture for agriculture (Adane *et al*., 2020a; Maru *et al*., 2022). Upper Awash is distinguished from the middle and lower parts due to the relatively high concentration of rainfed and small-scale irrigation agricultural practices (Bayable and Gashaw, 2021; Damtew *et al*., 2022). The livelihood of farmers in the middle and lower parts of the basin is mainly pastoralism.

Previous studies indicated that small-scale irrigation has improved crop production and enhanced overall rural livelihoods (Mwangi and Crewett, 2019; Adela *et al*., 2019; Baddianaah *et al*., 2020; Maru *et al*., 2021). However, in these studies, there are a lot of generalizations. No explicit evidence supported how irrigation impacts the livelihood capital of the irrigators. Because rural livelihoods are heterogeneous, generalizations and aggregations on the effects of SSI on rural livelihoods are misleading (Dagunga *et al*., 2020).

Studies on irrigation and livelihood were carried out in various parts of Ethiopia. The dominant irrigation practices have been in northern Ethiopia (e.g., Mengistie and Kidane, 2016; Annys *et al*., 2020; Weldesenbet, 2020; Kassie and Alemu, 2021). The main focus of these studies was analyzing the role of small-scale irrigation on the livelihood of farm households taking a single or a few livelihood indicators such as income, food security, and poverty. Studies are conducted on irrigation and livelihood improvements in other locations in Ethiopia. To mention Southern Ethiopia (Abebe, 2017; Jambo *et al*., 2021), Eastern Ethiopia (Dawit *et al*., 2020), and Western Ethiopia (Wondimagegnhu and Bogale, 2020). A generalized approach, representing livelihood with a single indicator, was also the focus of these studies. Methodological gaps have been observed in some related studies as some used descriptive statistics, such as percentages and frequencies, to measure the impacts of SSI on livelihood (for example, Mengistie and Kidane, 2016). Due to the irrigation intervention, this methodology could hide the actual difference in livelihood capital assets between SSI irrigation users and non-users. This can be best captured by model-based analysis methods such as PSM.

In studying the impacts of irrigation on the livelihood improvement of farmers, it is essential to consider factors that affect farmers' livelihoods and the relationship between them (Aazami and Shanazi, 2020). Furthermore, the study must focus on what aspects of their livelihood are improved by irrigation and the trade-offs between them (Etana *et al*., 2021; Akudugu *et al*., 2021). This information is also crucial for development practitioners, policy formulators, and decision-makers to expand SSI based on their essential role in improving the farmers' livelihood.

Upper Awash sub-basin is one of the drought-prone areas of Ethiopia, where smallholder farmers suffer continuous crop production reduction, crop failure, and livestock deaths due to moisture stress (Borgomeo *et al*., 2018; Maru *et al*., 2021; 2022). This is because most farmers use the naturally available rainfall for their agriculture, which is highly variable at an interannual and intra-annual scale (Gedefaw *et al*., 2018b). Hence, irrigation is being expanded in the sub-basin to reduce moisture stress challenges on crops and livestock, improving smallholder farmers' livelihoods. Farmers' participation in small-scale irrigation is expected to improve their livelihoods, and assessing the impact of irrigation on livelihood capital is timely.

The main source of irrigation in the study area is river water through SSI schemes. The Water Users' Association (WUA) does the irrigation water allocation. Farmers use open channel gravity to reach the water to their farmlands. Since the government implements the SSI structures, the major costs associated with irrigation practice are the costs of land, agriculture inputs, and labor. The farmers maintain the SSI structures during malfunctioning unless the cost is huge. When a large maintenance cost is required, the government handles it.

This study aims to analyze the impact of SSI on smallholders' livelihood improvements, considering the five capitals (human, physical, natural, financial, and social) through quantitative data (through the PSM model) and qualitative data. The study's outcomes can inform the government and irrigation development practitioners to identify the livelihood capital enhanced by small-scale irrigation usage.

5.2. Materials and Methods

5.2.1. The Study Area-Location and Characterization

Location and characterization of the study area

Awash is one of the 12 river basins in Ethiopia. Based on physical, climatological, agricultural, social, and water resource characteristics, the basin is divided into three parts: lower, middle, and upper (Taye *et al*., 2018). The study's geographical scope is the basin's upper part (Figure 5.1). Geographically 37°54′35″ E–40°16′53″ E longitude and 7°53′15″ N–9°25′15″ N latitude limits define the study areas, which cover 24,545 square kilometers. Administratively the study area encompasses three districts: Dendi from the highland, Adea from the midland, and Fentale from the lowland agroecological zones.

The climate condition of the upper Awash sub-basin ranges from arid to afro alpine. The annual temperatures average between 15 and 20 degrees Celsius. In the upper Awash sub-basin, altitude ranges from 4055 to 742 meters above mean sea level (a.m.s.l.) (Figure 5.1), implying a wide altitude range within the study area (Shawul and Chakma, 2020), which influences local biophysical settings and associated livelihood activities (e.g., climatic factors). The mean annual precipitation in the sub-basins ranges from 800 to 1400 mm, depending on the elevation difference (Tolera *et al*., 2018). The duration and amount of precipitation show variations in the different seasons. The primary rainy season, known in Ethiopia as *Kiremt* lasts from June through September. The movement of the global atmospheric system called the Inter-Tropical Convergence Zone (ITCZ) to the Northern Hemisphere brings a large amount of rainfall in Ethiopia and the sub-basin during this season. Plantation of the most rainfed crops occurs during the summer, and the need for irrigation water is less.

The sub-basin is very dry during the Ethiopian *Bega* season (December to January), and irrigation is vital. The temperature is high during this season, so high evapotranspiration is experienced. From September to November and March to May, there is some rainfall in the sub-basin, but it cannot support crop and pasture production unless it is supported by irrigation water.

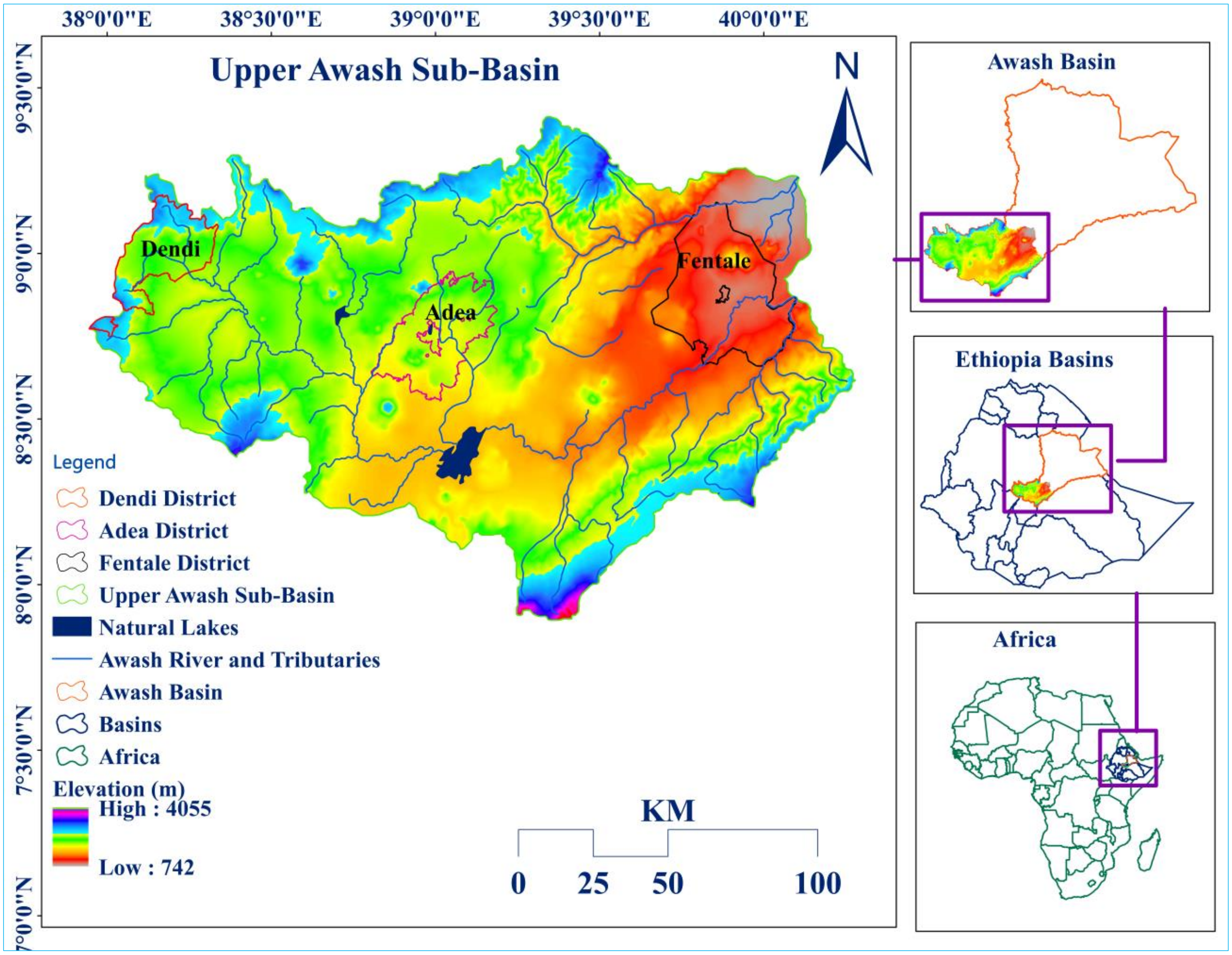


Figure 5.1. Location map of the study area showing elevation and sample districts.

Livelihood characterization of the study farmers

Farmers' livelihoods in the highlands and midlands rely on crop-livestock mixed systems that take advantage of naturally occurring rains. Wheat, teff, barley, maize, peas, beans, *enset*, and potatoes are among the dominant crops grown in the highlands (e.g., Dendi District) (Karthikeyan and Tadesse, 2014). Maize, wheat, teff, and other cereals are the most important crops in the Adea District (midland). In the midland and highland areas, livestock is incorporated into crop production and is a source of income while enhancing the crop production system using manure as fertilizer. Crops and livestock are complementary components, supporting crop production via animal plowing and agricultural leftovers feeding animals (Haileslassie *et al*., 2009a; 2009b). Lowland areas are known for their agropastoralism and pastoralism (Haileslassie *et al*., 2016). Sorghum and maize are common crops. In lowlands, households' significant assets depend on animals and their products. In Fentale, goats, camels, and cattle are the most common livestock.

The reduction amount and seasonal variability of rainfall necessitate the shift from rainfed to irrigation agriculture to sustain the most fragile livelihood of the farmers. There are two types of farmers in the study sub-basin. The first is only rainfed dependent who produce crops and livestock based on rainy seasons (*kiremt* and *belg*). They are non-irrigators mainly because they do not have irrigation land or good water access. During the non-farm periods, some engage in trade and daily labor to support their livelihood.

The second category of farmers is irrigators. They produce crops using irrigation during the dry season and a rain-fed system during the rainy season. The probability of drought-induced crop failure and production reduction is less than for rainfed farmers. This category of farmers has better crop production and diversified income sources. Sometimes, they hire labor for irrigation (Maru *et al*., 2021).

5.3. Sampling and Data Sources

Sampling

The upper Awash sub-basin has three major agroecological zones (AEZs): highland, midland, and lowland. The target sample households were chosen using a three-stage sampling approach. First, Dendi District was selected to represent the highland, Adea District to represent the midland, and Fenatle District to represent the lowland AEZs. Second, the sample size was calculated using Equation (5.1) (Kadam and Bhalerao, 2010). This formula was preferred because it provides an acceptable sample size, which is important in any survey requiring the optimum number of participants to generate ethically and scientifically valid results.

$$n = \frac{2\left(Z_{\alpha} + Z_{1-\beta}\right)2\sigma^2}{\Delta^2} \tag{5.1}$$

where

$n =$ Required sample size for the HH survey

$Z_{\alpha} =$ Constant (1.96) at 5% margin of error

$Z_{1-\beta} =$ Constant (1.6449) at 5% margin of error

σ = the standard deviation (estimated)

$\Delta =$ estimated effect size

Equation 5.1 suggested a total sample size of 360 households. The total sample size is 396 (198 irrigators and 198 non-irrigators) after accounting for a 10% non-response rate (36 people). Thirdly, respondent household heads were chosen at random using a lottery method. Two *Kebeles* (the lower administration structure in Ethiopia) from every three districts were chosen based on both availabilities of irrigator and non-irrigator farm households in the *Kebele*. Although the focus was on including the SSI implementation *Kebeles* in the sample frame, the AEZs were also considered in the selection process to have a variety of AEZ perspectives. Experienced survey enumerators who speak the local language (Afan Oromo) and have relevant experiences were recruited and trained to fill out the questionnaire. Before the commencement of the household survey, the questionnaire was pre-tested, and the HH survey was conducted from November 2018-February 2019. Table 5.1 shows the districts' characteristics and the distribution of sample HHs.

Table 5.1. Characteristics of districts and the distribution of sample HHs.

AEZs	**Sample Districts**	**Altitude (m)**	**Major Livelihood**	**Major Crop Type**	**Major Livestock**	**Number of Respondents**		
						IUs	**INUs**	**T**
Highland (HL)	Dendi	2300–3600	Mixed farming	Wheat, Barley, Teff	Sheep, Cattle, Equines	66	66	132
Midland (ML)	Adea	1500–2300	Mixed farming	Teff, Wheat, Maize	Cattle, Sheep	66	66	132
Lowland (LL)	Fentale	500–1500	Agropastoralism and Pastoralism	Sorghum, Maize	Camels, Goats, Chickens	66	66	132

m = meter; IUs = irrigation users; INUs = irrigation non-users; T = total

Data type and sources

The current study is based on a household survey among smallholders in the three districts. Key Informant Interviews (KIIs) with selected irrigation users and non-user farmers were conducted to supplement the information of the HH survey. Farmers' livelihoods were characterized using data from the HH survey using indicators that attribute the human, physical, natural, financial, and social capitals (Table 5.2).

In studying the impact of small-scale irrigation on the livelihood improvement of farmers, the variables of livelihood indicators in Table 5.2 were prioritized. In other words, the subject of inquiry was what happened to the livelihood capitals of farmers who used small-scale irrigation compared to their non-user counterparts. Livelihood is conceptualized as a means of living (De

Haan and Zoomers, 2003) for farmers and was expressed in the five capitals (human, physical, natural, financial, and social) (Sseguya *et al*., 2009). Significant indicators attributing to these livelihood capitals were carefully selected from the literature and used accordingly. The indicators used to characterize livelihood capitals and their sources are presented in Table 5.2.

Table 5.2. Livelihood capitals, their indicators, and literature sources

Livelihood capitals	Indicators	Variable label	Source
Human	Food varieties	Average number of varieties of food consumed by the household in a day	Adela *et al*., 2019
	Health expenditure	Estimated household's annual health expenditure (ETB)	Zeweld *et al*., 2015
	Education expenditure	Estimated household's annual education expenditure (ETB)	Zeweld *et al*., 2015
Physical	Crop types	Number of crop types produced in the production year	Maru *et al*., 2021
	Productive assets	The estimated monetary value of the household's productive assets (ETB)	Olwande *et al*., 2015
	Household assets	The estimated monetary value of the household assets (ETB)	Wossen *et al*., 2017
	Livestock	Number of livestock in the household (TLU)	Gwiriri *et al*., 2021
Natural	Land expenditure	Estimated expenditure of the household for rented agricultural land (ETB)	Zhang *et al*., 2020
Financial	Saving	The annual amount of money saved by the household (ETB)	Khan *et al*., 2008
	Credit	The annual amount of credit money accessed by the household (ETB)	Njeru *et al*., 2016
	On-farm income	Annual on-farm income of the household (ETB)	Jordán and Speelman, 2020
	Off-farm income	Annual off-farm income of the household (ETB)	Mumin, 2017
	Non-farm income	Annual non-farm income of the household (ETB)	Nahayo *et al*., 2017
	Agricultural input	The annual amount of money spent on agricultural input expenditure (ETB)	Kamara *et al*., 2019
Social	Mobile cellphone	The estimated monetary value of the mobile cell phones in the household (ETB)	Sikundla *et al*., 2018
	'*Edir*' expenditure	The annual amount of money spent for '*edir*' expenditure (ETB)	Abbay *et al*., 2018

TLU=tropical livestock unit (A TLU is equivalent to 250kg of live weight of the animal)

5.4. Analytical Model

Small-scale irrigation agriculture impacts rural livelihoods (Feleke *et al*., 2019; Mhembwe *et al*., 2019). In analyzing the effects of SSI on household livelihoods, it is essential to assume that farm households are risk neutral. Their decision to practice small-scale irrigation agriculture depends on the value of the expected utility of wealth (livelihood) from usage and non-usage (Zeweld *et al*., 2015). Since livelihood is too broad and complex to capture in a single indicator, selecting certain indicator variables is necessary. Hence, livelihood was considered a function of the five capital assets. Subsequently, as indicated in Table 5.2, three variables constituting human capital, four variables attributing physical capital, one variable making natural capital, six variables attributing financial capital, and two variables representing social capital were selected. Then, following Khandker *et al*. (2009), for the expected utility of wealth (livelihood), the general model of the study can be given by Equation (5.2) as follows:

$$U_i(HHL) = Y_i\beta + \eta D_j + \varepsilon_i i = 1, 2, 3, \dots n \qquad (5.2)$$

where $U_i(HHL)$ is the expected utility of wealth or household livelihood (HHL) for household i; Y_i is the vector of observed explanatory variables; D_j is the decision to participate in small-scale irrigation ($D_j = 1$, if farmers participate in small-scale irrigation and $D_j = 0$, otherwise); η is the impact of participation in SSI on the expected utility of wealth of household livelihood (variables stated in Table 5.2); ε_i is an error term with a mean of zero and a variance δ_ε^2 that apprehends the errors in measurement and unobserved factors that affect the participation decision and its outcomes. If SSI was randomly assigned to farmers, the difference in wealth between users and non-users might be used to determine the causal effect of participation in irrigation on farmers' wealth. However, participation in irrigation is not assigned at random. Instead, it is a procedure of 'self-selection' by farmers. Whether a farmer participates in irrigation is determined by socio-economic variables at the household level. Because all sample households in the study area are part of the SSI schemes, irrigation does not depend on water access.

An average treatment effect (ATE) is the expectation of the treatment effect across all farmers (Wu *et al*., 2010). A problem occurs using non-experimental data (such as the data in the current study) because only either $Y_i(1)$ or $Y_i(0)$ is observed for each farmer i, but not both. Hence, the expected utility of wealth (*HHL*) is not observable, and the choice of participation or non-participation is observable; the (*HHL*) is represented by $U^*(HHL)$. Subsequently, farm households would participate in irrigation only when the participation's expected to benefit $\left(U_{i1}^*(HHL)\right)$ exceeds nonparticipation's $\left(U_{i0}^*(HHL)\right)$.The main objective is to find the estimated average treatment effect for the treated population (ATT_i). The average treatment effect is the difference between the treated and controlled smallholder households, which implies whether $\left(U_{i1}^*(HHL)\right) > \left(U_{i0}^*(HHL)\right)$ due to irrigation usage, where HHL_{i1} and HHL_{i0} are the differences in the expected utility of wealth using the predefined factors if farmers belong to treated or non-treated groups, respectively.

Since the aim is to determine the SSI impacts on household livelihoods, the question of "how to estimate the average treatment effect of the livelihood indices" must be considered. The treatment's effect on the unit i could be observable as $Y_i(1) - Y_i(0)$, if $Y_i(1)$ and $Y_i(0)$ were observable. We may then use this information to estimate the population's average treatment effect (ATT) for the entire sample N (Abadie *et al*., 2004). To determine the average treatment effect on the treated $(ATTi)$, Equation (5.3) was used. Various evaluation strategies are available, and an appropriate technique has to be chosen depending on the nature of the study and information availability (Adela *et al*., 2019).

$$ATT_i = E\{HHL_{i1} - HHL_{i0} \big| D_j = 1, P(Y_i)\} = E\big(HHL_{i1} \big| D_j = 1\big) - E\big(HHL_{i0} \big| D_j = 0\big) \qquad (5.8)$$

There are different methods by which impacts can be evaluated. These include randomized selection methods, difference-in-difference, instrumental variable estimation, regression discontinuity design, and PSM methods. They vary in their underlying assumptions concerning how to solve the bias in selection in estimating the intervention treatment effect (Rahut *et al*., 2016). Randomized assessments involve a randomly assigned initiative throughout a sample of subjects (community or individuals); treatment and control subjects with similar pre-intervention characteristics progress and are followed over time (Menon *et al*., 2009). A difference-in-difference method can be used in non-experimental and experimental settings, assuming that unobserved selection presents and is time-invariant. The regression discontinuity method compares participants and non-participants in a close region around the eligibility cutoff using exogenous intervention criteria (eligibility requirements). Finally, PSM approaches examine treatment effects within participants and the matched non-participant units, using a variety of observed attributes to do so (Khandker *et al*., 2009). PSM techniques imply that selection bias is based solely on observed features and cannot account for unseen factors influencing participation.

The PSM method is preferred in this study because there was no baseline data on SSI participants and non-participants in the study area. Households were either purposefully placed or self-selected to participate in small-scale irrigation, and the field data was generated based on a cross-sectional survey.

Using observed features, PSM creates a statistical comparison group based on a model of the probability of participating in the intervention (Gemici *et al*., 2012). In PSM, the first step is calculating the propensity score and ensuring the balancing requirement is met. The balancing characteristic of the propensity score, according to Caliendo and Kopeinig (2008), is done via Equation (5.4):

$$HHL_{i1}\,, HHL_{i0}\,(\perp|Y_i) \Rightarrow E(HHL_{i1}|P_i = 1, X_i) = E(HHL_{i0}|P_i = 0, Y_i) \qquad (5.4)$$

The second phase involves matching propensity scores using selection and outcome equations. To estimate the probability of treatment for each observation and generate the collection of matched observations, the selection equation (5.5) is used. The binary logit model can estimate the value of the propensity score (selection equation). Because the study's participation choice contains dichotomous values, this is the case (1 for farmers who participated in irrigated farming and 0 otherwise). To do so, one must make a common support assumption. By this assumption, treatment units must be comparable to non-treatment units in terms of observed attributes unaffected by participation; as a result, some non-treatment units have to be dropped to ensure comparability. Due to comparing incomparable individuals, breaking this assumption is a primary source of bias.

$$P(D_i = 1|X_i) = \Phi\big(f(X_i)\big) = \sum_{i=1}^{n} a_i X_i + \varepsilon_i = \frac{e^{f(X_i)}}{1+e^{f(X_i)}} \Rightarrow \hat{P}(X_i|D) = 1 \qquad (5.5)$$

where Φ denotes the normal cumulative distribution of the livelihood index's function and $f(X_i)$ represents a specification of the household practicing irrigation. A propensity score will be calculated for each participant and non-participant household, which might be a continuous variable between 0 and 1.

Lastly, suppose the propensity score model using Equation (5.6) is statistically significant. In that case, SSI participants and non-participants will be matched using criteria, including Nearest-Neighbor matching, Radius matching, Kernel matching, Mahalanobis matching, and Stratification matching (Diaz and Handa, 2006). The weights assigned by the matching process may impact the resultant intervention estimate. It is advisable to use and compare all the matching criteria (Becker and Caliendo, 2007).

$$ATT_i = E\left(\frac{HHL_1 - HHL_0}{D} = 1, P(Y_i)\right) = E\left\{E\left(\frac{HHL_1}{D} = 1, P(Y_i)\right) - E\left(\frac{HHL_0}{D} = 0, P\left(\frac{Y_i}{D}\right)\right) = 1\right\} \qquad (5.6)$$

Bias out of self-selection is an important limitation in the PSM technique in impact evaluation. There will be less self-selection bias. Most empirical investigations demonstrate that a 3 to 5%

bias reduction is sufficient. As a result, the reduction of bias due to matching is determined using Equation (5.7) as follows (Titus, 2007).

$$BR = 100\left(1 - \frac{B_M}{B_O}\right) \qquad \text{whereby}$$

$$B_M = \frac{\left(100(\bar{X}_{MC} - \bar{X}_{MP})\right)}{\sqrt{\frac{S^2{}_{OC} + S^2{}_{OP}}{2}}} = \text{Standardized bias before matching, and}$$

$$B_M = \frac{\left(100(\bar{X}_{MC} - \bar{X}_{MP})\right)}{\sqrt{\frac{S^2{}_{MC} + S^2{}_{MP}}{2}}} = \text{Standardized bias after matching} \qquad (5.7)$$

where subscript O denotes before matching, and M denotes after matching.

5.5. Results and Discussions

5.5.1. The socio-economic and demographic characteristics of the households

Table 5.3 depicts the socio-economic and demographic characteristics of the study households, disaggregated by irrigation users and non-users. Relatively, irrigators are younger than non-irrigators. The mean age of the households for irrigators and non-irrigators was 40.5 and 41.6 years, respectively. Similarly, the average family size of irrigators was 4.26, larger than that of non-irrigators. Since irrigation is more labor-demanding, the younger age of the irrigation users explains this truth.

Similarly, the diversity in family size between irrigators and non-irrigators can be accounted for by the level of labor required for irrigation practices. Moreover, irrigation users and non-users were diverse in terms of the education level of the study household head. Accordingly, 78.3 percent of the irrigation users and 75 percent of the non-users were literate, indicating irrigation users' more literate status. Agriculture as the main occupation was 86.8% and 85.3% for irrigation users and non-users, respectively.

The One-way ANOVA and Chi-Square independent tests showed statistically non-significant differences between irrigation users and non-users across all the socioeconomic and demographic variables. This result suggests that allocating households in the treated and control groups was based on a randomized control trial. In other words, households were assigned randomly to the treated and control group to determine the impact of small-scale irrigation on livelihood improvements which contributed positively to the robust performance of the PSM model. This is because, except for the treatment, random assignment ensures that the only difference in attributes between the two groups is entire to treatment (small-scale irrigation intervention). As a result, the difference in outcomes following the intervention should be attributed to the treatment, which shows the treatment's causal influence (Bayer *et al.*, 2020).

Table 5.3. Socio-economic and demographic characteristics of the study households (ANOVA for mean and Chi-Square Test for percent)

Variables	Irrigators	Non-irrigators	Average	P-value
AGE-HH	40.5	41.6	40.8	0.210
MH-HH	85.9%	83.8%	84.8%	0.337
SIZE-HH	4.26	3.98	4.12	0.102
MR-HH	85.4%	88.9%	87.1%	0.349
LIT-HH	78.3%	75%	76.6	0.238
AGRI-HH	86.8%	85.3%	86%	0.544

ANOVA = analysis of variance; AGE-HH = age of the household head (years); MH-HH = male-headed household; SIZE-HH = household size; MR-HH = married household head; LIT-HH = literate household head; agriculture as a primary occupation.

5.5.2. Description of the explanatory variables

As illustrated in Figure 5.2, most covariates were similar between the treated and untreated groups during the pre-matching stage. After the matching process, more similarity was observed in the covariates for the treated and untreated groups ensuring the selection of PSM to compare the two groups was appropriate and precise. The balancing property of the propensity score was found to be satisfactory, and the assumptions made were met.

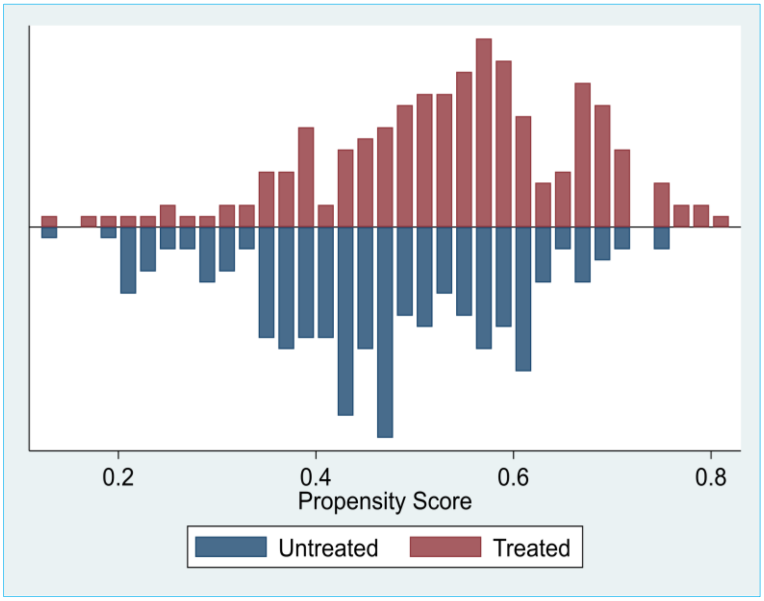


Figure 5.2. Balance for propensity score before matching

Before doing the propensity score, some explanatory (dependent) variables were used to estimate the mean of a continuous dependent variable. As Table 5.4 depicts, four of the selected explanatory variables (proportion of male-headed households, literate household heads, perceived food security status, and size of agricultural land) were statistically significant at different levels. This suggests that these variables were the most critical determinants in explaining the likelihood of farmers participating in small-scale irrigation.

Table 5.4. Estimation of the coefficients of the propensity score in the logit regression model

Variables	Coefficients (Standard error)	Variables	Coefficients (Standard error)
AGE-HH	0.004 (0.010)	LIT-HH	-0.017 (0.009)**
M-HH	-0.344 (0.207)*	PER-FSS	-0.305 (0.148)**
SIZE-HH	-0.011 (0.043)	ACC-FC	-0.100 (0.147)
MR-HH	0.103 (0.075)	AGRI-LAND	-0.266 (0.072) ***
cons	1.392 (0.482) ***	LR-HH	-0.008 (0.009)
Obs. = 396; LR Chi2 (9) = 28.98; Prob > Chi2 = 0.0007; Log Likelihood = -259.9975			

***Significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$.

PER-FSS = perceived food security status; ACC-FC = access to financial credit; AGRI-LAND = size of agriculture land (ha); LR-HH = length of residence of the household head (years); Obs. = observations; LR = logistic regression

5.5.3. Impact of Small-Scale Irrigation on Farmers' Livelihood Improvement

To investigate the impact of practicing SSI on livelihood, we have attributed livelihood in the five capitals (human, physical, natural, financial, and social) and identified relevant indicators as demonstrated in Table 5.2. Tables 5.5 and 5.7 show the PSM's average treatment effects in the treatment (SSI users) and control groups (SSI non-users). Five matching methods (Nearest Neighbor, Radius, Kernel, Mahalanobis, and Stratification) were used. Diaz & Handa (2006) suggested using all available matching criteria to examine the differences between each technique. The following sections illustrate these impacts categorized by the five livelihood capitals.

Human Capital Assets

Human capital was attributed to three variables: the variety of food consumed by the household members in a day and the health and education expenditures of the household. As can be seen from Table 5.5, participation in SSI in the upper Awash sub-basin had a positive and statistically significant effect on the variety of food consumed by the household at the 95% level at the Nearest Neighbor, Kernel, and Stratification matching criteria; and at 90% using the Radius and Mahalanobis methods. For instance, participation in SSI increased the variety of household food consumed by 0.28±0.13 and 0.31±0.12 based on the Nearest Neighbor and Mahalanobis at 95% and 90% significance levels, respectively.

A balanced diet is an essential aspect of human development. One of the irrigator farmers who took part in the key informant interview (KII) from the Adea district stated that one of the main benefits of being an irrigator is having fresh and diverse food on the plate throughout the year. Framers ascribe this to the opportunity to produce all over the year. In this relation, Passarelli *et al*. (2018) reported that using small-scale irrigation enhances the consumption of a balanced diet by diversifying farmers' production and leading farmers to higher agricultural income. The result also suggests that irrigation is vital adaptation practice and helps meet critical sustainable development goals (Maru *et al*., 2022). Differences were observed regarding education and health expenditures between the SSI users and non-users. Participation in SSI increased the households' annual education and health expenditures by 728±438 SE and 317±186 SE ETB, respectively, as per the Nearest Neighbor and Mahalanobis methods results and at a 90% significance level (Table 5.5). However, the differences were not statistically significant for most matching methods. Rural areas are known for free access to public education and health service centers, reducing the differences in the expenditures between irrigators and non-irrigators. Zeweld *et al*. (2015) have also found statistically non-significant education expenditure differences between SSI adopters and non-adopters in the rural areas of northern Ethiopia. To generalize, participation in SSI has positively contributed to the human capital assets enhancement of rural households in the upper Awash sub-basin.

Physical Capital Assets

The study found statistically significant differences in physical capital elements, such as the type of crops produced and the monetary value of household assets, at 99% and 90%, respectively (Table 5.5). Variables such as the type of crops grown, the value of productive and household assets (e.g., irrigation watering jar, spade, sickle, etc.), and ownership of livestock (in TLU) characterized the physical capital of the study households (see also Shivakoti and Shrestha, 2005; Hunecke *et al*., 2017). The differences in the monetary value of productive assets and livestock ownership between the SSI participant and non-participant groups were statistically non-significant. The non-significant difference in TLU can be explained by the fact that farmers use common grazing areas for livestock grazing. Despite the difference between the two study groups, the issues of common property resources might have influenced the result. One of the roles of SSI utilization is producing verities of the crop. That was why the difference between the two groups of farmers was highly significant for all five estimation methods. The discussion we had with KII also substantiates these findings. In this regard, KII participants from the Dendi district explained that producing varieties of crops would help stabilize household income. When the income from the sale of onions drops due to the market, the price of tomatoes will rise. For example, participation in SSI made households have more than 0.56±0.16 SE to 0.60±0.17 SE varieties of crops produced in a year compared to non-participating counterparts.

Similarly, households participating in SSI possessed more valuable household assets than SSI non-participants. Table 5.5 shows that irrigators and non-irrigators have a monetary value of household assets differential of 3932±2370 SE to 5598±3217SE ETB, making the earlier groups more advantageous. The differences in the monetary value of productive assets and livestock ownership between the SSI participant and non-participant groups were statistically non-significant.

Natural Capital Assets

Land is an essential resource in agriculture. In most places in the upper Awash sub-basin, the availability of agricultural land, either by possession or rent, determines the participation of smallholders in SSI schemes. The suitability of the land for irrigation is also an essential factor. As presented in Table 5.5, all five estimator models predicted that the difference in expenditure for agricultural land between irrigators and non-irrigators was statistically significant at the 99% level. The result also suggests that the irrigation users' annual land expenditure for irrigation is more significant, up to 3118±877 SE ETB, than non-irrigation users. According to interview data, the yearly cost of renting a quarter hectare of irrigation land in some study areas, such as Adea, was up to 5000 ETB. A farmer needs at least 20000 ETB to rent a hectare of land for a production year, a very high investment for a smallholder farmer. Due to the higher rent cost, irrigator farmers are more likely to access an additional plot of land to expand their irrigation than non-irrigator farmers. In this case, it is reasonable to infer that the irrigator's expenditure on renting irrigation land has improved due to their participation in small-scale irrigation.

Table 5.5. Average treatment effect (standard errors in brackets) for human, physical, and natural capital variables

Livelihood capital	Livelihood Indices	Nearest Neighbor Matching	Radius Matching	Kernel Matching	Mahalanobis Matching	Stratification Matching
Human	VFC	0.28 (0.13)**	0.18 (0.11)*	0.22 (0.10)**	0.31 (0.12)*	0.25 (0.11)**
	EDUCEXP	728.83 (438.00)*	-356.38 (514.09)	-5.47 (520.45)	288.57 (565.96)	-28.44 (513.72)
	HLEXP	173.99 (215.93)	-85.05 (367.28)	-135.65 (340.75)	317.10 (186.92)*	-175.89 (411.76)
Physical	CTYP	0.60 (0.17)***	0.60 (0.15)***	0.57 (0.14)***	0.56 (0.16)***	0.59 (0.14)***
	PRASSET	398.04 (251.11)	391.28 (263.15)	198.68 (249.10)	237.70 (292.95)	233.65 (291.37)
	HHASSET	5438.34 (2815.84)*	4513.30 (2869.80)	4374.63 (2729.84)	5598.41 (3217.25)*	3932.19 (2370.64)*
	LVST	0.90 (1.11)	0.56 (1.01)	0.94 (0.96)	1.24 (1.06)	0.78 (1.01)
Natural	LANEXP	3064.77 (709.51)***	2953.19 (791.93)***	2877.91 (755.96)***	3118.24 (877.12)***	2821.33 (677.87)***

***Significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$.

VFC=variety of food consumed in 24 hours; EDUCEXP = education expenditure (ETB); HLEXP = health expenditure (ETB); CTYP = crop types produced in the past production year; PRASSET = monetary value of productive assets (ETB); HHASSET = monetary value of household assets (ETB); LVST = number of livestock owned by the household (tropical livestock unit); LANEXP = agricultural land rent expenditure (ETB).

Financial Capital Assets

Irrigation agriculture requires financial capital to purchase specific irrigation equipment, improved seeds, and agricultural inputs like chemical fertilizers, pesticides, and herbicides (Chazovachii, 2012). At the same time, participation in irrigation contributes positively to acquiring financial capital assets. As can be referred from Table 5.6, a statistically significant difference in the annual on-farm income between the irrigator and non-irrigator groups was found at a 99% significance level with all the five matching criteria. The annual non-farm income also showed a statistically significant difference between the two groups at a 95% significance level using the four estimators. It was found that the yearly on-farm income of irrigators was higher (9024±2267 SE ETB), and the non-farm annual income difference between the two groups was estimated at 3766 ETB. Participating in small-scale irrigation agriculture in the study area gave the irrigator group more on-farm and non-farm incomes than the non-irrigator group. This implies that irrigation participant households are more likely to purchase agricultural inputs to enhance production. This can be inferred from the agricultural input expenditure findings of this study. There was a significant difference in expenditure on agricultural inputs such as fertilizers, improved seeds, pesticides, and herbicides between irrigation users and non-users at a 99% significance level across all five estimators (Table 5.6). For example, from the nearest neighbor matching, irrigation users' annual agricultural input expenditure was more significant in 3718 ETB than the non-irrigation users. A further explanation for this is that farmers are risk-averse. Having access to water throughout the year encourages irrigators to invest more in inputs as there is less risk of crop failure with rainfall variability.

Accessing credit money from formal finance institutions aiming for long-term agricultural and non-agricultural investments is almost none for households. As revealed in Table 5.6, the amount of annual credit accessed showed a significant negative difference between irrigator and non-irrigator at 99% with Radius matching and 95% levels using Nearest Neighbor and Kernel matchings. This result informed that the non-irrigators accessed more money than the irrigators. The credit is primarily accessed in the study area for daily needs from local individuals and informal village sources. An interviewed small-scale irrigation non-user farmer in the Dendi district also noted, "*I cannot access credit from the banks and formal financial sources as I do not* *have the collateral it demands. Even if I do, I do not want to have it from these sources as I cannot engage in long-term investments besides farming*".

The irrigators are usually lenders as they have relatively better annual income. Hussain and Thapa (2012) indicated that the probability of smallholders accessing credit from formal financial institutions is limited, especially in developing countries. The above findings suggest that small-scale irrigation participation's financial capital asset impact is the highest of the remaining capital assets, positively influencing the other capital assets.

Social Capital Assets

Social capital includes reciprocity, relations of trust, everyday standards, norms, consequences, and connections in institutions. In rural areas, healthy communication and participation in different gatherings define the social capital asset of the community (Pretty and Ward, 2001). That was why we used the monetary value of mobile cellphones in the household and the local gathering called '*edir*' to constituent social capital assets in the current study. As presented in Table 5.6, participating in SSI in the study area had a positive and statistically significant impact on the better monetary value of mobile cellphones at the 95% level by all the estimators except the Radius matching. For instance, using the Mahalanobis matching method, the monetary value of mobile cellphones for the irrigation user group was about 529±213 SE ETB higher than that of the irrigation non-user group. There was no significant difference in the annual 'edir' expenditure. Although some households have more '*edir*' and hence payments, this could be because every household pays the same amount. Maru *et al*. (2021) indicated that the involvement of brokers in marketing irrigation products had been a significant challenge for irrigators. This is due to irrigators' lack of trusted market information and the perishable nature of the products. It has created a distorted market value chain by over-strengthening the role of brokers in the market.

Table 5.6. Average treatment effect (standard errors in brackets) for financial and social capital variables

Livelihood capital	Livelihood Indices	Nearest Neighbor Matching	Radius Matching	Kernel Matching	Mahalanobis Matching	Stratification Matching
Financial	SAVE	2833.01 (1867.03)	3187.41 (1517.11)**	3076.85 (1456.60)**	3601.65 (1819.99)*	2844.87 (1517.31)**
	CREDIT	-2927.98 (1449.80)**	-2744.72 (880.53)***	-2440.55 (837.18)***	-1613.59 (1427.41)	-1478.48 (1048.14)
	ONFINC	7730.62 (2358.28)***	8176.91 (2069.67)***	8014.28 (2010.05)***	9024.48 (2267.63)***	8133.09 (2016.72)***
	OFFINC	1737.57 (487.48)***	776.25 (725.20)	519.15 (696.93)	-194.10 (868.39)	513.20 (669.58)
	NFINC	3727.46 (1598.71)**	3766.27 (1466.77)**	3509.47 (1426.99)**	2734.66 (1735.43)	3395.27 (1459.54)**
	INPEXP	3718.32 (977.98)***	3268.03 (1034.05)***	3230.31 (998.87)***	3688.97 (983.31)***	3192.16 (942.26)***
Social	MOBCEL	496.79 (215.77)**	400.61 (207.84)*	405.06 (199.30)**	529.67 (213.82)**	410.46 (190.12) **
	EDREXP	55.87 (61.26)	55.61 (57.98)	57.37 (55.62)	57.83 (58.28)	60.07 (51.75)

***Significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$.

SAVE = amount of money saved by the household in a year (ETB); CREDIT = amount of annual credit accessed by the household for production purposes (ETB); ONFINC =annual on-farm income (ETB); OFFINC = annual off-farm income (ETB); NFINC = annual non-farm income (ETB); INPEXP = annual agricultural input expenditure (ETB); MOBCEL = monetary value of mobile cell phones in the household (ETB); EDEXP = annual *edir* expenditure (ETB).

Livelihood capital transformation is more important for rural households to improve livelihood capacities and reduce vulnerabilities (Wei *et al*., 2016). The transformation of one livelihood capital of rural households can also enhance the other livelihood capitals. As shown in Table 5.6, the financial capital of irrigators is significantly better off than non-irrigators. This might influence other livelihood capitals through capital transformation. The higher financial capital gain gave irrigator households better other livelihood capitals. For instance, better finance could lead to better human capital for food, education, and health expenditures. The same applies to physical capital in crop production, asset ownership, and natural capital such as land expenditure. The current study's findings indicate that the strong impact of participating in small-scale irrigation has boosted the irrigator households' financial capital, influencing the other livelihood capital of households through livelihood capital transformation.

5.6. Conclusions

The study analyzed the impact of small-scale irrigation on farm households' five livelihood capital assets in the upper Awash sub-basin, Ethiopia. The study used propensity score matching between treated (irrigators) and control (non-irrigators) to achieve its objective. Nearest Neighbor, Radius, Kernel, Mahalanobis, and Stratification matching models were applied to estimate the magnitude of the impact differences.

The study results show that participation in small-scale irrigation improves most of the indicators considered in the five capital assets. However, the magnitude of the impact and the level of significance varies. For example, for human capital indicators, only the variety of food consumed by the household was statistically significant, which has implications for enhancing the quality of life of irrigation participants. Regarding physical capital assets, a significant difference was observed between irrigators and non-irrigators in the number of crop types produced in the production year. This has increased the stability of farmers' income during fluctuating market prices. In terms of natural capital assets, using all five matching propensity scores, the farmland rental expenditure between the two groups was significantly different at 99%.

Participation in SSI improves farmers' social capital assets. The significant impact of SSI participation was on the financial capital assets. For example, under all five PSM estimates, the annual farm income and expenditure of agricultural inputs at a significance level of 99% show a significant difference between irrigation participants and non-participants. For example, under all five PSM estimates, the annual farm income and expenditure of agricultural inputs at a significance level of 99% show a significant difference between irrigation participants and non-participants. However, considerable market information gaps and the involvement of local brokers in marketing irrigation products have reduced the benefits of irrigation agriculture. Hence, establishing farmers' cooperatives, involving farmers actively in the market value chain, and limiting the involvement of brokers through enforcement of regulations could be the option to manage market distortion affecting farmers.

It is found that participation in SSI has improved most elements of the livelihood capital. Hence, participating the non-irrigator farmers in the irrigation schemes could enhance the livelihood of the non-irrigators. This could lead to a higher demand for the existing irrigation water supply and may result in the poor performance of the overall SSI scheme. Therefore, focusing on considerations such as improving the water usage mechanism and productivity, establishing proper water allocation institutions between up and down streams, and limiting the role of brokers in the irrigation product marketing chain through legal regulations could be future policy directions.

CHAPTER SIX

6. General Discussions, Conclusions, and Recommendations

6.1. Introduction

Climate change and human-caused challenges threaten farmers' livelihoods in the twenty-first century (Ericksen *et al*., 2009). The amount, duration, and spatial distribution of rainfall, temperature, and streamflow impact smallholder farmers' agricultural production (Faramarzi *et al*., 2013). Human-caused threats such as LULC change exacerbate climate change-related challenges (Dey & Mishra, 2017). Changes in LULC affect surface water availability by increasing or decreasing surface flows that contribute to the water required at the surface, including irrigation (Dibaba *et al*., 2020a).

The results of the threats from climate change and human activities are extreme climate events like drought, flooding, and the deterioration of livelihood (Warner *et al*., 2010). Smallholder farmers are among the victims of climate change-related extremes and human-caused LULC changes because their livelihoods are highly dependent on naturally available ecosystem services. (Obwocha *et al*., 2022). Moreover, because of their limited capacity for adaptation, the challenges to their livelihood have serious consequences (Simões *et al*., 2010).

In response to the frequent impacts of drought on farmers' livelihoods, irrigation has been prioritized in developing countries (Miyan, 2015). A study conducted by Uddin *et al*. (2014) put the utilization of small-scale irrigation as the first-ranked farm-level adaptive measure for the challenges imposed by climate change and environmental degradation-related risks. The analysis of LULC change impact on surface water, drought, livelihood vulnerability to drought, and utilization of small-scale irrigation as an adaptive mechanism to enhance the livelihood of smallholders enables us to understand these issues in detail.

Consequently, the current study examined surface water availability as affected by LULC and climate change; meteorological drought characterized by its magnitude, duration, frequency, and spatial distribution; the level of smallholder farmers' livelihood vulnerability to the drought; and the roles of small-scale irrigation in enhancing the livelihood (in terms of the five capitals) of farmers whose livelihoods were harmed by the recurring drought in the upper Awash basin, Ethiopia.

This study used a mixed research method combining climate and socioeconomic household survey data. Based on the study's specific objectives, streamflow, precipitation, temperature, and other data were used. A 27-year trend analysis of streamflow, precipitation, temperature, and climatic water balance was performed to examine the study area's long-term climate and hydrology changes. The climatic water balance was used to analyze the seasonal water balance. The soil and water assessment tool (SWAT) was used to simulate streamflow using the LULC parameters from 1993 to 2016. The climatic water balance allowed us to quantify the seasonal water balance in the upper Awash sub-basin. The changes in surface water availability in response to the LULC change between 1993 and 2016 were analyzed to understand the LULC change impact on surface water in terms of surface runoff and total water yield.

The meteorological drought analysis of the Awash basin was done using a time series (1983-2016) of precipitation and minimum and maximum temperature using the two drought analysis indices. The standard precipitation index (SPI) and the standard precipitation and evapotranspiration index (SPE) were used to tackle the limitation of using a single drought analysis index. The analysis was based on the basin's major agroecological setting. The drought magnitude, duration, frequency, and return period were then calculated using the two indices. Using the SPI and SPEI-based long-term meteorological drought magnitudes, the basin's drought hot spot areas were identified and mapped using ArcGIS.

Considering drought incidents in a specific area entail analyzing the impact on each agricultural household's livelihood capital. Then analyzing the vulnerability of smallholder farmers' livelihood to the drought in the upper Awash basin was the other objective of the study. Long-term precipitation, minimum and maximum temperature, the regional drought characteristics of the farm households, and the household survey data were used. The IPCC-DVI was used after the principal livelihood indicators of the farmers were known based on the principal component analysis (PCA) result. Farm typology was created using cluster analysis based on the characteristics of the farmers. The results were analyzed using agroecology and farm typology to overcome the disadvantage of generalizing farmers in a large agroecology zone and failing to demonstrate the vulnerability of farmers' livelihoods to drought in the study area. Drought sensitivity, exposure, and adaptive capacity levels among farmers were also mapped to show the spatial extent of these three drought vulnerability elements. Small-scale irrigation is commonly recommended to respond to the drought's impact on farmers' livelihoods. In this case, it is reasonable to understand the impact of small-scale irrigation on farmer livelihood. This was covered in the previous paper. The household survey data collected from the subbasin's sample farmers were used to quantify the level of livelihood (in terms of the five capitals). The analysis was made by comparing the livelihood capital assets between small-scale irrigation users and non-users using the propensity score matching (PSM) model. The PSM's five matching criteria were used to measure the level of capital assets of smallholder farmers in the irrigation-using and non-using groups.

Accordingly, the study's major findings and their limited discussions are presented in the following sections as they appeared in the individual papers discussed above.

6.2. General Discussions of the Study

Surface water availability, drought, and the impact of small-scale irrigation on the livelihood of smallholder farmers in Ethiopia's upper Awash basin were studied using various methods. The study findings indicate that over the 27 years (1990-2016), all the streamflow, minimum and maximum temperatures showed a significant increasing trend while a non-significant decreasing trend in the Akaki catchment of the upper Awash sub-basin. Similarly, between 1993 and 2016, the built-up area and barren land expanded by 41.55 km^2 (5.3%) and 27.13 km^2 (3.4%). The major change in the LULC in the catchment was associated with the expansion of Addis Ababa city. The city has been expanded in the surrounding rural agricultural lands through ever increased construction of buildings and condominium houses. The climate change was associated with a significant decrease in seasonal climatic water balance in the catchment, whereas the LULC change increased surface runoff and total water yield. From 1993 to 2016, the LULC change increased surface runoff from 236.01mm to 272.59mm and total water yield from 366.7mm to 382.01mm in the study area. The figures indicate the enhancement of surface water availability in the catchment. Unless this surface water is utilized for agricultural activities, it may cause challenges in the life of the inhabitants.

According to the study results from Mann Kendall and Sen's Slope trend analysis, the potential seasonal evapotranspiration (PET) and climatic water balance (CWB) decreased for the three seasons (except for the *Tsedey* season) based on long-term precipitation, minimum and maximum temperature. The above finding could explain a sub-precipitation basin's shift from the Belg to the *Tsedey* season. *Belg and Kiremt* were the two rainy seasons in the Awash basin (Takele *et al*., 2022). These findings also directly relate to the basin's consecutive drought events over the last 34 years (1983-2016). The study area's main causes of meteorological drought are rising temperatures and declining precipitation.

Agroecology-based meteorological drought analysis helps design and implement an agroecology-specific drought management measure (Amare & Simane, 2017). In line with this, the greatest number of drought years, seasons, and months occurred in the tepid to cool humid mid-highlands, hot to warm arid lowland plains, and hot to warm humid lowlands, respectively, over 34 years (1983-2016), regardless of changes in SPI and SPEI methods. For example, ten drought years, 49 drought seasons, and 150 drought months were recorded in the Awash basin using the SPEI method. The SPI method determined 12 drought years, 46 drought seasons, and 126 drought months over 34 years. These findings revealed that SPEI predicted more drought months and seasons, whereas SPI focused more on identifying drought years.

Temporarily, dry years predominated in the 2010s, while wet years predominated in the 1990s, indicating the occurrence of climate extremes such as drought and flooding. The 1980s and 2000s were typical years in most Awash basin AEZs. These findings back up previous research by Tefera *et al*. (2019) and Yisehak & Zenebe (2020), which claimed that the 2010s were plagued by droughts, with 2012 being the worst. Drought was at its worst in the Awash basin during the 2010s, with more than half of the basin under drought threat. These drought incidents resulted in famines responsible for the displacement and death of humans and livestock.

In drought assessment, comparing the SPEI and SPI revealed that the SPI overestimated the number of normal years because it does not account for evapotranspiration. These "normal" years have insufficient soil moisture. The SPEI did a good job of capturing the years of drought at most timescales. However, when the additional temperature is considered, dry episodes are more accurately detected using the SPEI than the SPI. In AEZs with high rainfall and humidity, SPI may be considered for drought monitoring. With high PET, SPEI can efficiently capture drought characteristics in arid and semi-arid regions.

The study found that tepid-to-cool sub-moist mid-highlands are among the newly drought-prone areas in the Awash basin, despite the severity of the drought. Due to the aridization of the climate, manifested in a rise in the number of days with extremely high temperatures in this AEZ, rainfall amounts have been steadily declining. According to a recent study by Gebrehiwot *et al.* (2020), rainfall in this AEZ has reduced significantly in recent years, reaching as low as 401 mm annually compared to its normal annual rainfall of 700 mm.

Understanding the frequency of droughts in AEZs allows policymakers and practitioners to implement drought-pattern-based interventions. The tepid to cool humid mid-highlands experienced the most frequent annual droughts. Droughts occurred in this AEZ every three years on average between 1983 and 2016. On average, droughts occurred every 4.1 years in the hot to warm arid lowland plains. The findings suggest that the drought spreads to previously non-drought AEZs, such as the humid mid-highlands.

The mapping of the drought hotspot areas in the Awash basin revealed that the drought hotspots' geographical distribution varies between AEZs. While the escarpments and central parts of the Awash basin have experienced mild to moderate drought in recent years, the upper and lower parts of the basins have been affected by severe to extreme drought. Moreover, it has been determined that the tepid to cool moist mid-highlands, hot to warm moist and humid lowlands, and hot to warm arid lowland plains are the basin's drought hotspot AEZs, where future proactive drought risk management activities should be targeted.

With drought events dominating the Awash basin, what happened to the vulnerability of smallholder farmers' livelihoods to it piques interest. Based on the findings of the two objectives, smallholder farmers' perception of drought and actual meteorological drought computation were used to understand the drought exposure of the farmers. To this end, the midland demonstrated the greatest vulnerability to the change and variability of the climate, with a 0.439 index value, followed by lowland and highland AEZs. This shows that temperatures are rising compared to the other AEZs, and precipitation is falling in the midlands. This contradicts the widely believed understanding that the climate in the arid lowland regions is changing quickly. The overall exposure of farmers' livelihood to drought attributed to computed and perceived climate change and variability and drought risk indicated that the farmers in midland AEZs were highly vulnerable to drought impacts with an index value of 0.447 compared to the farmers in other AEZs. As a result, places, where real change is visible, must be the focus of efforts to adapt to and mitigate the effects of climate change, particularly in terms of drought**.** It also indicates where to focus intervention in drought management in agricultural, agropastoral, and pastoral livelihood environments. A thorough examination of farm typology revealed variation in exposure level. Based on the perception data, the marginal and off-farm-income-based and intensive-irrigated-farming-based smallholders were highly exposed to the overall exposure index, suggesting the need to increase climate change awareness among these farm typologies. Farmers' behavior is altered due to the awareness level improvement tasks, which positively impact irrigation water consumption and productivity and open up possibilities to utilize the water saved for all other ecosystem services.

On the other hand, the sensitivity of smallholder farmers' livelihoods to drought was examined using crop failure, diseases, and crises as sensitivity components at both the AEZ and farm typology levels. Crop failure and diseases dominated the lowland AEZ, while crises exacerbated drought sensitivity in the midland AEZ. Based on the AEZ settings, the results revealed that the overall sensitivity of smallholder farmers' livelihood to drought was highest in the lowland (0.420), followed by the highland (0.347), and the midland (0.347). (0.344). Farmers in the livestock and on-farm-income-based livelihood typology were the most vulnerable to drought impacts in terms of crop and livestock diseases, putting them at greater risk of illness than farmers in the other farm typologies.

In addition to exposure and sensitivity, the adaptive capacity of farmers reflects his\her vulnerability to the effects of drought. The adaptive capacity index comprises six sub-components: socio-demographics, information access, wealth, rural technology, livelihood diversification, and social network. As a result, with index values of 0.603, 0.507, 0.292, 0.278, and 0.506, the midland farmers' adaptive capacity was the best in terms of socio-demographics, access to information, wealth, livelihood diversification, and social network, respectively. The lowest adaptive capacity was observed in lowland farmers' livelihoods regarding information, wealth, livelihood diversification, and social network availability.

Depending on the farm typology, there were variations in the adaptive capacity components. The sociodemographic adaptability of *livestock and on-farm income-based* typology was higher. However, it was discovered that the farmers' ability to adapt was comparatively poor in terms of their use of rural technology, diversification of their sources of income, and wealth. On the other hand, farmers who rely on intensive irrigation have greater adaptability in terms of access to infrastructure, wealth, use of rural technology, and diversification of livelihood—however, only 9% of all smallholders in the study area practice intensive irrigation farming. The remaining 91%, which included smallholders who relied on livestock and on-farm revenue as well as marginal and off-farm income, had lower levels of adaptation capacity, indicating that they were less able to withstand the effects of drought.

The capacity for adaptation is frequently fluid and susceptible to external forces. There is a need to deliberate efforts to include high-scoring components in future drought-fighting mechanisms because the proper functioning of all components influences total adaptive capacity as a system rather than each component as a separate unit. Finding the right balance between the various elements is critical. Because their adaptive capacities are weaker than their counterparts who rely on intensive irrigation farming, livestock, on-farm income-based, and marginal farmers should be prioritized. The overall system performance should be continuously improved to deal with the impacts of drought risk and capitalize on the opportunities it presents.

Regarding the overall livelihood vulnerability to the drought index, the relative exposure was higher (0.447) in the midland. At the same time, adaptive capacity was lower (0.288) in the lowland. Coupled with the relatively higher sensitivity (0.420) in the lowland (compared to the rest of the agroecological zones), this resulted in a larger negative vulnerability score (-1.956), implying relatively higher livelihood vulnerability to the drought of lowlanders compared to farmers in the highland (-3.045) and the midland (-4.257). Conversely, the midland's lower exposure (0.396) and higher adaptive capacity (0.380) compared to the rest resulted in a relatively small negative vulnerability score (-4.257), indicating that the midland's overall vulnerability is estimated to be low in comparison to the lowland and highland. In comparison, lowlands were highly vulnerable to the effects of drought (-1.956), highlands were moderately vulnerable (-3.045), and midlands were least vulnerable (-4.257). The study's findings have implications for proactive extreme climate event management at the sub-basin, agroecology, and farm typology levels to improve the livelihood of rural farm households. The identified vulnerable AEZs can be better entry points for the target regions, while the farm typologies to tailor drought-copping technologies at the household level.

Small-scale irrigation utilization is one of the adaptive capacity options for farmers whose livelihoods are affected by recurrent drought (Mburu *et al*., 2015). We assigned livelihood in the five capitals (human, physical, natural, financial, and social) and identified relevant indicators to estimate the impact of SSI practice on farmers' livelihoods. The findings show that participation in SSI in the upper Awash sub-basin had a positive and statistically significant impact on small-scale irrigator households' human capital (variety of food consumed, education, and health expenditure). For instance, according to the nearest neighbor and Mahalanobis methods results and at a 90% significant level, participation in SSI raised the households' annual education and health expenditures by 728±438 SE and 317±186 SE ETB, respectively. One of the advantages of SSI use in terms of physical capital is the ability to grow various crops. Because of this, for all five estimation techniques, there was a substantial difference between the two groups of farmers. These conclusions are also supported by the conversation we had with KII. Participants in the KII from the Dendi district noted that growing a variety of crops would assist in stabilizing household income, meaning that the price of tomatoes would increase when the income from the sale of onions, for example, fell as a result of the market fluctuations.

In the farming community, land is a valuable natural capital. Farmers who do not own irrigation land are forced to rent it from landowners under the scheme. Thus, all five estimator models indicated that the difference in agricultural land expenditures between irrigators and non-irrigators was statistically significant. The results also show that irrigation users spend more money on land for irrigation (3118±877 SE ETB) than non-irrigation users. Irrigator farmers are more likely than non-irrigator farmers to have access to an additional plot of land to extend their irrigated farming because of the higher rent costs. In this case, it is reasonable to conclude that the irrigator's expenditure on renting irrigation land has decreased due to their involvement in small-scale irrigation farming.

The primary impact of small-scale irrigation use on smallholder farmers' livelihoods was on their financial capital. The study indicates that irrigators had a greater annual on-farm income (9024±2267 SE ETB). In contrast, the difference in non-farm annual income between the two groups was estimated at 3766 ETB. The irrigator group earned the non-irrigator group in both on- and off-farm incomes from participating in small-scale irrigation agriculture. This suggests that households participating in irrigation are more likely to buy agricultural inputs to raise production—the study's findings on agricultural input expenditure support this conclusion. At a 99 percent confidence level, there was a significant difference in the amount spent on agricultural inputs such as fertilizer, improved seeds, pesticides, and herbicides among irrigated agriculture users and non-users. Though the magnitudes vary, small-scale irrigation has improved all five livelihood capital assets.

6.3. General Conclusions

The analysis of the LULC change on streamflow and surface water availability; meteorological drought and farmers' livelihood vulnerability to drought; and the impact of small-scale irrigation on drought-impacted livelihood provides a general picture of surface water management, agroecology-based proactive drought management, and small-scale irrigation implementation while taking into account the actual impact on farmers' livelihood. Due to the changing climate, the long-term climatic trend analysis revealed that evapotranspiration, minimum and maximum temperature exhibited an increasing trend, which was the main reason for the declining seasonal climatic water balance in the study area. In addition to climate change, human activities in terms of LULC change impacted surface water availability. Both surface runoff and total water yield were enhanced by the LULC change between 1993 and 2016. Drought occurred in many parts of the Awash basin due to a decreased climatic water balance. The increased availability of surface water, driven mainly by the development of built-up areas and barren lands, has implications for flood hazards, particularly during rainy seasons.

The meteorological drought analysis revealed that the AEZs most frequently affected by annual, seasonal, and monthly drought events over the previous three decades included tepid to cool humid mid-highlands, hot to warm arid lowland plains, and hot to warm humid lowlands. Frequent annual drought in the tepid to cool humid mid-highlands shifts the perspective of drought management in that droughts are only known phenomena in dry lowland areas. Temporally, dry and wet years dominated the 2010s and 1990s, respectively. The 1980s and the 2000s were drought-neutral years in most AEZs of the basin.

The study also discovered that drought assessment methods have benefits and drawbacks in terms of space and time. A more in-depth examination of the two approaches is required from the standpoint of agricultural land management. Due to their comparative superiority in identifying monthly and seasonal drought situations, SPEI approaches, for instance, provide improved prospects for soil moisture balance and influence crop choices. In AEZs, where evapotranspiration plays a substantial role, SPEI produces superior outcomes (e.g., hot to warm arid lowland plains). While the value of evapotranspiration determines the number of drought episodes in some AEZs (such as the tepid to cool moist and sub-moist mid-highlands), its influence is limited in others (such as the cold to very cold moist sub-afro alpines). The correlation between the SPI and the SPEI was temporarily relatively strong at shorter time scales (1-6 months) but significantly weakened at longer time scales (9-24 months). This demonstrates that SPEI and SPI techniques clearly understand the drought status in various AEZs, especially at monthly and seasonal timescales. To this end, the ability of the SPI and SPEI approaches to characterize meteorological droughts depends on the specific AEZ; SPEI performs better in AEZs with higher potential evapotranspiration. SPI is advantageous over SPEI in giving more wet and drought normal episodes regarding the type of drought. Moreover, the SPEI characterized the dry events better than SPI, while SPI values for the normal events were superior to SPEI.

Examining the drought frequency in the Awash basin reveals that the SPEI and SPI results show that annual drought has occurred almost every year since 2011, with the earlier predicted drought in recent years. Events of drought were concentrated spatially in different regions of the basin. Regarding the drought hotspot AEZs, mild to moderate drought has affected the escarpments and middle parts of the Awash basin. In contrast, the upper and lower portions have been hit by severe to extreme drought, with drought persisting in nearly every part of the basin in recent years. AEZs identified as the basin's drought hotspots include hot to warm, moist, and humid lowlands, hot to warm arid lowland plains, and tepid to cool moist mid-highlands. These AEZs should focus on future proactive drought risk management activities.

The livelihood vulnerability to the drought indicated that compared to their counterparts in midland and lowland AEZs, farmers in highland AEZs were more exposed. Drought hazards and long-term climate change effects were the main factors raising the exposure score. Farms in all AEZs were sensitive to drought in terms of household sensitivity. Most households in the sub-basin with livestock and on-farm income-based livelihood typologies were more sensitive to drought than the farmers who relied primarily on intensive irrigated farming at the scale of farm typology. Farmers in midland AEZs have higher adaptive ability than those in highland and lowland AEZs, which helps farmers deal with the consequences of exposure and sensitivity.

The farm typology level analysis revealed that the livelihood typology based on intensive irrigation farming had a greater capacity for adaptation. In contrast, the components of the livelihood typology based on livestock, on-farm income, and marginal and off-farm income-based had a lower capacity for adaptation, indicating that they are more vulnerable to the effects of drought. In comparison, smallholder householder farmers in the lowland AEZ scored extremely vulnerable on the IPCC-DVI scale. On the other hand, farmers in the highland and midland AEZs had IPCC-DVIs that were low and medium, respectively.

The study findings also show that participating in small-scale irrigation increases most indicators considered in the five capital assets. However, the significance and magnitude of the impact vary. Only the household's varieties of food were statistically significant for human capital indicators, which has implications for improving the quality of life for irrigation participants. Regarding physical capital assets, a significant difference was observed between irrigators and non-irrigators in the number of crop types produced in the production year. This has increased the stability of farmers' income during fluctuating market prices. In terms of natural capital assets, using all five matching propensity scores, the farmland rental expenditure between the two groups was significantly different at 99% in favor of the irrigators.

The financial capital assets were the main impact of SSI participation. A significant difference between irrigation participants and non-participants was observed in the annual on-farm income and expenditure of agricultural inputs for all five PSM estimations, at a significance level of 99 percent. Nonetheless, the benefits of irrigated agriculture have been mitigated by significant gaps in market information and the role of local brokers in marketing irrigation products.

Furthermore, using multiple gridded datasets (up to 1655 points in the case of chapter three) can significantly contribute to similar future studies. It provides an advantage over the traditional use of station-based data, notorious for measurement errors, inconsistency, missing data, incompleteness, and spatial limitations. This study produced strong evidence based on agroecology and farm typology. According to the methodology used in this study, the use of gridded data enabled the creation of a detailed dataset, allowing for simple extrapolation and ensuring the validity of the data analysis. Applying farm typology-based analysis to the drought vulnerability study represented a new paradigm in climate change-related research, as it disaggregated the farmers' livelihood vulnerability to drought at the cluster of farms level.

6.4. Contributions of the Study

Because the study examined surface water availability, drought, and livelihood vulnerability to drought, as well as the impact of SSI on farmers' livelihoods at the basin, sub-basin, catchment, agroecology, and farm typology levels, empirical evidence that guides policymakers and implementers toward the right choices and decisions is documented at all levels. The current study's conceptual, empirical, theoretical, and methodological contributions are also discussed.

Conceptual contributions: The study has helped to clarify, refine, and contextualize the concepts of drought and farm livelihood at various scales, which are frequently complex and misunderstood. It also pioneered drought hotspot areas at the basin level in the Awash basin. Furthermore, the study attempted to shed light on understanding surface water availability in response to changing climate and human action, which is frequently understood only from two perspectives at the catchment level. It also introduced the concept of cluster analysis-based farm typology to the context of livelihood vulnerability research, which had not previously been explored.

Empirical contributions: integrating surface water availability, drought, vulnerability, and irrigation at basin and sub-basin scales; using as many as 56 indicators of exposure, sensitivity, or adaptive capacity in the livelihood vulnerability to drought study; examining the impacts of SSI on each of the five livelihood capital elements; and mapping the drought hotspots, the exposure, sensitivity, and adaptive capacity of farmers can be considered a significant empirical contribution of this study.

Theoretical contributions: The study used the climatic water balance with SWAT data to assess surface water availability at the catchment level, as well as the IPCC-DVI deduced from the IPCC vulnerability framework in terms of exposure, sensitivity, and adaptive capacity based on perception and climate data. As a result, the current study examined whether both theories are applicable in the study area. The research made a further theoretical contribution by combining different theories to achieve a common goal.

Methodological contributions: using a 4km-by-4km gridded dataset for 1655 points at the basin level was quite challenging. Accordingly, it is a unique contribution of this study to the study of drought and the vulnerability of livelihood to drought impacts both at a wider and local scale. Moreover, studying livelihood vulnerability to drought with long-term climate and household perception data using a newly prompted dataset can be regarded as of major methodological value addition to the current studies.

This study introduced the methodology of farm typology analysis to the livelihood vulnerability assessment and downscaled the AEZ level vulnerability analysis at the farm household level. On top of this, deriving the DVI from IPCC's LVI was a unique contribution of the current study to the arena of vulnerability study.

The utilization of hydrological models (such as climatic water balance, streamflow calibration, and validation); climate models (like SPEI, SPI, DVI, and trend analysis); econometrics models (such as PSM and logistic regression); and spatial models (mapping and interpolation) make this study multidimensional in terms of methodologies used. This can be considered as the other methodological contribution of the study.

6.5. Recommendations

Depending on the findings of this Ph.D. research, the following are suggested for future policy considerations:

- Because the study has produced empirical evidence on water availability and drought over the past three decades in the agroecology setting in the upper Awash sub-basin, it is suggested that Awash Basin Authority use the generated evidence, regional and local governmental and non-governmental organizations in the planning, design, and implementation of an agroecology-specific water and drought management and livelihood resilience building strategy for smallholder farmers.
- The study found that due to the LULC change, particularly the expansion of built-up areas and barren lands in the Akaki catchment of the study area, surface water has increased over 27 years, implying the occurrence of flood hazards. Therefore, this excessive water has to be utilized through integrated water resources management practices such as surface water harvesting, hydroponics, and aquaponics for urban agriculture. Moreover, proactive flood

management strategies such as improving the drainage and surface water disposal system of the urban areas need to be done to minimize the impact of the flood. This can be implemented by the consortium of the city administrations in the catchment and Awash Basin Authority through time-specific projects.

- The study identified that the two drought assessment methods (SPEI and SPI) could be used for different climatic conditions and time scales. Future drought analyses could use SPI for AEZs with high rainfall and humidity. With a high PET, SPEI can efficiently capture drought characteristics in semi-arid regions. Two components are suitable for short periods because they produce balanced scores, but as the time scale increases, SPI outperforms SPEI.
- Based on the research findings, the tepid to cool sub-moist mid-highlands were AEZs where annual drought occurred frequently. Drought expansion in the sub-moist mid-highlands is not expected, as is customary. In these AEZs, where meteorological drought is becoming a new and growing phenomenon, future drought management is better considered. A drought hotspot AEZs in the Awash basin were identified as hot to warm moist and humid lowlands, hot to warm arid lowland plains, and tepid to cool moist mid-highlands. Drought risk management efforts in the future should prioritize those AEZs. The Awash Basin Authority can work with local government offices in drought-affected places to highlight drought management, prioritizing such AEZs.
- The study findings suggested that higher exposure and sensitivity of farmers' livelihood to drought are associated with climate variability and drought incidents, hence crop failure and production reduction that lowered the adaptive capacity of the farmers. This could be highly related to the moisture stress and overexploitation of the farmlands in the basin. Crop and livestock insurance programs for smallholders are thus recommended, particularly for rainfed-dependent farmers in highland and lowland AEZs, even though management options to increase moisture, such as irrigation schemes and soil and water conservation practices, are possible.
- The study's results on the farm typology-based livelihood vulnerability to drought in the upper Awash sub-basin indicated that intensive-irrigation-based farmers are better at adapting to the impacts of drought as their wealth, asset base, and livelihood diversification are better than the marginal-off-farm-based farmers. However, the involvement of local brokers in selling their irrigation products is becoming intense and reducing their benefits.

Hence, to minimize market distortion that affects farmers, it may be necessary for local government to create farmers' cooperatives, actively include farmers in the market value chain, and limit the involvement of brokers by enforcing regulations.

- The generated scientific data on smallholder farmers' livelihood vulnerability to drought at the farm typology level can be used to identify farm households based on their farm typology and design and implement local-level drought risk management in future farmers' resilience-building initiatives. Training development agents on farmers' livelihood vulnerability to drought could enable them to reassure smallholder farmers on how to apply adaptation and mitigation measures in their specific localities.
- Finally, it was revealed that participation in the SSI improved most of the farmers' livelihood capital. Involving non-irrigator farmers in irrigation schemes may therefore improve their ability to improve their livelihood capital. However, this may result in increased demand for the scheme's available irrigation water supply and possibly the poor overall performance of the SSI scheme. As a result, future policy initiatives could include increasing the productivity of available water and adequately allocating water between upstream and downstream. Local farmers' participation in regular soil and water conservation practices can improve water efficiency in response to rising SSI utilization demands.

6.6. Future Research Areas

Although the drought analysis was carried out at the Awash basin level, the vulnerability of farmers to drought and the impact of irrigation on farmers' livelihoods were limited to the upper Awash sub-basin, with only three districts and 396 sample households covered. This was due to financial constraints, which hampered the collection of socioeconomic survey data at the basin level. As a result, future studies should better cover the basin in survey data to triangulate climate data with household perception data.

Moreover, due to the low performance of the SWAT model in larger geographic areas (since datasets simulated in the model are bulk), the surface water availability analysis was restricted to the Akaki catchment in the upper Awash sub-basin. This made it difficult to compare the surface water availability with drought incidents in the basin's AEZs. Hence, study designs that apply powerful models that can simulate bulk data at the basin level are highly recommended in the future.

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Appendix I. Glossary

In the context of the current study, the basic concepts and terms are defined in the following way:

Surface water availability – water stored on the surface of the earth that has the potential to be used for different purposes.

Surface runoff – down-the-slope water movement exclusively over the soil surface, mostly during heavy rain.

Total water yield – the amount of water in the catchment that remains after evapotranspiration, measured annually.

Lateral soil flow – concentrated water and solute flow travel laterally along a sloped soil-layer interface.

Percolation out of soil – the amount of water moving from soil layers due to capillary and gravity forces.

Total aquifer recharge – the total volume of water moving from the land's surface unsaturated zone to the saturated zone.

Potential evapotranspiration – the amount of moisture that would be used if sources were limitless and there was a full vegetative cover.

Land use land cover change – the alteration of the current land use and land cover or total conversion to new use and the cover type, primarily due to anthropogenic influences.

Meteorological drought – a prolonged lack of precipitation (or moisture availability) (e.g., weekly, monthly, seasonal or annual timescales).

Agroecological zones – areas on the surface of the earth defined by their core characteristics, such elevation, temperature, rainfall, major crops and livestock produced, dominant economic activities, and crop growing period.

Farm typology – a group of farmers with similar socioeconomic characteristics and agricultural practices.

Intensive irrigation farming – a type of farming where irrigation is used more frequently than rain-fed farming.

Cluster analysis – a sequential splitting analysis method that works better with some types of problems than others.

Livelihood – a means of living for smallholder farmers.

Livelihood capitals – the five livelihood capabilities including human, physical, natural, financial, and social aspects.

Appendix II: Household Survey Questionnaire

Addis Ababa University

College of Development Studies

Centre for Environment and Development

Ph.D. Program in Environment and Development

Household Survey Questionnaire

Dear respondents,

This survey questionnaire aims to collect data for the study "**Analysis of Surface Water Availability, Drought and the Impact of Small-Scale Irrigation on Farmers' Livelihood in Upper Awash Sub-Basin, Ethiopia**." This study partially fulfils the requirement of the Ph.D. degree in Development Studies (Specialization in Environment and Development) at Addis Ababa University. Hence, the data provided by you will have a huge significance in meeting the objectives of this study. Accordingly, you are kindly asked to provide genuine and correct data. I want to assure you that your responses will be kept confidential and used for academic purposes only.
I appreciate your willingness!

MODULE 1: HOUSEHOLD IDENTIFICATION

N	**Date of the enumeration:**	**Time: Start: Finish:**
1.1	HH identification number:	
1.2	Zone: 1=West Shewa 2=East Shewa	
1.3	*Wereda*: 1=Dendi 2= Ada'a 3= Fentalle 4=Other _______________	
1.4	*Kebele*:	
1.5	Village/Gott:	
1.6	Agro-ecology type: 1=Highland 2= Midland 3=Lowland	
1.7	GPS Reading: Latitude=___________ Longitude=___________ Elevation (m) =___________	
Enumerator name: _______________________		**Signature: _____________**

MODULE 2: BASIC DEMOGRAPHIC INFORMATION

2.1. Relation to the head **[Code 1]**	**2.2.** Age (Write in years)	**2.3.** Sex **[Code 2]**	**2.4.** Marital status **[Code 3]**	**2.5.** Family size [in number]	**2.6.** Religion **[Code 4]**	**2.7.** Highest level of education (completed) [For education levels different from 1-12*]* ***[Code 5]***	**2.8.** Length of years in the current residence [write *years]*	**2.9.** Occupation **[Code 6]**	
								Main	Secondary

Codes for 1:1= Head 2= Wife/Husband/Partner3= Son/daughter 4= Grandchild 5= Father/Mother 6= Sister/Brother 7= Niece/nephew 8= Uncle/Aunt 9=Son/Daughter-in-law 10= Father/Mother-in-law 11= Brother/Sister-in-law 12= Grandparent 13= Other relative of head or of his/her spouses 14=Servant (farm worker, herder, maid) 15= other (specify) ______________

Codes for 2: 1=Male 2= Female

Codes for 3: 1=Married, single spouse; 2= Married with more than one spouse/ polygamous; 3=Single; 4=Divorced; 5=Widowed; 6= Separated

Codes for 4: 1=Orthodox; 2=Muslim; 3=Catholic; 4=Protestant, 5=Waqefeta; 6= other (specify) ______________

Codes for 5: 0=Cannot read and write; 13=10+1; 14=10+2; 15=10+3; 16=Certificate; 17=Diploma; 18=Degree; 19=Masters and above; 20=non-formal education (can read and write); 21=KG (Completed)

Codes for 6: 1=None, 2=Farmer; 3=Farm assistant, 4= Salaried work; 5=Student; 6= Farming/crop production and sales; 7= Livestock production and sales; 8=Non-farm product trader; 9=Beverage (*tella*, *tej*, *areke*, etc), 10= Wage labor (local); 11=Pensioner; 12=Handicraft, 13=Mining, 14=Carpentry, 15=House help, 16= Sale of wild/bush products (including charcoal;17=blacksmith 18=Broker; 19=looking for work 20=other (specify) ______________

MODULE 3: LIVELIHOOD STRATEGIES

3.1. How many varieties of crops have you produced in the past production year? 1= only one 2=two 3=three 4=four 5=More than four (specify the number)_______________

3.2. Mention the varieties of crops, your production amount, and estimated annual income in table 3.1:

Table 3.1: **Variety of cropping and its estimated annual income**

Type	**Production amount [Kg]**	**Estimated annual income [Birr]**	**Type**	**Production amount [Kg]**	**Estimated annual income [Birr]**
A. *Teff*			K. Potato		
B. Sorghum			L. Carrot		
C. Maize			M.Garlic		
D. Wheat			N. Chili peppers		
E. Haricot bean			O. Cabbage		
F. bean			P. Beetroot		
G. Pea			Q. Orange		
H. Lentil			R. Banana		
I. Onion			S. Mango		
J. Tomato			T. Avocado		
Other:			Other:		

3.3. Have family members migrated to cities and other places seasonally to get employment opportunities? 1=Yes 2=No

3.4. If yes, for QN #3.3., what is their number? _____________people

3.5. Has any of your family members engaged in off-farm activities? 1=Yes 2=No

3.6. If yes, for QN #3.5., what is their number? _____________people

3.7. Have you generated income from homestead gardening? 1=Yes 2=No

3.8. If yes, for QN #3.8., what is the estimated annual income? ________Birr

3.9. Have you generated income from perennial plants [coffee, mango, avocado, papaya]? 1=Yes 2=No

3.10. If yes, for QN #3.9., what is the estimated annual income? _________Birr

3.11. Have you planted and harvested crops considering the best time? 1=Yes 2=No

3.12. If yes, for QN #3.11., what is the timing? 1=early plantation 2=late plantation 3=early harvesting 4=late harvesting 5=others (specify) ________________

MODULE 4: HUMAN CAPITALS

4.1. Do you have access to health care institutions near your locality? 1=Yes 2=No

4.2. How many hours do you travel to access the nearest health institution? _______ hours

4.3. If yes, for QN #4.1, have you benefited from access to these health institutions? 1=Yes 2=No

4.4. Do you have access to education institutions near your locality? 1=Yes 2=No

4.5. How many hours do you travel to access the nearest education institution? _______ hours

4.6. If yes, for QN #4.4., have you benefited from the access to these educational institutions? 1=Yes 2=No

4.7. Do you think that your family is food secure all the year? 1=Yes 2=No

4.8. How many varieties of food do you consume in a day on average? 1= only one 2=two 3=three 4=four 5=More than four (specify the number)______________

4.9. What is the number of unemployed person in your family? ________person

MODULE 5: SOCIAL CAPITALS

5.1. Do you access market information (input availability, input, output price, buying and selling times)? 1=Yes 2=No

5.2. Is anyone from your family a member of farmers' associations/unions? 1=Yes 2=No

5.3. Is there anyone from your family who is a member of WUA in your community? 1=Yes 2=No

5.4. Is anyone from your family a member of "*edir*" in your community? 1= Yes 2=No

5.5. How many "*edirs*" do you have as a family? 1= only one 2=two 3=three 4=four 5=More than four (specify the number)______________

5.6. Do you think the Water Users Associations are trusted to allocate irrigation water fairly? 1=Yes 2=No

5.7. Rank [from 1 to 5] the social capitals based on their contribution to your household's adaptive capacity:

Social capitals	**Perceived rank**
Accessing market information easily has assisted me in my agricultural work	
Being a member of farmers' associations/unions has increased my income	
Being a member of WUA has helped me to access irrigation water	
Being a member of "*edir*" decreased my social life burdens	
Having trusted WUA members helped me to access irrigation water	

MODULE 6: PHYSICAL CAPITALS

6.1. Do you have full agricultural equipment? 1=Yes 2=No

6.2. Could you please tell us the number of productive assets you own currently, the number of each asset, and the cash equivalence of each asset in Birr?

Table 6.1: **Productive assets**

Type of assets	**Response 1=Yes; 2=No**	**If yes, for each number of assets owned**	**Cash equivalence of the asset**
1. Axe (Metirabia)			
2. Knife (Billa)			
3. Sickle (machid)			
4. Spade (Akafa)			
5. Hoe(doma)			
6. Bucket (Baldi)			
7. Grain mill(weficho)			
8. Plough(maresha)			
9. Plow/Yoke/ Kenber			
10. Plow/ Beam/			
11. Plow/Share			
12. Horse/Mule/Ox Cart			
13. Modern beehive			
14. Traditional beehive			
15. Weaving equipment			
16. Gotera or Dibignit			
17. Hammer (fas or martelo)			
18. Saw (megaz)			
19. Irrigation watering *jar*			

6.3. Could you please tell us the number of household assets you own currently, the number of each asset, and the cash equivalence of each asset in Birr?

Type of assets	**Response 1=Yes 2=No**	**If yes, the number of assets owned**	**Cash equivalence in Birr**
1. Blankets/buluko/gabis			
2. Bed (alga)			
3. Chairs/Berchuma			
4. Tables			
5. Cupboard (Sanduk/Kumsatin)			
6. Leather Mat (Kurbet, Agoza, Debdab)			
7. Flashlight (torch)			
8. Watch/clocks			
9. Kerosene stove			
10. Radio/cassette player			
11. DVD player			
12. Television			
13. Refrigerator			

14. Mobile phone			
15. Bicycle			
16. Motor bicycle			
17. Bajaj			
18. Car			
19. Plowing machine (Tiraktor)			
20. Harvesting machine (Kombainor)			
21. Iron (Kawuya)			
22. Leather Pouch (Silicha)			
23. Mechegia (Leather Sofa)			
24. Jewelry/Gold/Maria Theresa Coin, Ring			
25. Guns (Tebmenja)			
26. Spear/Sword (Gorade)			
27. Shield (Gasha)			

6.4. Do you have access to transport to move your inputs and products to places you need them? 1=Yes 2=No

6.5. How long do you travel to reach the nearest marketplace in your locality? _________Minutes

6.6. Do you have access to a marketplace to buy inputs or sell your products? 1=Yes 2=No

6.7. Do you have access to electricity service in your home? 1=Yes 2=No

MODULE 7: NATURAL CAPITALS

7.1. Do you have access to land?

Yes = 1 No = 2

7.2. If yes for QN #7.1., describe your land in the following table:

Table 7.1: **Land access**

Land type	**Ownership type**		**Size Kada/Timad/Qarxii**[2]
A. Irrigation land	Owned	1=Farmed by owner	
		2= Shared-out	
		3=Rented-out	
	Rented	1= Shared in	
		2=Rented in	
B. Rain-fed land	Owned	1=Farmed by owner	
		2= Shared-out	
		3=Rented-out	
	Rented	1= Shared in	
		2=Rented in	

[2]Timad/Kada/Qarxii are local land measurement unit usually equivalent to 0.25 ha

7.3. Do you have access to irrigation water? 1=Yes 2=No

7.4. If yes, what are the main sources of water for your irrigation? 1=River 2=Lake 3=Ground water 4=Flood water 5=Other (Specify)______________________________

7.5. Do you catch fish from the nearby lakes and rivers? 1=Yes 2=No

7.6. If yes, for QN #7.5., for what purpose do you catch fish? 1=family consumption 2=Income generation from the sale 3=Both

MODULE 8: FINANCIAL CAPITAL

8.1. Did you have access to any cash credit service from any source during the last 12 months?

1= Yes 2= No

8.2. If yes, for QN# 8.1, please indicate your access to credit services, the amount, and the purposes of the loan.

No.	Source of credit	Amount of credit received in *Birr*	For what purpose did you receive the money? [use code 6]
1.	Marketing cooperative		
2.	Local money lender		
3.	Friends/relatives		
4.	NGOs		
5.	MFIs		
6.	Banks		
7.	Various funds		
8.	Religious institutions		
9.	Saving group		
10.	Women group		
11.	*Edir*		
12.	*Equib*		
13.	Others, specify		

Codes for 6: 1= Petty trade; 2 = Food grain purchase; 3 = Input purchase for crop production; 4 = Animal purchase; 5 = Other income generating activities; 6 = Repay debt; 7= others, specify

8.3.If no for QN # 8.1, what was the problem? 1= Did not want to take loan; 2=could not find a loan that met my needs; 3=Afraid I couldn’t pay back; 4= No loan providers in the locality; 5= others, specify _______________

8.4. Do you save cash as a household? 1=Yes 2=No

8.5. If yes, for QN # 8.4, where is the saving held? 1= Credit or micro-finance institution; 2=Banks; 3=Religious institutions; 4=Saving group; 5=Various funds; 6=Women's group; 7=Others specify__________________

8.6. What is the total amount of saving in *Birr*? __________________________

8.7. What is the primary purpose of saving? 1=To use in time of emergencies; 2=To buy livestock; 3=To buy agricultural inputs; 4=To pay debts; 5=Others specify_________________

8.8. Do any of the household members have existing debt from anyone? 1=Yes 2=No

8.9. If yes, for QN # 8.8, what is the total amount of credit to be paid? ___________________*Birr*

MODULE 9: SOURCES OF INCOME [ON-FARM, OFF-FARM, AND NON-FARM]

9.1. What are the sources of livelihood and estimated earnings for all household members? (Answer all that apply)?

Farming activities	**Codes** **(**1=Yes 2=No**)**	Estimated monthly income	Estimated yearly income
Crop production			
Livestock rearing			
Fruit production (Apple, mango, Banana)			
Beekeeping			
Off-farm activities			
Non-farm activities			
Other (specify)			

9.2. Do any of your household members work in activities apart from crop production? 1=Yes 2=No

9.3. If yes, for QN #9.2, what types of off-farm livelihood activities have you engaged in the last 12 months?

No.	**Type of off-farm activities**	**Participation code** **(**1=Yes 2=No**)**	**Number of months engaged in off-farm activities**	**Estimated annual income earned in *Birr***
1.	Sale of agricultural labor			
2.	Sharecropping (cash or food)			
3.	Sale of firewood or charcoal			
4.	Sale of grass or fodder			
5.	Sale of crop residue(straw, hay, stalks)			

6.	Sale of wood			
7.	Sale of fish			
8.	Petty trading (salt, soap, sugar, etc.)			
9.	Migratory labor (for a week or more)			
10.	Commission works			
11.	Remittances			
12.	Gifts/inheritance			

9.4. If yes, for QN #9.2, in which of the **non-farm** activities have you engaged in the last 12 months?

No.	**Type of non-farm activities**	**Participation code** **(**1=Yes 2=No**)**	**Number of months engaged in non-farm activities**	**Estimated annual income earned in *Birr***
1.	Trading grains and pulses			
2.	Trading livestock			
3.	Trading of fruits & vegetables			
4.	Drinks production and sales			
5.	Weaving /spinning			
6.	Carpentry			
7.	Pottery			
8.	Blacksmithing or metal work			
9.	Traditional healers	`		
10.	Renting out pack animals			
11.	Renting out land			
12.	Renting out machinery			
13.	Others (specify)			

9.5. For what purpose did you use the income obtained from off-farm/non-farm activities? (Multiple responses are possible) 1=Buy food; 2=Saving; 3=Buy clothes; 4=Pay taxes; 5=Pay loan; 6=Buy agricultural inputs; 7=others specify______________________

9.6. If you think that there is a challenge to engage in non-farm activities, what do you think are the possible reasons? (Multiple responses are possible) [**use tick [√]mark in front of the selection**]

1. Lack of spare time from agriculture		2. No employment opportunities	
3. Lack of awareness about its use		4. Jobs are too far away	
5. Lack of work skills		6. Poverty/lack of funds	
7. Unable to work due to old age		8. Income is intermittent	
9. Health problem		10. Others specify	

MODULE 10: LIVESTOCK OWNERSHIP/PRODUCTION

10.1. Indicate the number of livestock owned by the household and the estimated current value per each

Type	Number of livestock ownership status		Equivalence in cash currently (in *Birr*)
	Last year	This year	
1. Cows			
2. Oxen			
3. Bulls			
4. Heifers			
5. Calves			
6. Sheep			
7. Goats			
8. Camels			
9. Mules			
10. Horses			
11. Donkeys			
12. Chicken			
13. Bee colony			

MODULE 11: IRRIGATION TECHNOLOGIES

11.1. Do you perceive that cost of irrigation land is cheap? Yes = 1 No = 2

11.2. What is the cost of 1 *kada*/*timad*/*qarxii* irrigation land in your locality? ________*Birr*

11.3. Do you have a water sprinkler? Yes = 1 No = 2

11.4. If yes, for QN #11.3, how many do you have? ____________

11.5. Do you have a water pumping generator? 1=Yes 2=No

11.6. If yes, for QN #11.5, how many do you have? ____________

11.7. Do you use any of the water harvesting techniques? Yes = 1 No = 2

11.8. If yes, for QN #11.7, which water harvesting technology? 1=Ponds 2=Hand-dug wells 3=river/stream diversion 4=flood diversion 5=others (specify) _______________

MODULE 12: AGRICULTURAL INPUT USE AND CROP PRODUCTION

12.1. Would you list the type and amount of agricultural inputs you used in the 2010 E.C cropping year?

Type of agricultural inputs	Responses 1=Yes 2=No	Total amount used in Kg.	Total amount of costs	Total area covered using inputs (in Ha)

Chemical fertilizers	DAP				
	Urea				
	Blended fertilizer				
	Manure				
	Compost				
Pesticides					
Herbicides					
Improved seeds					
Others specify					

12.2. If there are constraints in using agricultural inputs, what are the problems? (Multiple responses are possible) 1=Drought/erratic rainfall; 2=High price of inputs; 3=Lack of cash; 4=Indebtedness; 5 =Farm land is inappropriate to use of fertilizers; 6=Crop disease; Excessive rain/flooding; 7=Unavailability of improved seed; 8=Untimely input distribution; 9= Other, please specify______________________

12.3. In general, what is the trend of your crop production for the following crop types over the last 5-10 years?

Crops produced	**Trends in crop production**				
	Highly decreased (1)	**Decreased (2)**	**No change (3)**	**Increased (4)**	**Highly increased (5)**
1. Maize					
2. Wheat					
3. Barely					
4. Teff					
5. Sorghum					
6. Peanuts					
7. Chickpea (shinbira)					
8. Bean (baqella)					
9. Pea (atar)					
10. Lentil (Misir)					
11. Enset					
12. Taro (Boye)					
13. Sweet potatoes					
14. Other					

12.4. What are the possible reasons for any increase in your cultivated land productivity? (Multiple responses are possible) 1=Increased soil fertility; 2= Improved seed supply; 3= Improved agrochemical use; 4= Improved use of organic fertilizer; 5=Suitable weather conditions/good rainfall; 6=Soil and water conservation practices; 7= Other, please specify______________________

12.5. What are the possible reasons for any decrease in your cultivated land productivity? (Multiple responses are possible) 1=Land degradation; 2=Lack of timely input supply; 3= Lack of oxen; 4=Erratic rainfall /variability;5=Drought; 6= Land scarcity; 7= Non-use of fertilizer; 8=Pests and crop diseases; 9= Other, please specify______________________

MODULE 13: FARMERS' PERCEPTION OF CLIMATE VARIABILITY OR CHANGE

13.1. To what extent would you agree or disagree that the options indicated in the table below apply as possible reasons for responses by your household to the climate trend (Changes in temperature and precipitation)

No.	Perception indicators	Level of agreement or disagreement (five-point scale)				
Change in temperature		Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
1	Temperature has increased					
2	No change in temperature					
3	Temperature has decreased					
4	Rainy season temperature has decreased					
5	Dry season temperature has increased					
6	Number of hot days in a year increased					
Change in Amount of rainfall						
1	Rainfall has increased					
2	No change in rainfall					
3	Rainfall has decreased					
4	Rainfall starts lately					
5	Early cessation of rainfall					
6	*Belg* rain has decreased					
7	Rainfall during the main rainy season has decreased					

MODULE 14: CLIMATE-INDUCED SHOCKS INDICATORS

14.1. Have you ever faced crop failure during the last five to ten years? 1=Yes 2=No

14.2. If yes, for QN# 14.1, what are the main reasons for crop failure? [Multiple response is possible] 1=Erratic rainfall; 2=Lack of Improved seeds; 3=Unaffordable price of inputs; 4=Low level of soil fertility; 5=Pest and disease; 6=Shortage of farm oxen; 7=Other (specify)_________________

14.3. Have you ever experienced flooding due to excessive rainfall over the last 10-20 years? 1=Yes 2=No

14.4. If yes, for QN# 14.3., how do you rate the frequency of flooding in your locality over the last 10-20 years? 5= Highly increased; 4= Increased; 3= No change; 2= Decreased; 1= Highly decreased

14.5. Have you ever experienced drought due to climate variability/change over the last 10-20 years? 1=Yes 2=No

14.6. If yes, for QN # 14.5., how do you rate the drought frequency in your locality over the last 10-20 years? 5= Highly increased; 4= Increased; 3= No change; 2= Decreased; 1= Highly decreased

1) Self-Reported Climate Related Shock Indicators

14.7. Please indicate your experiences with climate-induced shocks, frequency of occurrences over the last 10-10 years, and estimated costs of the damage due to the shocks

Experience of the following shocks	Frequency of shocks over the last (10-20 years)	Severity 1=High, 2=Medium, 3=low	Estimated costs of the damage on property/livelihood/health in *Birr*
1. Flooding			
2. Drought			
3. Crop failure			
4. Crop pests and diseases			
5. Livestock disease			
6. Infectious human disease/human health problem			
7. Food crisis			

14.8. Who has been affected most by the shocks mentioned above? 1=Men; 2=Women; 3=Children; 4=Elders; 5=All segment of the society

14.9. Do you perceive temperature has increased in your locality for the last 35 years? 1=Yes 2=No

14.10. Do you perceive rainfall has decreased in your locality for the last 35 years? 1=Yes 2=No

14.11. Has drought occurred in your locality? Yes = 1 No = 2

14.12. If yes, for QN #14.11., what is the occurrence frequency of the drought? 1=Every year 2=Every two years 3= Others ____________ years

14.13. If yes, for QN #14.11, how long does the drought stay in a year on average? ___________ Months

14.14. Have you encountered drought's crop productivity reduction/loss in the last production year? 1=Yes 2=No

14.15. If yes, for QN #14.14, what is the estimated amount of loss? ______________Kg.

14.16. Have you reported the crop productivity reduction/loss to the local administrators? 1= Yes 2=No

14.17. Have you encountered livestock death in the last production year due to drought? 1=Yes 2=No

14.18. If yes, for QN #14.17, how many? _____cattle; ____ equines; ____ goat/ship; ____camels; _______ chickens

14.19. Have you reported the livestock death to the local administrators? 1=Yes 2=No

14.20. Is there irrigation water scarcity in your locality? 1=Yes 2=No

14.21. If yes, for QN #14.20, in which months does the irrigation water get scarce? ____

14.22. Have you ever engaged in conflict with other farmers due to water use in your locality? 1=Yes 2=No

MODULE 15: IMPACTS OF SMALL-SCALE IRRIGATION ON THE LIVELIHOOD OF FARMERS

1) Expenditure on education and health care (Human capital)

15.1. Is anyone from your family going to an educational institution? 1=Yes 2=No

15.2. If yes for QN # 15.1., fill table 15.1 regarding the education expenditure you pay for each person under each category in a year:

Table 15.1: **Education expenditure (Birr)**

S.N.	Education category	Expenditure category	Average expenditure/person (a)	No. of people (b)	Total expenditure (a*b)
1.	Elementary & High school	1. Education fee			
		2. Uniform fee			
		3. Stationery fee			
		4. Transport fee			
		5. Pocket money			
		Subtotal			

2.	College	1. Education fee			
		2. Stationery fee			
		3. Transport fee			
		4. Pocket money			
		Subtotal			
3.	University	1. Education fee			
		2. Stationery fee			
		3. Transport fee			
		4. Pocket money			
		Subtotal			
Grand total education expenditure					

15.3. Does your family have health insurance? 1=Yes 2=No

15.4. If yes, for QN # 15.3., how much do you pay in a year? ________ Birr/ year

15.5. Is the health insurance you pay enough for your family's health expenditure? 1=Yes 2=No

15.6. If no, for QN #15.5, how much do you add to the health insurance? ___________ Birr/year

15.7. If no for QN #15.3, fill table 15.2 based on your family's annual health expenditure:

Table 15.2: **Health expenditure (Birr)**

S.N.	**Member type**	**Avg. Expenditure (a)**	**Number (b)**	**Total expenditure (a*b)**
1.	Wife/Husband			
2.	Children			
3.	Other/s			
Grand total health expenditure				

2) Expenditure on agricultural equipment and inputs (Physical capital)

15.8. Have you bought any agricultural equipment in the last production year? 1=Yes 2=No

15.9. If yes for QN #15.8, fill table 15.3 based on the expenditure on the equipment you bought:

Table 9: **Expenditure on agricultural equipment (Birr)**

S.N.	**Equipment type**	**Avg. Expenditure (a)**	**Number (b)**	**Total expenditure (a*b)**
1.				
2.				
3.				
4.				
5.				
6.				
7.				
8.				
Grand total equipment expenditure				

15.10. Have you bought agriculture inputs in the last production year? 1=Yes 2=No

15.11. If yes for QN #15.10, use table 15.4 to describe the inputs you bought:

Table 15.4: **Expenditure on agricultural inputs (Birr)**

S.N.	**Input type**	**Avg. Expenditure/Kg or /Liter (a)**	**Amount Kg or Liter (b)**	**Total expenditure (a*b)**
1.	Modern seed			
2.	Fertilizer			
3.	Pesticide			
4.	Herbicide			
5.	Manure[3]			
6.	Compost [4]			
Grand total input expenditure				

3) Expenditure on rented agricultural land (Natural capital)

15.12. Have you rented agricultural land during the last production year? 1=Yes 2=No

15.13. If yes for QN #15.12, fill in table 15.5 regarding the expenditure on the agricultural land you rented in:

Table 15.5: **Expenditure on rented agricultural land (Birr)**

S.N.	**Rented land type**	**Land size in *kada*/timad '*Qarxii*' (a)**	**Cost/ kada/timad/ '*Qarxii*' (b)**	**Total expenditure (a*b)**
1.	Rain-fed			
2.	Irrigation			
Grand total agricultural land expenditure				

4) Expenditure on '*edir*[5]' (Social capital)

15.14. Do you have a membership of '*edir*' in your locality? 1=Yes 2=No = 2

15.15. If yes for QN #15.14, use table 15.6 to characterize the annual payment for 'edir' you are in:

Table 15.6: **Expenditure on '*edir*'(Birr)**

S.N.	**'*Edir*' type**	**Number of '*edir*' (a)**	**Payment/ '*edir*' (b)**	**Total expenditure (a*b)**
1.	Males'			
2.	Females'			
Grand total '*edir*' expenditure				

[3] Estimated cost

[4] Estimated cost

[5] '*edir'* is a locally organized payment which is collected on the monthly basis and given to family during a family during marriage, death or other family issues

Appendix III: Key Informant Interview Guide

Addis Ababa University

College of Development Studies

Centre for Environment and Development

Ph.D. Program in Environment and Development

Interview Guide for selected individuals

- What are the major sources of your livelihood?
- What are the challenges related to drought in your locality?
- Have you perceived climate change in terms of rainfall and temperature in your area?
- How much is your livelihood vulnerable to the impacts of climate change in general and drought in particular?
- What are the main challenges related to your livelihood?
- Do you use small-scale irrigation? If yes, could you tell me about your engagement, challenges, and opportunities related to participation in SSI?
- If no, tell me your perception about utilizing SSI as a supplementary for rainfed agriculture. What makes non-user of the SSI?
- What suggestions do you have to improve your current livelihood condition? How? What is expected from who?

I appreciate your cooperation.