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SYNERGIES AND TRADE-OFFS BETWEEN FOOD SECURITY STATUS WITH *PROSOPIS JULIFLORA* (SWARTZ DC.) INVASION AND CLIMATE VARIABILITY IN MIDDLE AWASH, AFAR REGION, ETHIOPIA

BY

AMEHA TADESSE

A DOCTORAL DISSERTATION SUBMITTED TO CENTER FOR FOOD SECURITY AND DEVELOPMENT STUDIES, COLLEGE OF DEVELOPMENT STUDIES, ADDIS ABABA UNIVERSITY

PRESENTED IN FULFILLMENT OF THE REQUIREMENTS FOR PH.D. DEGREE IN FOOD SECURITY AND DEVELOPMENT

ADDIS ABABA UNIVERSITY
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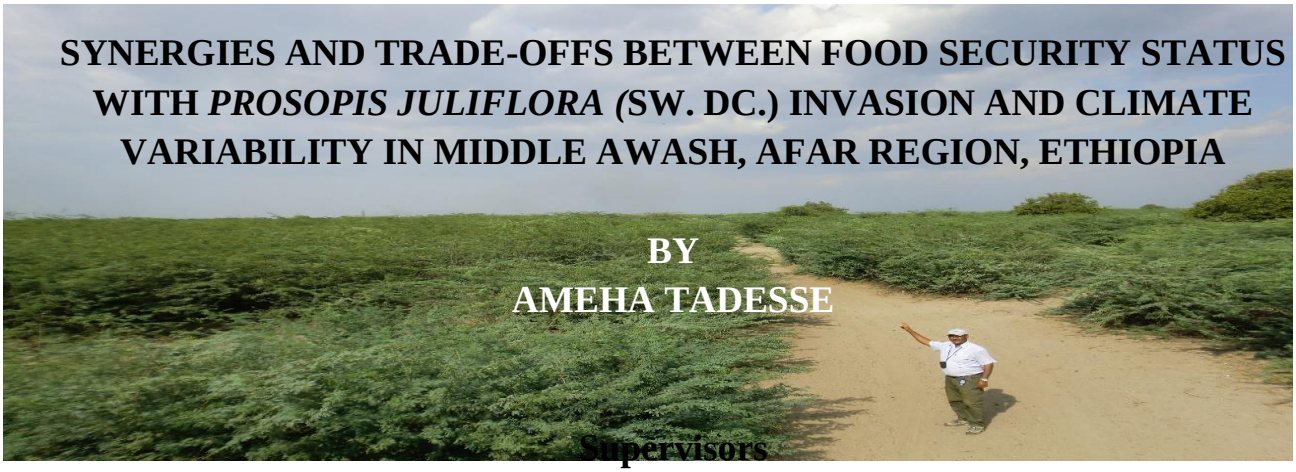

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Approval Sheet

This is to certify that the dissertation prepared by **Ameha Tadesse** entitled **"Synergies and Trade-offs between Food Security status with *Prosopis juliflora (*Swartz DC.) invasion and climate variability in middle Awash, Afar region, Ethiopia"** and submitted in fulfillment of the requirements for the degree of Doctor of Philosophy in Food Security and Development complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Dedication

Memory of my father Tadesse Aytenfisu Desta

Declaration

I, the undersigned, hereby declare that this Ph.D. dissertation is a result of my research investigations and findings. It has not been submitted to any other University for any academic degree and all the resources and materials used have been fully acknowledged.

In presenting this dissertation in fulfillment of the requirements for the degree of Doctor of Philosophy in Food Security and Development, I grant to Addis Ababa University the nonexclusive royalty-free right to archive, reproduce, distribute, and display in any form including electronic format, via any digital library mechanisms maintained by the University.

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Autobiography

Ameha Tadesse Aytenfisu is currently pursuing a Ph.D. at the Center for Food Security Studies within the College of Development Studies at Addis Ababa University. With over 25 years of professional experience, his expertise spans various domains including dryland agricultural research, sustainable development, humanitarian assistance, and activities focused on food security and resilience building. He holds both a bachelor's and master's degree in forestry, providing him with a robust academic foundation in natural resource management, biodiversity, and ecology. During his work at the Ethiopia Agricultural Research Institute, specifically at the Melka Worer Research Center, Ameha researched into the impact of invasive alien tree species, particularly on *Prosopis juliflora*, its impact on biodiversity and soil physico-chemical properties. His research in this area reflects his deep understanding of the historical context and the environmental challenges posed by invasive species in Ethiopia. Motivated by his academic background and comprehensive knowledge of the local context, Ameha's current research focus is on assessing the impact of *Prosopis juliflora* on the food security of pastoral and agropastoral communities. This endeavor not only underscores his commitment to addressing pressing environmental and socio-economic issues but also highlights his dedication to contributing meaningfully to the well-being of vulnerable communities in the region.

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Acronyms

ATT	Average Treatment effects
CDRC	Centre for Dialogue, Research and Cooperation
CSA	Central Statistical Agency of Ethiopia
CV	Coefficient of Variation
DOS	Dark Object Subtraction
ESVs	Ecosystem Service Values
FAO	Food and Agriculture Organization of the United Nations
FDRE	Federal Democratic Republic of Ethiopia
FIES	Food Insecurity Experience Scale
FS	Food Secure
HFIAS	Households Food Insecurity Access Scale
IFAD	International Fund for Agricultural Development
IRT	Items Response Theory
Landsat 8OLI	Landsat 8 Operational Land Imager
Landsat TM	Landsat Thematic Mapper
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
LULCC	Land Use Land Cover Changes
MFI	Moderate Food Insecure
MK test	Mann-Kendal test
MRA	Minimum Recommended Allowance
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red
OA	Overall Accuracy
OLI	Operational Land Imager
PA	Producer Accuracy
PSM	Propensity Score Matching
SFI	Sever Food Insecure
SPI	Standardized Precipitation Index
UA	User Accuracy
USGS	Unites State Geological Survey
WFP	World Food Program

List of published and accepted papers

Submitted and published articles:

1. **Paper1.** Ameha Tadesse, Degefa Tolossa, Solomon Tsehaye, Desalegn Yayeh, Aramde Fetene, Tekalign Zewdu (2023). Dynamics of Land Use and Land Cover Changes in *Amibara* and Awash-Fentale Districts, Ethiopia, *Journal of Remote Sensing Applications: Society and Environment) (published).*
2. **Paper 2.** Ameha Tadesse, Degefa Tolossa, Desalegn Yayeh, Solomon Tsehaye (2023). Spatiotemporal Climate Variability and Extremes in Middle Awash Afar region Ethiopia: Implications to Pastoralists and Agro-pastoralists Food Security. *International Journal of Climate Change Strategies and Management (published)*
3. **Paper 3.** Ameha Tadesse, Degefa Tolossa, Desalegn Yayeh, Solomon Tsehaye (2023). Impacts of Prosopis juliflora (Swartz DC.) on Food Security of pastoral and agro-pastoral communities in middle Awash, Afar region of Ethiopia. *Journal of Sustainable Development in Africa (Accepted (published).*
4. **Paper 4.** Ameha Tadesse, Degefa Tolossa, Desalegn Yayeh, Solomon Tsehaye (2023). Determining the status of food insecurity of households in *Prosopis juliflora (*Swartz DC.) invaded and non-invaded areas in Afar Region. An application of the Rasch model. (*Journal of Sustainable Development in Africa (published)*

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Abstract

Prosopis juliflora invasion has become a serious issue in Afar, Ethiopia, particularly affecting the districts of Amibara and Awash-Fentale. This study investigated the interconnected impact of P. juliflora on land use, climate variability, and food security among pastoral and agro-pastoral communities in these areas. A mix of quantitative and qualitative methods was employed, involving household surveys, key informant interviews, and focus group discussions. A total of 438 households were randomly selected for the study. The research also utilized meteorological data from 1988 to 2018.The study found significant land use and land cover changes (LULCC) in both districts. In Amibara, a highly invaded area, there were notable shifts from 1985 to 2021, with an increase in Prosopis-dominated shrubland and concentrated agriculture. In contrast, Awash-Fentale saw a decrease in bare land dominance, with expansions in agriculture, built-up areas, and shrubland. Climate analysis revealed a declining trend in seasonal and annual rainfall, accompanied by rising temperatures and frequent droughts, exacerbating the food security challenges for pastoral and agro-pastoral households. Econometric analysis indicated that households in invaded areas were more likely to have fewer livestock assets and less access to veterinary and government support services. The Average Treatment Effect estimation showed that households in invaded areas had on average, 1,167 Birr lower annual consumption expenditure compared to those in non-invaded areas. The study found that only 3% of households in invaded areas were food secure, compared to 28% in non-invaded areas. Severe food insecurity was higher in invaded areas (50%) compared to non-invaded areas (43%), while moderate food insecurity affected 47% of households in invaded areas versus 30% in non-invaded ones. The prevalence of food insecurity was significantly higher in Amibara, the Prosopis-invaded district. In conclusion, the invasion of P. juliflora has significantly harmed food security in Afar, reducing livestock, food consumption, and access to essential services. The study calls for immediate action from stakeholders, including private sectors and local administrations, to address the policy implications and mitigate the ongoing threat to food security in this region.

Key words: *Climate changes, Food security, Invasion, Land use and land cover change Pastoralist, Prosopis juliflora, welfare*

CHAPTER 1: INTRODUCTION

1.1. Background of the Study

Invasive alien species are species that are introduced intentionally or unintentionally into new areas and cause loss on an environment they invade (Shiferaw et al., 2018). *Prosopis juliflora* is one of the worst invasive alien species in the world (Lowe et al., 2000). It is a perennial green tree or shrub which expands by overtaking other land uses such as woodlands, grazing lands, and farmlands, which had reduced their ecosystem services of the land uses (Rai & Singh, 2020; Shiferaw et al., 2018).

Prosopis juliflora (hereafter *P. juliflora*) is native to the Caribbean, North and South America and has transported into other places through human activities (Pasiecznik et al., 2001; Shiferaw et al., 2020; Wakie et al., 2016). It was introduced to African countries, for instance, since 1822 in Senegal, South Africa in 1880, Egypt in 1900, Kenya since 1973, and into Eritrea from Sudan probably during the early 1980s (Shiferaw et al., 2018). It has been declared as noxious weed in many of these countries including in Argentina, Australia, India, Africa, Pakistan, and USA, where it forms impenetrable thickets (FAO, 1990; Pasiecznik et al., 2001).

In Ethiopia, *P. juliflora* was introduced early in the 1970s, with the belief that it would adapt and reclaim the dryland environment successful and would improve the livelihood of the pastoral and agro-pastoral communities of Afar by providing fuel wood, fodder and income (Mehari, 2015a; H Shiferaw et al., 2019; Wakie et al., 2014). Some studies rather confirmed that *P. juliflora* has been causing challenges on the livelihood of the pastoral and agro-pastoralists communities of Afar and some other parts of the country (Bekele, Haji, et al., 2018b; Ilukor et al., 2016a; Zeray et al., 2017b).

Yet, different countries utilize *P. juliflora* for different purposes. Its pods have nutritive value as a food for human and as feed for animals in the arid and semi-arid regions (Harden & Zolfaghari, 1988; Pasiecznik et al., 2001). *P. juliflora* is also used for firewood and charcoal and has high timber quality(Nigatu et al., 2012). Its wood is used for making parquet/ wooden floors, furniture, turnery items and fence posts (Duke, 1983; Felker & Bandurski, 1979). *P. juliflora* is also recognized for its positive effect on soil amelioration in arid and semiarid areas. *P. juliflora*

increases the organic matter of the soil, hence raises the contents of exchangeable base cations like Calcium (Ca) content in the soil (Pasiecznik et al., 2001). Therefore, the afforestation of dryland soils with *P. juliflora* especially on soils with high sodic properties, has received increased attention as a means of restoring the productivity of these sites (Bhojvaid & Timmer, 1998) and hence contributing for improvement of food security.

Despite these advantages, however, this invasive alien species has been creating problems to the ecosystems, biodiversity, health, economic, social and several aspects of human welfare (Bongers & Tennigkeit, 2010; Pasiecznik et al., 2001). It reduced palatable grasses of livestock and replaced grass and valuable woody species, changing the land use land cover (Shiferaw et al., 2019; W. Shiferaw et al., 2019). *P. juliflora*, can easily grow and reclaim degraded grasslands and wastelands and suppress the growth of other valuable trees species (FAO, 1990; Shackleton et al., 2014). *P. juliflora* resulted also in economic hardship, placing constraints on economic growth, poverty alleviation, and food security in Afar region (Admasu, 2008; Haile, 2008; Seid et al., 2020a). It caused harm or is likely to cause harm to the environment, people, economy, or human health (Shiferaw et al., 2019). Millions of dollars have been spent annually around the world to eradicate *P.juliflora* by means of wide range of herbicides, by mechanical and manual removal and by the application of used motor oils on the cut stumps. However, some of the methods are effective for a short period, but *P.juliflora* generally returns later (Pasiecznik et al., 2001) and no cost-effective solutions have been found so far. When there is an increase of invasive abundance, the cost of management increases and the benefit reduced (Shackleton et al., 2014) which becoming the management challenges. The rapid expansion of *P.juliflora* leads to a continuous land use land cover changes and degradation of agricultural and pasture lands, eventually contribute for the reduction of crop and livestock production and becoming food security concerns for the pastoral and agropastoral communities. The potential risk of *P. juliflora* invasion increases with increase of mean temperature and arid and semi-arid lands are at higher risk of invasion compared with other moist areas (Dakhil et al., 2021). Besides, water use of *P.juliflora* is increasing with increase of it coverage and has a serious impact on water availability of Afar region (Shiferaw et al., 2021). It has deep root system that can tap into groundwater resources and potentially reduce the water table and affecting water availability leading into drier conditions and increases the drought situation in the area which impacts the livelihoods of pastoralists leading to economic losses and food insecurity.

In Ethiopia, the (Ethiopia & Headquarters, 2019) estimate shows that 25.5% of the people experiences food insecurity, with varying levels across regions. For instance, the highest percentage of food insecure households is recorded in Amhara region (36.1%), followed by Afar (26.1%) and Tigray (24.7%). About 22.7% of rural households and 13.9% of urban households are food insecure (Ethiopia & Headquarters, 2019). The food security situation has been increasingly becoming worst from time to time in Tigray, northeastern Amhara and Afar due to drought and conflicts. More than 21.5 million people require humanitarian assistance, including 15.4 million children and women and nearly 4.4 million displaced people (OCHA, 2024).The average monthly household expenditure in Afar was 775 birr (Ethiopia & Headquarters, 2019) and the study made by (Hirvonen & Wolle, 2019) in Afar also confirmed as there was none (0 percent) of the rural children and 10.1 percent of the urban children met the minimum dietary diversity. The same source also indicated that only about 11% of the households in Afar consumed from more than six food groups and the total calorie production declined by 6 percent between 2012 and 2015. The rapid expansion of *P. juliflora* in the Afar region exacerbates the transformation of land use patterns, reductions of biodiversity and rangeland productivity leading to interrelated livelihood and food insecurity concerns.

This study aims to bring together the issue of land use land cover changes, climate variabilities and food security in relation with the impact of rapid expansion of *P. juliflora* in the areas for better management and policy formulation towards reducing the adverse effect of it.

1.2. Problem statement and rationale

The agriculture sector is highly affected by different environmental calamities including invasion of noxious plant species (FDRE-MoA, 2017). Most of the Ethiopia population are smallholder farmers and pastoralists who are highly dependent on agriculture, livestock and natural resources for their survival and livelihoods. Especially in dry lowland areas, where pastoralist and agro-pastoralist is mainly practiced, the communities are highly affected by invasive plant species (Andersson, 2005)

In Afar, *P. juliflora* has been affecting the daily activities and livelihood system of pastoralists and ecosystem of the area. As per the information from the FGD, the current view of the people on *P. juliflora* is overwhelmingly on the side of its harmful effects. Some key informants mentioned, they consider it as "devil tree" although some of its effects are beneficial or potentially useful. As indicated above, *P. juliflora* has been invading agricultural and grazing lands, competing with native trees, affecting both human and animal health, and hence expected to contribute for food insecurity. The potential agricultural lands, vast areas of wet- and dry-season grazing lands particularly in Zone 3 (*Amibara* and *Gewane*) and Zone 1 (*Asayita* and *Mile*) areas of the region have been heavily invaded by *P.juliflora*.

Though the agricultural development enterprises in the area have spent much money in clearing of *P. juliflora* from their farms, it is still a huge problem in the area (information from KII). The local pastoralists have been highly disturbed by the invasion of wet and dry seasons grazing lands and wasting much of their time and money in search of open grazing pasture lands and seasonal settlement sites. In addition, valuable and indigenous native tree species of the area have also been gradually disappeared since the introduction of *P.juliflora* in to the Region (Shiferaw et al., 2022b; Taye et al., 2004). It has been reported that *P. juliflora* has inhibited the germination and growth of many plant species growing in its vicinity due to its an allelopathic substance exude from its leaves, roots and fruits (Al-Humaid & Warrag, 1998; Getachew et al., 2012). Currently, it is observed that most desirable native trees and grass species of Afar region such as *Acacia nilotica, A. tortilis, Cadaba rutinidifolia, Dobira glabra, Cordia sinensis* and *Salvadora persica* are gradually disappearing and being replaced by *P. juliflora* bushland. Besides, studies showed that the change of perennial grasslands into annual grasslands or to barren land by 25% since 1986 (Shiferaw et al., 2018). In addition, the increase of *P.juliflora* invasion has resulted in loss of indigenous grasses and other plant species which in turn contributing for the substantial reduction of the number and productivity of livestock in Afar (Hamedu, 2014; Haregeweyn et al., 2013; Yosef et al., 2013). Related studies also indicated that cattle and camel populations in the *Amibara* district declined at a rate of 36% and 20%, respectively, between 1997 and 2011 (Ilukor et al., 2016a). Previously known the richest pastoralists for having large cattle herds in Afar have appeared to live under conditions of chronic food insecurity (Rettberg, 2010). Still livestock are owned by wealthier households (Catley, 2017). The number of livestock is declining as households are selling off animals to buy food, and about 64% of the rural Afar households are consuming

only three or fewer food groups out of seven (Ethiopia & Headquarters, 2019; Ilukor et al., 2016a). Afar Region has also households with the highest food expenditure and malnutrition as well as the lowest household cereal stock per capita (1 kg/person) at any given time (WFP, 2009).

On the other hand, semi-arid and arid regions like Afar and Somali are highly vulnerable to climate change. Study on climatic suitability for *P. juliflora* under two climate scenarios (RCP4.5 and RCP8.5) in Ethiopia indicated that 94.8% of the country was non-suitable for *P. juliflora* establishment are becoming highly suitable as per the two models(Sintayehu et al., 2020b). In 2050, highly suitable area for *P. juliflora* is expected to increase by 55.6% and 63.6%, while moderately suitable area is projected to increase by 33.3% and 42.9%, in semi-arid and arid regions, respectively (Sintayehu et al., 2020a). This revealed that the climatic suitability for *P.juliflora* invasion will increase and create conducive environment for *P.juliflora* expansion and threatening the livelihoods of the community.

In general, climate change has been affecting all four dimensions of food security: food availability, food accessibility, food utilization and food systems stability (Al et al., 2008b). People who are already vulnerable and food insecure are likely to be the first affected by climate induced crises. Study shows that an average of 500 weather-related disasters are taking place each year, compared with 120 in the 1980s and more people are being affected by catastrophic weather events (Al et al., 2008a). This will have continuous impact on human health, livelihood assets, food production and distribution channels, as well as changing purchasing power and market flows. Agriculture-based livelihood systems that are already vulnerable to food insecurity face immediate risk of increased crop failure, new patterns of pests and diseases, lack of appropriate seeds and planting material, and loss of livestock.

So far, some research activities were conducted on *P.juliflora* which mainly have focused on its coverage (extent of annual expansion), ecological and environmental impact (Shiferaw et al., 2022b; Wakie et al., 2016) and means of utilization as a useful resource (Pasiecznik et al., 2001). And some other research have dealt with the biological characteristics that promote its invasive ability and its impact on ecological services (Shiferaw et al., 2019). Despite these significant impacts, there is a lack of comprehensive research examining the interconnected effects of *P.juliflora* on food security, LULCC, and climate variability in pastoral contexts. Addressing this

gap is crucial for developing effective management strategies to mitigate the adverse effects of this invasion, ensuring the sustainability of pastoral livelihoods, and enhancing regional climate resilience. Therefore, the purpose of this study was to examine the comprehensive and interconnected impacts of *P. juliflora* on food security, LULCC, and climate variability taking in to account the context of pastoralists and agro-pastoralists livelihoods in Afar region and has proposed possible implications and recommendations for *P.juliflora* management strategy for the region and the country.

1.3. Objectives

1.3.1. General objectives

The primary objective of this study was to investigate the interconnected impact of *P. juliflora* invasion on food security, land use land cover changes and climate variability in the middle Awash of the Afar Region.

1.3.2. The specific objectives

The specific objectives of the study are to:

1. Assess the effects of *P. juliflora* invasion on dynamic of land use land cover (LULC) in the study area,
2. Determine the spatiotemporal climate variability and extremes and its implications to pastoralists and agro-pastoralists food security in the study area, and
3. Identify the impacts of *P. juliflora* invasion on food security of the households in the study region.

1.4. Research questions

The following research questions were proposed to address the research objectives

- To what extent can *P. juliflora* invasion affects the food security status of pastoralists/agro pastoralist communities in Afar Region?
- What are the effects of *P. juliflora* invasion on dynamic of land use land cover (LULC) changes in the study region?
- What are the effects of *P. juliflora* tree on the spatiotemporal climate variability and extremes and its implications to pastoralists and agro-pastoralists food security in the study

area,

1.5. Significance of the study

In the advent of the invasive *P. juliflora* tree, and the high concern for climate change and food security in the contemporary development discourses, this study has brought various results that could be of paramount importance for the local administrative bodies, policy makers, environment and/or development practitioners and the general body of literature.

As such, the study's result on the impact of this invasive species on food security, the spatiotemporal climate variability and extremes and its implications to pastoralists and agro-pastoralists food security and the dynamic of land use/land cover changes is significant for the administrative bodies and environmental practitioners working to ameliorate the environment and mitigate climate change in the pastoral areas.

In addition, the result of the study could also be used as an input for policy makers for the design of *P. juliflora* management strategy and policy formulation in the country. As results highlighted the high association among the *Prosopis* invasion, food security status, and major household assets (livestock ownership) in the pastoralist communities; its implications for a call for multifaceted and immediate intervention is eminent which policy makers could potentially engage in.

Moreover, the results of the study could also be helpful for further researchers who are interested to work in the area, as the study brought not only empirical findings, but also some methodological approaches that could be helpful in arid and semi-arid, and sparsely populated areas of pastoralist communities.

1.6. Scope and limitation of the study

In due process, the study has some limitations merit acknowledgment. Firstly, the temporal scope of the land use and land cover (LULC) study, covering the period from 1985 to 2021, may not adequately capture short-term fluctuations. This highlights the need for more frequent and yearly time series data. Secondly, limited stakeholder engagement due to civil unrest hindered interactions with local communities. To address this, the researcher made repeated visits to the study area, providing training to local individuals to serve as intermediaries, facilitating a continuous flow of information. Lastly, ethical considerations, particularly as Afar region was in

conflict during data collection period, added complexity to the research process, potentially constraining the study's scope and depth. Despite these challenges, the study successfully employed mobile survey platforms, structured phone interviews, capacity-building initiatives within the local community, and meticulous ethical considerations, ensuring a comprehensive data collection in the specified study districts.

The study's measurement of food security using the Food Insecurity Experience Scale (FIES) has some limitations. While FIES is a valuable tool, complementing it with other measuring tools could enhance the study's robustness. Food security, being multifaceted, requires a nuanced approach, and such study would contribute significantly to decision-making by examining contextual factors in pastoral communities, such as climate changes and related variabilities and extremes that can exacerbate the effects of invasive species on food security.

The study has addressed the research objectives, given the scope of this study and variables of interest. In the meantime, the study could highlight some aspects on the scope for potential future researchers. Studying the impact of prosopis invasion on food security in pastoral areas necessitates considering several potential factors: Complexity of ecosystems: Pastoral areas often have complex ecosystems with numerous interacting factors, making it challenging to isolate the impact of one invasive species. Data availability and quality: Limited comprehensive and reliable data in pastoral areas may hinder robust studies, especially in assessing long-term impacts. Funding constraints and time shortage: Comprehensive research may be expensive and time-consuming, requiring sustained funding to capture the dynamic nature of invasive species' impact. Adaptive coping strategies: Pastoral communities develop adaptive strategies to cope with environmental changes, and understanding these strategies is crucial for a comprehensive analysis. Policy and governance issues: The effectiveness of policies and governance structures in managing and controlling invasive species can influence the success of food security interventions, necessitating a holistic approach. Addressing these limitations requires an interdisciplinary approach that integrates ecological, social, and economic perspectives to provide a comprehensive understanding of the complex dynamics in pastoral areas impacted by invasive species.

1.7. Review of Related Literature

1.7.1. Conceptual foundations

1.7.1.1 The concept of plant invasion

The abiotic environment is being greatly altered because of massive land-use alteration and emerging climate change (Mooney & Cleland, 2001). The concept of plant invasion refers to the process by which plant species spread into areas where they are not native and establish populations and plant invasion is one of the major threats to biodiversity (Rai, 2015). These invasive plants can increase rapidly and often have significant ecological, economic, and social impacts (Mussa et al., 2018; Pasiecznik et al., 2001). Invasive alien species (IAS) re-engineer natural and semi-natural ecosystem integrity and have global consequences mainly on ecosystems goods and services, while ultimately affecting the livelihoods of local households (Gordon, 1998; Pimentel et al., 2001). The International Union for Conservation of Nature and Natural Resources (IUCN) defines an Alien Invasive Species as species that become established in natural or semi-natural ecosystems or habitats, an agent of change, and threatens native biological diversity. Invasive alien species do not respect political boundaries, and can expand from other continents, neighboring countries, or even other ecosystems within regions. Biological diversity has received great attention during the past two decades, due to the numerous threats it faces throughout the world (Bambaradeniya et al., 1998). In addition to these two anti-biodiversity and anthropogenic factors, another danger to our biological diversity today is the growing threat of invasive alien species. It is documented that invasive alien species (IAS) have resulted in massive and rapid losses of biodiversity of especially in dry land. In tropical regions, the majority of invasive events occur in disturbed habitats and half of the invasions reported from forested habitats (Binggeli et al., 1998). Introduction into new areas through various means, quickly adapting the local environment and rapid spreading across the landscape are key aspects of plant invasion. *P.juliflora* is one of the invasive alien species that has been invading the rangelands of Afar Region.

The name *P. juliflora* is drive from the Greek words “Pros”, meaning “towards”, and “Opis”, wife of Saturn, the Greek goddess of abundance and agriculture, and hence *Prosopis* means “towards abundance`` (Pasiecznik et al., 2001). This author also noted that the name *juliflora*, came from “julus”, meaning “whip-like", referring to the long inflorescences, and flora being the flower. *P.*

juliflora is capable of extracting water from water tables 15 m deep (FAO, 1990). Some studies have also shown as the tree can grow up to 53m down to the ground. In Ethiopia, it has two local names, the first one was "Dergi Hara" in the Afar language, meaning the tree of the Derg owing to its introduction at the end of the Derg regime". Its second and most popular local name is "Woyane tree" the name given after "Tigray`s People Liberation Front", known for its successful invasion strategy of the country during its struggle against the military government of Ethiopia which they related it with similar to *P. juliflora* invasion in the country (personal communication with the local people). *P. juliflora* is one of the top listed invasive alien species of Ethiopia (EARO, 2005; Pasiecznik et al., 2001).

1.7.1.2 The concept of climate variabilities and plant invasions

Climate variability is the changes of climate patterns mainly because of natural processes through time in long years or decades. It includes fluctuations in temperature, precipitation, wind patterns, and other climatic elements. On the other hand, plant invasion involves the introduction and establishment of plant species in areas where they are not native. These invasive plants often spread rapidly, causing significant ecological and economic impacts (Haji, et al., 2018a). They tend to outcompete native vegetation, leading to reduced biodiversity and alterations in the structure and function of ecosystems(Bellard et al., 2018).

Climate change is one of the main drivers for invasions and invasive alien species distributions either through increase the areas occupied by invasive species or limit the distributions (Bellard et al., 2018; Bellard et al., 2013). There is a complex and dynamic pathways and interactions between climate change, invasion, anthropogenic environment and the ecosystem (Wakefield, 2008).The interaction between climate variability and plant invasion is a crucial and climate variability can affect plant invasions in several ways: 1) create change of habitats: Changes in climate can create new habitats that invasive species can take advantage of. For instance, shifts in temperature and precipitation patterns can make areas that were previously inhospitable more suitable for certain invasive plants. 2) Variations in climate can stress native plant species, making them more susceptible to competition from invasive species. For example, drought conditions can weaken native plants, allowing more drought-tolerant invasive species to establish and spread. 3) Climate variability can alter the frequency and intensity of disturbances like fires, storms, and floods. These disturbances can create opportunities for invasive plants to establish, especially if they are adapted

to quickly colonize disturbed areas. 4) climate changes can affect invasive plants spread such as though shifts in wind patterns and water flow can help disperse seeds or plant fragments to new areas. 5) climate variability can lead to mismatches in the timing of life cycle events (phenology) between native and invasive species. Invasive species that adapt more quickly to changing conditions may gain a competitive edge over native species.

Understanding the relationship between climate variability and plant invasion is vital for managing invasive species and protecting ecosystems (Thuiller et al., 2007). This involves monitoring climatic changes, predicting potential invasion hotspots, and implementing management strategies to mitigate the impacts of invasive plants.

1.7.1.3 The concept of food security/ insecurity

The concept of food security gradually broadened out during the 1980s a move from global and national-level issues into food security concerns at local, household, and individual levels. The 1996 World Food Summit adopted the following definition that is more complex:

> *"**Food security** at any level is defined as physical and economic access by all people at all times to enough, safe, and nutritious basic food to meet their dietary needs and food preferences for an active and healthy life" (FAO, 1996).*

Then later the concept of **social access** was introduced in the definition, and it became,

> *"Food security is a situation that exists when all people, at all times, have physical, "social" and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2009; Nord et al., 2016).*

Food insecurity on the other hand is a situation in which individuals do not have physical or economic access to the nourishment they need, and they have no access to resources to produce food or cash. A household is also considered food insecure if its dietary intake is less than 80% of the daily minimum recommended allowance (MRA) of caloric intake required for an individual to be active and healthy (Owino *et al.*, 2014). Until recently there was lacking a common food security measure and the necessary data to study the individual-level determinants of food insecurity around the world (Meroni et al., 2017; Nord et al., 2016). Food insecurity exists in most countries around the world, but the common determinants of food insecurity across countries have

yet to be formally identified (Meroni et al., 2017). There are different measures of food insecurity, as a micro-level measure, experiential food insecurity measures offer insight into the determinants of food insecurity at the individual level and can show the characteristics and geographic concentration of the food insecurity (Ballard et al., 2014; Nord, 2014). Research has shown that the experience of households living with hunger or food insecurity is consistent in developed and developing countries; and across languages and cultures (Coates et al., 2006).

1.7.2 The theories on plant invasion, food security and climate change and climate variabilities

1.7.2.1 The theory of plant invasion

One of the most popular and contentious theories is the species-rich, productive, competitive habitats should be less vulnerable to plant invasion than species –poor, low productivity sites (Stohlgren, 2002). This theory holds true in relation with the current *P. juliflora* and some Acacia and other plant species invasion in Afar and other parts of the country. There are some studies indicated that species invasion increases with increase of plant biodiversity however most studies agreed that invasion decreases with increase of plant biodiversity. The below mathematical model (figure 1.1) of plant invasion indicated as most studies are in line with the fact that the area of low in diversity are vulnerable to invasion.

This theory has foundational concept for why *P.juliflora* invasion increases in the study area as historically the area has less plant diversity, bareland dominated (Shiferaw et al., 2019), high salinity (Adilo, 2006) that has created a conducive environmental setting for *P.julifora* expansion complemented by the role of livestock, wild animals and flood in disseminating the seeds to wider areas. This theory describes how invasive species like Prosopis juliflora take the opportunities of ecological niches and disturbances to establish and increase in new environments. This trend is tightly connected to land use/land cover (LULC) changes, as actions like deforestation, overgrazing, and agricultural activities create ideal conditions for invasions. Once *P. juliflora* takes hold, it changes the landscape by overrunning with other plants and reducing biodiversity, modifying soil characteristics, and competing with native plants and crops for resources like water and nutrients. These ecological shifts have serious consequences for food security because the invasion decreases the amount of arable and pasture lands and degrades pasture quality, resulting in lower agricultural yields and reduced food crops and pasture production. While some

communities' groups may adapt by using Prosopis for fuel and other products, this adaptation often does not fully compensate the decrease in agricultural and livestock production. A comprehensive approach that integrates and consider ecological and social factors (Figure 1.3 & 1.4) is essential for effectively managing invasive species and mitigating their impacts on land use and food security.

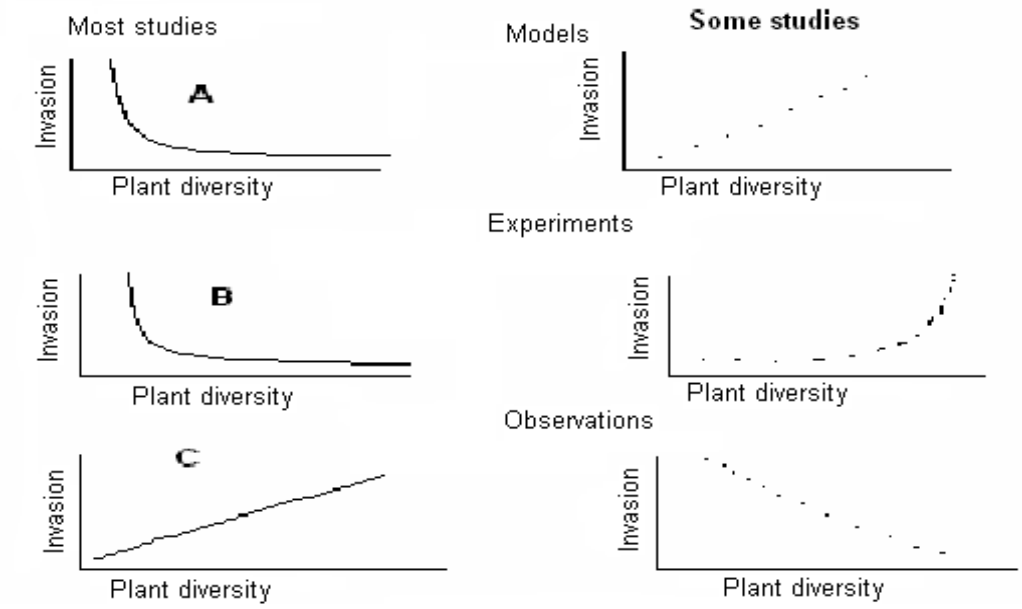

Figure 1.1: Mathematical model of plant invasion

Source: (Stohlgren, 2002)

Identifying key drivers, impacts and possible adaptations measures are key for designing appropriate mechanisms that can contribute for better management of the impact of land use land cover changes, climate extremes and food security of the area. Figure 1.2 illustrates some of the key drivers of *P. juliflora* invasion, its impacts, and key areas of adaptation options the community undertaking as part of coping strategy.

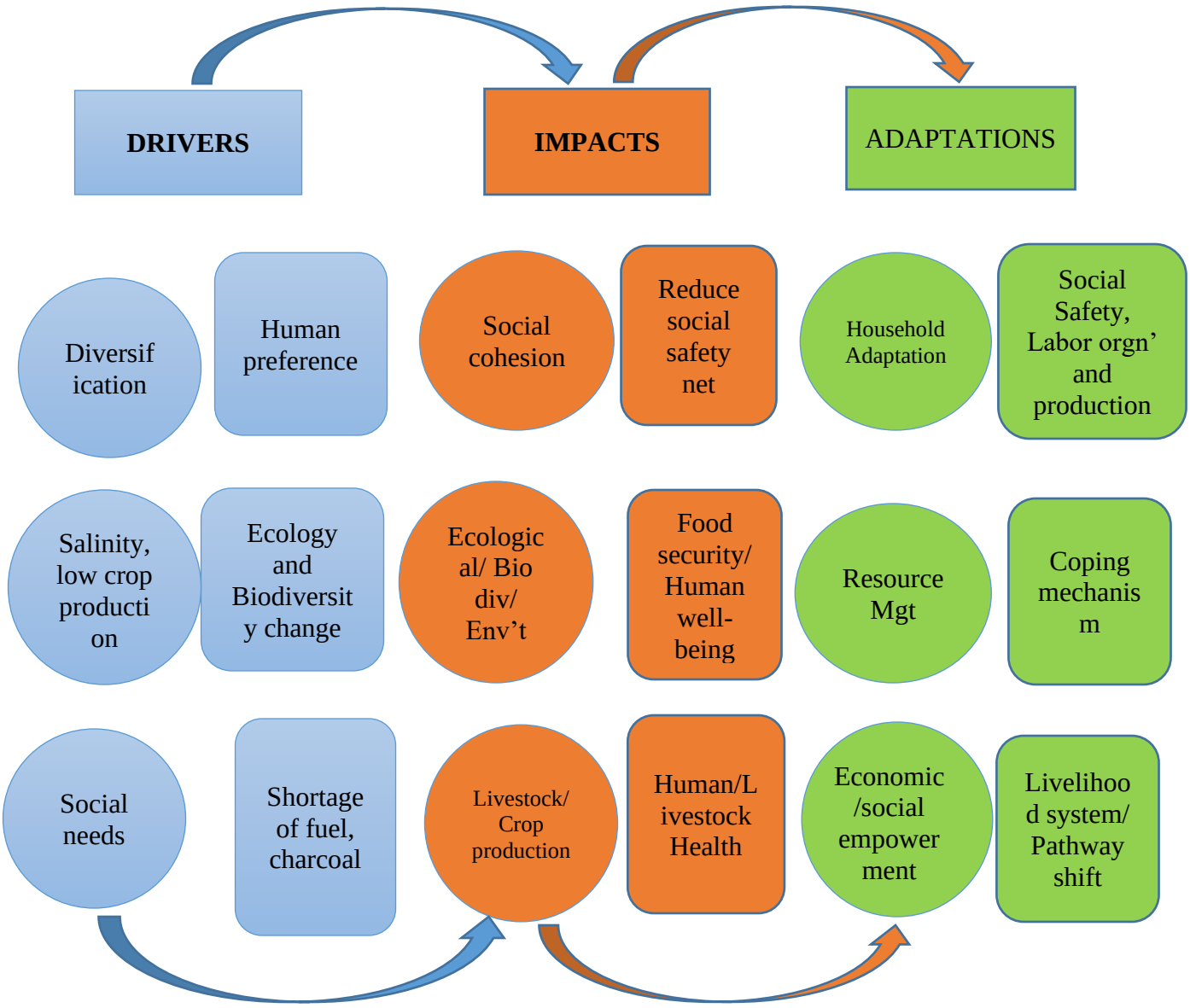

Figure 1. 2: Theoretical framework: driver`s, impact and human adaptation on *P. juliflora* invasion. *Source: own diagram*

1.7.2.2 The theory of food security

The theory of food security is built on four key dimensions: availability, access, utilization, and stability, which together ensure that all people have sufficient, safe, and nutritious food at all times. Availability focuses on the supply of food through production, distribution, and exchange, ensuring enough food is produced to meet population needs (Organization, 2022). Access pertains

to both economic and physical means, influenced by income levels, food prices, and infrastructure that facilitates the transport of food from production sites to consumers (Barrett, 2023). Utilization emphasizes the proper use of food, involving food safety, nutritional knowledge, and health care, ensuring individuals can effectively absorb and metabolize nutrients (Alaoui, 2023). Stability refers to the consistency of these factors over time, addressing potential disruptions such as economic crises, natural disasters, or political instability (Manikas et al., 2023).

Achieving comprehensive food security requires understanding food systems, promoting sustainability, ensuring equity, and establishing effective policies and governance. Contemporary research highlights the need for a multi-faceted approach involving governments, international organizations, the private sector, and civil society to create resilient food systems that can endure over the long term without degrading natural resources or harming the environment(Doherty et al., 2023). Key components of the theory include:

- Food Systems: Understanding the entire food system, from production and processing to distribution and consumption, is crucial for identifying points of vulnerability and opportunities for improvement.
- Sustainability: Sustainable food security involves practices that ensure food systems can endure over the long term without degrading natural resources or harming the environment.
- Equity and Social Justice: Food security theory emphasizes the importance of equitable access to food and the need to address social inequalities that contribute to food insecurity.
- Policy and Governance: Effective policies and governance structures are necessary to support food security, including regulations, subsidies, safety nets, and international cooperation.
- Community and Cultural Factors: Food security also involves understanding and integrating cultural preferences and community practices related to food production and consumption.

1.7.2.3 The theory of climate change and climate variabilities

The theory of climate change centers on the significant long-term alterations in Earth's climate, primarily driven by human activities. These anthropogenic causes include the burning of fossil fuels, deforestation, industrial processes, and agricultural practices, all of which elevate greenhouse gases (GHGs) like carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O) in the atmosphere, leading to a warming effect known as the greenhouse effect. This effect causes global temperatures to rise, influencing weather patterns, sea levels, and ecosystems (Lee et al., 2023).

The theory is supported by extensive evidence, such as rising global temperatures, historical climate data from ice cores, rising sea levels due to melting glaciers, and the increasing frequency of extreme weather events. These changes have far-reaching impacts, including altered ecosystems, threats to human health, and economic disruptions in sectors like agriculture and fisheries. Addressing climate change requires both mitigation strategies, such as reducing GHG emissions, and adaptation efforts to build resilience against its effects (Forster et al., 2023; Pujar et al., 2024).

The theory of climate variability addresses the natural fluctuations in climate that occur on different timescales, from years to centuries. These fluctuations are driven by natural processes, such as solar variability, volcanic activity, and ocean-atmosphere interactions like El Niño and La Niña. Climate variability operates on various temporal scales, including interannual variability (e.g., El Niño-Southern Oscillation), decadal variability (e.g., Pacific Decadal Oscillation), and longer-term changes observed over centuries and millennia. These natural variations can lead to unusual weather patterns, such as prolonged droughts or wet periods, significantly impacting ecosystems, agriculture, and human activities(Deser & Phillips, 2023).

While climate variability refers to these shorter-term natural fluctuations, it is distinct from climate change, which involves long-term trends primarily driven by human activities. However, the two are interconnected, as natural variability can influence or modulate the impacts of long-term climate change (National Academies of Sciences & Medicine, 2021). Both theories are integral to understanding the complexities of Earth's climate system. Climate change can influence the patterns and intensity of climate variability, and vice versa. Studying both concepts

helps scientists predict future climate scenarios and develop strategies to manage and adapt to their impacts.

1.7.3. Empirical review

P.juliflora introduced to different parts of the world with the aim to provide benefits to rural people, such as the production of fuel wood, charcoal and construction material, as well as to stabilize soil in degraded ecosystems (Shackleton et al., 2015). However, *P.juliflora* has become invasive in many places and is increasingly known for its negative ecological and socio-economic impacts (Shackleton et al., 2015; Shiferaw et al., 2004).

Although the exact date of introduction of the species into Ethiopia and particularly in Afar Region is not well known and documented. However, most of the local people and different institutions of the area agreed that the species was introduced to the country and the Region during the early 1970s. Some studies also indicated that *P. juliflora* was first introduced to the Afar region by the Ethiopian government in the late 1970s and early 1980s for the purpose of dryland rehabilitation to combat desertification. By 2006, approximately 700,000 ha of land had been taken over by *P. juliflora* out of which more than 70% is in the Afar region (Admasu, 2008; Ilukor et al., 2016a). Now a days, *P. juliflora* has covered an area of 1.17million ha (Shiferaw et al., 2019) and more than 12,000 hectares in Dire Dawa Administration (Jema & Abdu, 2013).

1.7.3.1. Impact of *P. Juliflora* invasion on the ecology, socio-economic and food security

The most ecological impacts of *P. juliflora* is due to its dense canopy cover and related influences on light transmission to the ground which in turn results in changes and suppression of the undergrowth species or vegetation. The underground or basal cover of native herbaceous vegetation and native tree diversity found to be much reduced under high *P. juliflora*-invaded areas (Ilukor et al., 2016b). The study indicated that if the optimal invasion dose (intensity) of *P. Juliflora* is above 22.23%, it will create negative impact on the biodiversity as well as income of the households (Bekele, Haji, et al., 2018a). Invasive alien plant species (IAPS) causes significant impacts on biodiversity and ecosystem services (ES) (Shiferaw et al., 2019), or promote ecosystem disservices (EDS) and thus alter the benefits people derive from nature (Hailu Shiferaw et al., 2019). As per the information from local elders *P. juliflora* has been killing larger number of cattle

than those killed by drought and which indicating how *P. juliflora* potentially leading to eliminate pastoralism system in the area in the near future (Haregeweyn et al., 2013).

P. juliflora has also been affecting the socio-economic condition of Afar communities. *P.juliflora* quickly invades a huge areas of pasture lands and severely affecting households' income from livestock production (Wakie et al., 2016; Zeray et al., 2017a). A study in Dire Dawa area indicated that *P.juliflora* as a source of fuel wood, charcoal and sales from charcoal constitutes around 26% of the average annual income of the households (Jema & Abdu, 2013). On the other hand, it also indirectly increases household health spending (Ayanu et al., 2015b; Bekele, Haji, et al., 2018b; Haregeweyn et al., 2013) due to causing legs and hands infections and records indicated that more than five cases/month treated in Afar (Haregeweyn et al., 2013). The thorns of the *P.juliflora* also causes severe injuries to the hooves of animals and have equally serious human health consequences (Ilukor et al., 2016a; Mehari, 2015a; Mwangi & Swallow, 2008). In addition, pastoralists also perceived the diminishing of water volume of the Awash River as the spread of *P. juliflora* increased around the water course (Hamedu, 2014; Ilukor et al., 2016a; Patnaik et al., 2017). In general, there is conflict of interest between pastoralists and urban dwellers in Afar on *P. juliflora*, in a way that all pastoralist viewed *P. juliflora* as it has no advantage whereas those community group engaged in firewood and charcoal considered it as useful tree and means of income generation.

Most pastoralists in Afar, previously known for their wealth due to large cattle herds, now live under conditions of chronic food insecurity (Rettberg, 2010). The number of livestock is declining as households are selling off animals to buy food, and about 64% of the rural Afar households are consuming only three or fewer food groups out of seven (Ilukor et al., 2016b). There is limited livelihood diversification options or alternatives in Afar to cope with this food insecurity challenge. Therefore, more and more pastoralists became sedentary within the last 20 years, performing different kinds of income-generating activities (wage labor, petty trading and sale of charcoal, firewood, grass mats, etc.) and small-scale irrigation agriculture (Rettberg, 2010; Rettberg & Müller-Mahn, 2012). Therefore, the study will consider the household income from livestock, sell of charcoal, fuel wood and household's health expenditure as key outcome variables.

1.7.3.2. The effects of climate changes and variability on vegetation and food security

Climate variabilities and associated effects are at the center of multiple hazards that are changing the household's production systems. Globally, climate variabilities have been severely impacting agriculture and food security and will make the challenge of ending hunger and malnutrition even more difficult. Climate change in Sub-Saharan Africa has had a negative impact on agricultural production leading to food insecurity (Wekesa et al., 2018). Climate variabilities has already caused significant impacts on water resources, human health and food security. It is a threat to food security systems and one of the biggest challenges in the twenty-first century (Kogan & Kogan, 2019). People who are already vulnerable and food insecure are likely to be the first affected. An average of 500 weather-related disasters are taking place each year, compared with 120 in the 1980s (Al et al., 2008a). Population increases, where most of the world's population now lives, mean that more and more people will be affected by catastrophic weather events (Al et al., 2008a). Environmental and human disasters have been causing Ethiopia to become food insecure and so far it has been reported that more than 44 severe famine catastrophes occurred in Ethiopia (Tolossa, 2005). There are many contributing factors such as population growth, high pressure on natural resource combined with low adaptive, absorptive and resilience capacity, rainfall dependence, traditional farming and poor land management practices for vulnerability of the community to climate changes and its adverse livelihood impacts.

The effect of climate change risks on crop and livestock production has adverse implications for producer prices through its effect on production quantity and quality. Droughts affect food prices by reducing the yield and thus the food availability at the household level and at the local markets (Abebe, 2018)

Climate change has been affecting all four dimensions of food security: food availability, food accessibility, food utilization and food systems stability[1]. Agriculture, forestry and fisheries will not only be affected by climate change, but also contribute to it through emitting greenhouse gases (Al et al., 2008a).

Prosopis invasion has been changing the ecosystem in the areas. Some study on the ecosystem service values (ESVs) made on *P.juliflora* invaded area in Afar estimations indicated that the

[1] Climate Change and Food Security: A Framework document, FAO, 2008

ecosystem changes caused by LULC changes resulted in an average loss of ESVs of about US$ 602million (range US$ 112 to 1091 million) over the last 31 years (Shiferaw et al., 2019). This LULC changes is mainly because of *P. juliflora* invasion and subsequent change of the ecosystem in the last three decades. Ecosystem management plays an important role in climate change mitigation and adaptation if properly managed and conserved to move towards sustainability(Epple et al., 2016).

1.7.3.3. Land use land cover changes

Land cover refers to the coverage of earth's surface by its natural physical features of existence like water, plain land, vegetation, deserts, mountains and valleys; land use is the extent of earth's surface being used by human beings and their habitations for survival (Geetha et al., 2019). Land use land cover (LULC) changes are aspects of global environmental change and affect ecosystem processes and services. A large amount of change in LULC has been observed, caused by different socio-economic and biophysical drivers, such as population growth, agricultural expansion and intensification, accessibility to infrastructure and markets, water availability or climate. According to the communities, some of important drivers of LULC dynamics are climate change, frequent droughts, invasive species and weak traditional law (Shiferaw et al., 2019). Drivers of land degradation in sub-Saharan Africa included the expansion of crop production, sustainable grazing and forestry practices, and climate change (Shiferaw et al., 2019).

The LULC change detection was assessed using the image-differencing algorithm, which describes the total net change between the time-series images (Haregeweyn et al., 2013). Remote sensing is one of the very important tools used for the production of land use and land cover maps through a process called image classification (Rwanga & Ndambuki, 2017). As LULCC is a continuous process, identifying those changes continuously is very important for decision-making and proper utilization of available resources.

1.7.4. Conceptual framework

The following conceptual framework is derived from the conceptual understanding of the expansion of *P. juliflora* invasion and its direct and indirect impacts on local climatic variabilities, dynamic of land use and land cover change, and socio-economic and how each of them related with changing the food security/insecurity of the community of the study areas. The research

focused on examining how the expansion of *P. juliflora* invasion changes the local climate variabilities and land use system and its impact on food security. Figure 1.3 indicates a cause and effect of Prosopis from global review of Prosopis, focusing on its distribution, impacts, benefits and approaches to management (Shackleton, 2014) which is in line with actual cause and effect situation in Ethiopia. The below conceptual framework indicated how different variables interconnected to impact the food security situation of the community in the study areas.

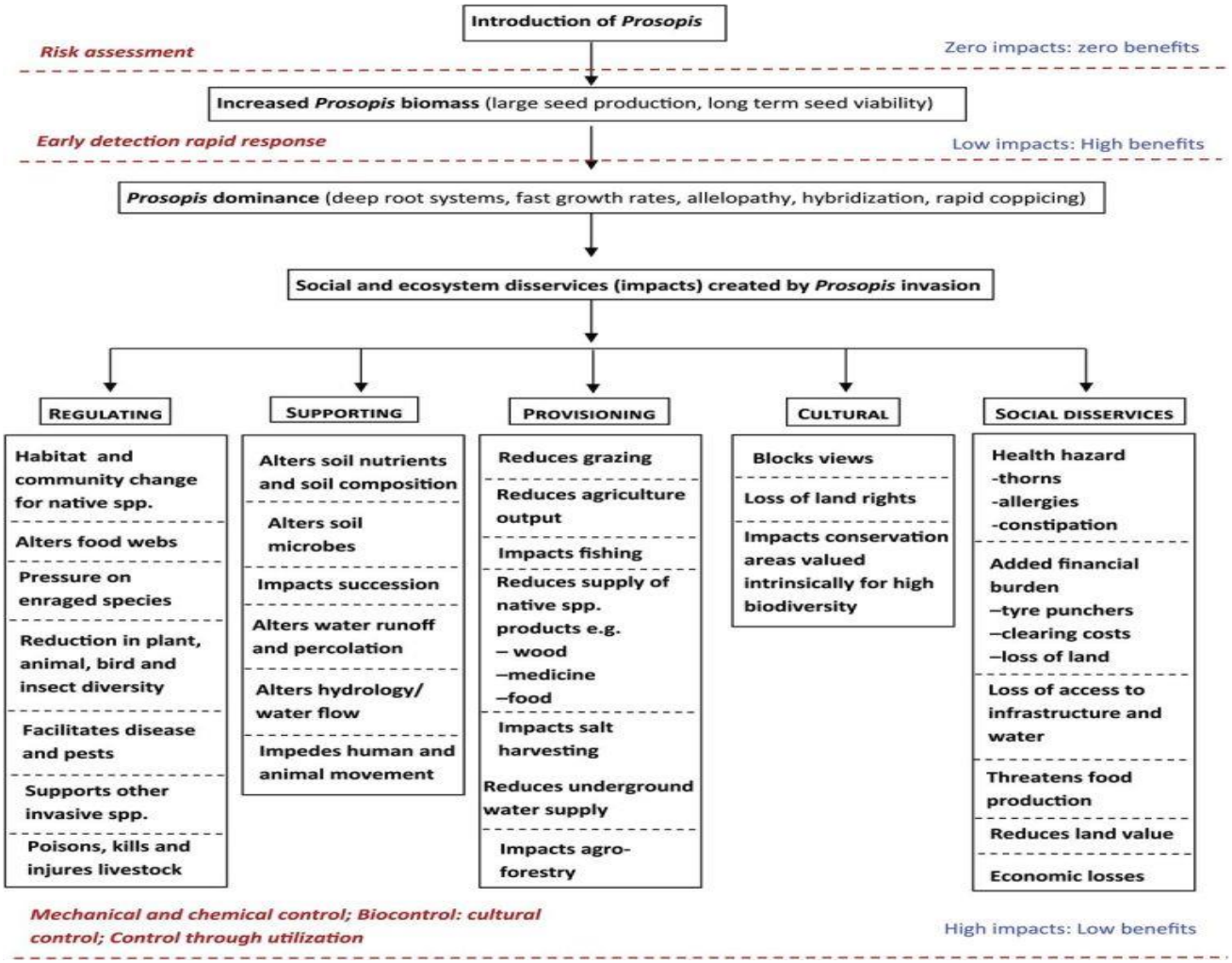

Figure 1. 3: Cause-and-effect network diagram from global review showing the negative effects of *Prosopis* invasions and management options that can be used to target each stage of invasion.(Source: Shackleton, 2014)

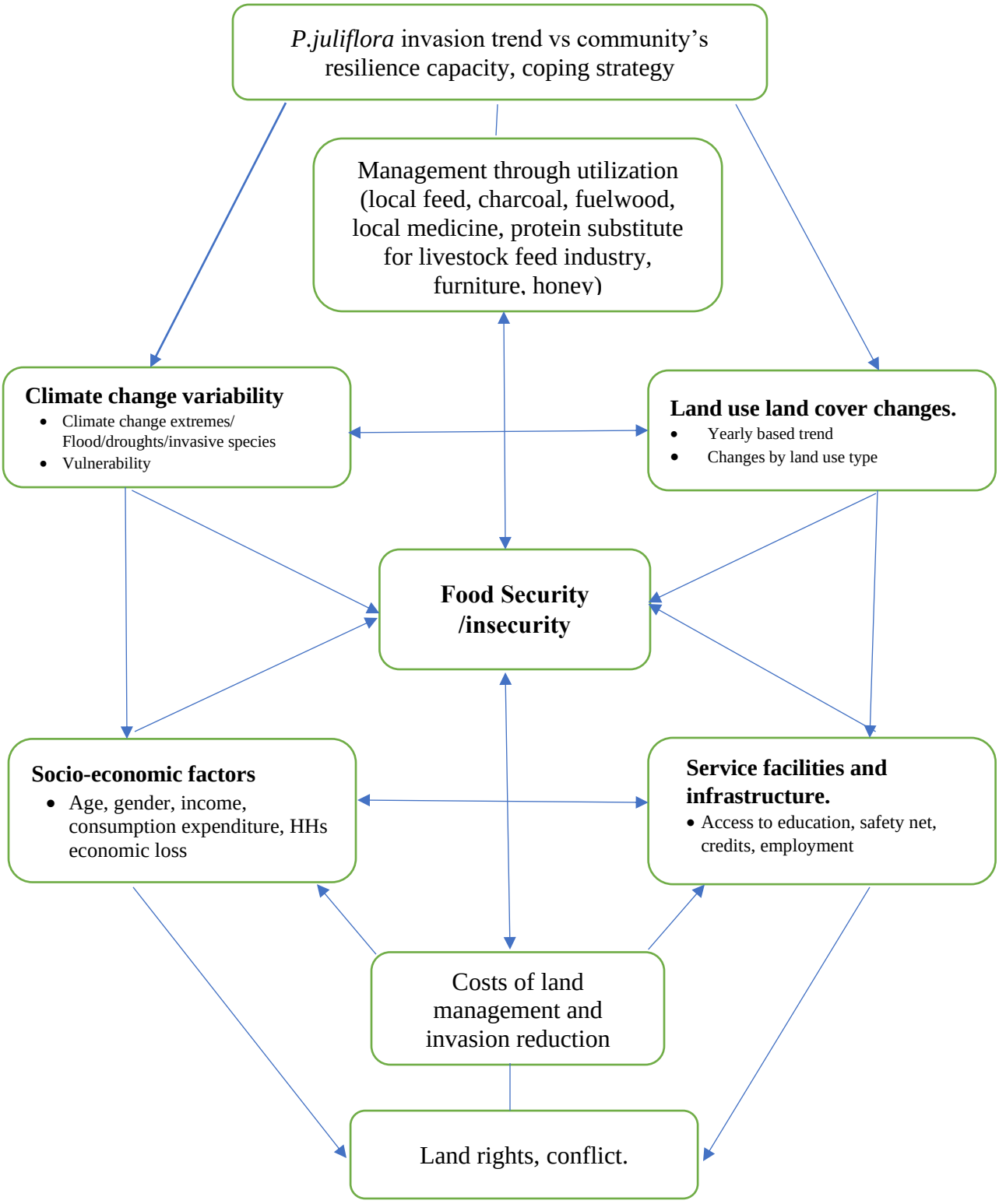

Figure 1. 4: Conceptual framework for impacts of *P. juliflora* invasion
Source: Own data

1.8. Methodology

1.8.1. Description of the Study Areas

The study was carried out in Afar National Regional State (ANRS) Zone 3 *Awash Fentale* and *Amibara* Woredas (40°08'- 40°12'E and 09°16'- 09°21' N) figure 1.5 and located at about 160 and 250 km Northeast of Addis Ababa respectively. The altitude of the study sites ranged between 740 and 820 meters above sea level.

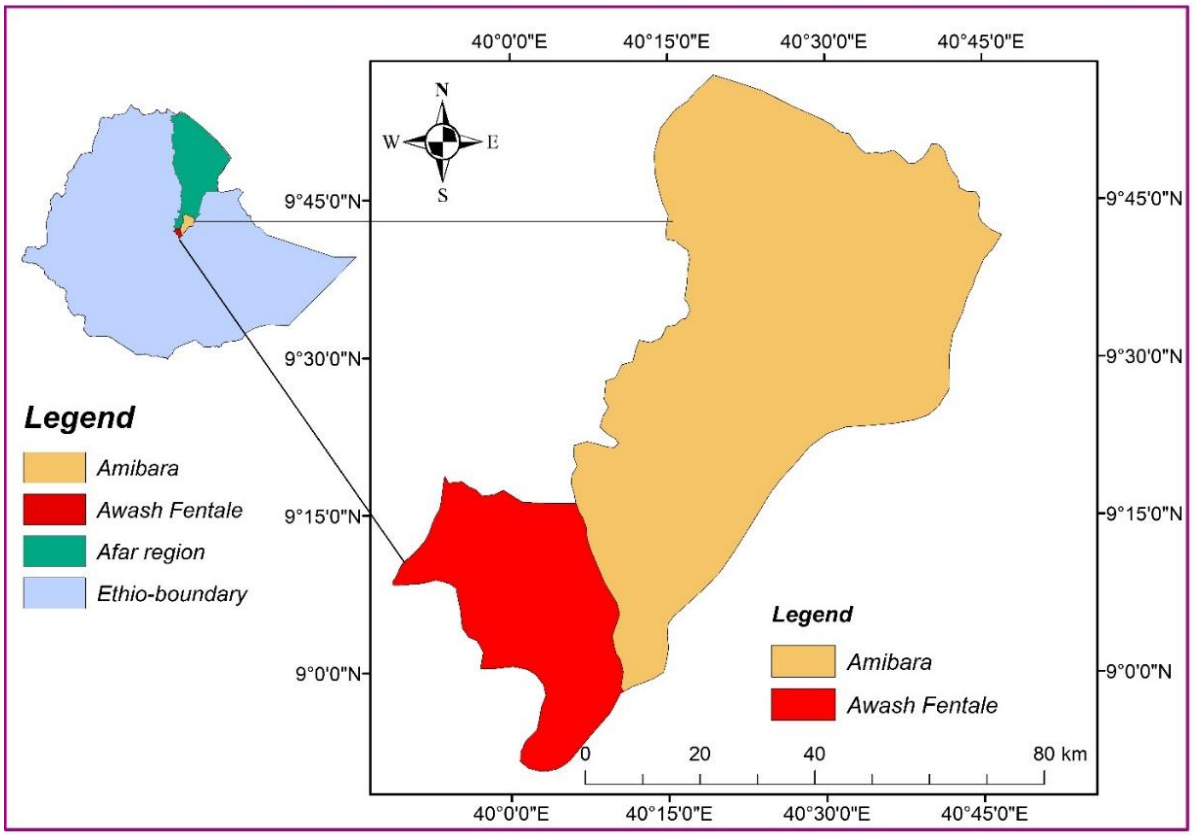

Figure 1. 5: Map of study sites, Afar

The Afar National Regional State (hereafter referred to as the Afar Region) in Ethiopia is part of the Great Rift Valley of East Africa. The Southern part of the region covers 6.67million ha (Shiferaw *et al.*, 2019) which is about 10% of the total landmass of Ethiopia and about 29% of pastoral lowlands. It is arid and semi-arid with a mean annual temperature of 31 °C. Rainfall is erratic and scarce with annual precipitation between 200 and 600 mm. The population is about 1.77 million (CSA, 2021). The production system of the region is dominated by pastoralism (90%) from which agro-pastoralism (10%) is now emerging following small-scale irrigation schemes developed on some permanent and temporary rivers. The Afar pastoralists and agro-pastoralists highly depend for their livelihood on floodplains of the Awash River

where they graze their livestock during the drought period and practice small-scale agriculture. Some recent studies revealed that the floodplains are under risk of invasion by *P. juliflora (Ayanu et al., 2015a; Ilukor et al., 2016b)*. The dominant vegetation types in the study area are bush lands, shrub lands, riverine forests, grasslands and seasonal marshes and swamps.

The livelihood of the population in the study area depends on livestock production. Since the introduction of *P.juliflora* in to the area, the livestock population of Afar has been affected mainly in two ways. First, due to reduction of grasslands and open grazing lands and hence directly affect the survival of livestock. Secondly, the pod of *P.juliflora* is highly relished by cattle and goats. However, when they feed on the pod it has been affecting them by twisting of jaw and neck and causing them to die. Livestock, mainly cattle, are the major dispersal agents of *P.juliflora* in the area. As (Yosef et al., 2013) indicated cattle and camel populations in the *Amibara*, declined at a rate of 36% and 20%, respectively, between 1997 and 2011. Although the population of cattle in almost all other zones is declining, the percentage decline in *Amibara* is the highest compared to other zones.

Figure 1.6: Camels in *P. Juliflora* invaded rangelands of Afar, Ethiopia

1.8.2. Philosophical foundation of the research

The researcher followed the pragmatic research philosophy which provides for the adoption of mixed methods (both qualitative and quantitative) as the data collection method. The use of both qualitative and quantitative research methodologies enabled to collect information and make inquiry into complex phenomenon of social and natural contexts. The research focused on the problem and tried to find practical solutions with the use of mixed methods. Therefore, appropriate tools were developed for each of the mixed method approaches and data were

collected properly based on the processes, procedures and understanding of the context of the area.

1.8.3. Research design and approach

The researcher considered appropriate research design indicating the logical plan and sequence starting from initial setting of research questions and layouts to the final conclusions. The research design guides the researcher in the process of collecting, analyzing, and interpreting observations (Gljsenberg, 2013). Research design also includes activities starting from stating the research problem, synthesizing research questions (formulating hypothesis), designing a research framework, and selecting appropriate methods of data generation and analyzing techniques (Tolossa, 2005).

This study utilized several statistical sampling procedures to select *Woredas*, *Kebeles* and households. The study was conducted in two *Woredas*, one with highly *Prosopis* invaded and the other with less or non-invaded areas which were selected using purposive sampling techniques. Then households were randomly selected from each three sample *Kebeles* per *Woreda* for individual interview using random sampling techniques (lottery methods). The total number of survey households in each Kebele were determined proportionally based on the total number of populations per kebele.

As indicated above mixed approach that involves quantitative (household survey) and qualitative methods (key informant interview and focus group discussions) were conducted using structured and semi-structure survey questionnaires, key informant interviews and focus group discussions were conducted at household and community levels.

1.8.4. Study areas population.

The total population of *Amibara* and *Awash Fentale Woredas* are 118,688 and 60,399, respectively (CSA, 2023).

1.8.5. Sampling Procedure

The study employed a multi-stage sampling procedure to select *Woredas* and *Kebeles*. First, selection of study region and *Woreda* and in this case Afar region- *Amibara* and *Awash Fentale Woredas* are chosen purposively as *Amibara* is the first most *P.juliflora* invaded *Woredas* in Ethiopia and *Awash Fentale* is relatively among with those less or non *P.juliflora* invaded *Woredas*. In the second stage, among all rural *Kebeles* in the two *Woredas, P.juliflora* invaded

and non *P.juliflora* invaded *Kebeles* were selected purposively in *Amibara* and *Awash Fentale*, respectively. Thirdly, sample number of pastoralist and agro pastoral households were randomly selected from list of households in each invaded and non-invaded *Kebeles*.

1.8.6. Sampling Technique

Data was collected from randomly selected household of the two sample *Woredas*. The sample households were selected for interview based on probability proportionate to the relative size of households in selected sample *Kebeles*. First, the list of all households of the kebele were obtained from kebele manager/administrator and this list was used as a sample frame. In circumstance when any randomly selected household head or an adult family member of that household refused to participate in the interview or not around, that household was replaced by the next household from the list of households in the kebele.

In addition, data was collected using focus group discussion (FGD) by considering the role of men, women, youth and disabled community member in the kebele and participants for key informant interview (KII) were selected considering the role of elders, customary institution or clan leaders, development agents in each *Kebeles* and *Woreda* experts and private sectors of the *Woreda*. Accordingly, a total of 12 FGDs and 12 KII were conducted in the two *Woredas*. The household data was collected using pre-tested survey questionnaire. The survey was administered using experienced enumerators who speak the local language and use mobile technology for data collection. Enumerators were selected based on educational level with the criteria of at least having minimum of first degree, pervious experience in managing similar survey with mobile/tablet data collection and fluent in local language. In addition, published and unpublished research reports from various governmental and non-governmental organizations were also reviewed and considered as input to develop comprehensive survey questionnaire.

1.8.6.1 Sample Size

Sample size for the study was determined by employing (Yemane`s, 1967 formula) to calculate sample size from each *Woreda*`s of rural population. The sample size calculation considered 5% acceptable error (e=0.05); 50% reasonable estimate for the key proportion to be studied (p =0.5); and 95% confidence level. The formula is given as:

$$n = \frac{N}{\left(1 + N\ (e2)\right)}$$ …… (Yamane, 1967)

Where:

n = desired sample size;

N= total number of population (i.e HHs)

e= the level of precision or the quality of being careful and accurate which is equal to 0.05. The data were collected in 2021 and during that time the total population of Amibara and Awash Fentale Woredas are 110,427 and 55,708, respectively (CSA, 2021).Accordingly, the sample size for *Amibara Woreda* was calculated as 398HHs and for *Awash Fentale Woreda* was 397HHs. An addition of 5% to compensate for those respondents which may not be around during the survey or may not be willing to respond makes it a total of 835 households to be involved in the household survey in both *Woredas*. However, taking into account of the then COVID 19 pandemic and related difficulties of physical data collection, the homogenous culture and nature of the two *Woredas* people, the researchers agreed to reduce the sample size and hence a total of 438 households were accessed for the field level collection by applying precaution measures of COVID 19.

1.8.7. Data Collection Methods and Tools

The study was conducted based on preliminary assessment and review of related literatures and other locally available information and observations. Data collection tools and questionnaires were developed in a way to gather the required information from field. Therefore, the researcher conducted both secondary and primary data collection methods. An organized and systematic ways of document review (secondary data collection) was made to ensure thoughtful and evidence-based data collection. Field level data was collected in lean season of the area which is in January and February 2021. In order to generate well-studied result, the researcher adopted different techniques/approaches including collecting time series data from all relevant sectors and data sources. The primary data collection was focused on data related with food security, climate change and land use land cover aspect of the research area.

Primary Data

Both quantitative and qualitative surveys were conducted at household/individual level through well-developed survey questionnaires, key informant interviews and focused group discussions. Participatory community level discussions were employed to generate complementary and reliable data and information from different sectors at different levels. All food security and climatic data were collected from the sample *Woredas* and *Kebeles* and satellite information; and each of them were identified and selected based on the knowledge

and experience of the researcher. The following categories of primary data were collected throughout the field survey.

1.8.7.1 Food security data collection

Various studies indicated that the full range of food security/insecurity of an individual and household cannot be measured by single indicator (Nord et al., 2016; Ballard, 2013). Instead, indicators of variety of information about the specific conditions, experiences, and behaviors of individual/household are recommended to be considered to determine the level of food security/insecurity of the households/individuals.

For this study, the researcher was interested to apply the Food Insecurity Experience Scale (FIES) tool to measure the food security status of households of both *P. juliflora* invaded and non-invaded sites. FIES contained eight dichotomous responses ("yes"/"no") questions (see Appendix I1) that provide a measurement tool for identifying the sensitivity and severity of food insecurity experienced in a household. Respondents` answer yes/no to the eight questions and the responses are aggregated to give raw scores ranging from 0 to 8. Food insecurity (FI) are classified into 3 categories: 1) food secure (FS) with raw scores = 0–3; 2) moderate FI (MFI), with raw scores = 4–6; and 3) Sever food insecure (SFI), with raw scores = 7–8. FIES establishes an experience-based metric for the severity of the food insecurity condition of individuals or households (Melgar & Quiñonez, 2019; Nord et al., 2016; Ballard, 2013).

FIES constitutes one of the main food insecurity measures at the household or individual level that provides the opportunity to generate internationally comparable, standard measures of food insecurity with details on levels of severity (Melgar & Quiñonez, 2019). Indicators derived from the FIES have the distinctive advantage of being more precisely comparable across countries, different cultural setting and contexts. An additional advantage of the FIES is that enables measurement of the food insecurity, which can then be analyzed together with indicators of its determinants and consequences to contribute to a more comprehensive understanding and inform more effective policies and interventions (Ballard, 2013). Hence, FIES was used to determine the prevalence of food insecurity of the households in *P.juliflora* invaded and non-invaded sites. The Rasch modeling procedure was applied and FIES largely met the Rasch model assumptions of equal discrimination and conditional independence (Wambogo, 2018).

Data on relevant socio-demographic and econometric variables (Appendix 1) such as sex, age, marital status, education level, income from livestock sale, income from crop sale, access to irrigation, credit, safety net support, engagement of household head in off/on farm activities and effect of drought was collected. The optimum level of annual household per capita consumption expenditure was also identified.

1.8.7.2. Climate change and climate variability trend analysis data

All-time series climatic data including the mean monthly, seasonal, and annual temperature and rainfall of the study area were collected from Meteorological Agency and also from satellite information sources. Information about climate extremes e.g. flood and drought of three decades were gathered and systematically integrated with all climate variability data to generate information.

1.8.7.3. Land use land cover change analysis data

Remote sensing landSat images was used to detect changes in land cover and land use between 1985 and 2021. Spatial resolution Landsat Thematic Mapper (TM) from Landsat 5 for 1985 and 2000 as well as Operational Land Imager (OLI) from Landsat 8 for 2021. Dry season images with less than 80% cloud cover were downloaded for the study area from Unites State Geological Survey (USGS/GLOVIS).

1.8.8. Data Analysis Methods

The data were analyzed using descriptive, inferential and econometric tools. The descriptive statistics such as mean, standard deviation, and percentages were used. Besides, t test and chi-square test were used to test whether there is a statistically significant difference between the two groups (invaded and non-invaded households) in terms of continuous and categorical variables. In general, all the data were analyzed using standard statistical and econometric models. And appropriate multivariate analysis and chi-square tests was also applied to suggest in the categorization of food secure and food insecure status.

1.8.9. Impact estimation techniques

This study examined the dynamics of food security/insecurity using the Rasch modelling approach. Rasch Model was used to measure the severity of food insecurity in the two study sites (invaded and non-invaded sites) in relation with the experience of individual households based on responses for those experience based FIES questions.

1.8.9.1 Rasch Model and its applications

As indicated above, Rasch Model is used to measure the severity of food insecurity in relation with the experience of individual households based on responses for those experience based FIES questions. Rasch model, which is also referred to as the one-parameter logistic (1PL) model (Boone, 2016; Nord, 2014; Rasch, 1960; Ballard, 2013) assume that households are more likely to answer "yes" to less-severe items or FIES questions than to more-severe items and that items are more likely to be answered "yes" by households of more-severe food insecurity than by households of less-severe food insecurity (Deitchler et al., 2010). Key Rasch Model assumptions include *equal discrimination of items* and *conditional item independence* (that is, independence conditional on severity of the latent trait) (Wambogo, 2018; Nord, 2014). In Rasch model, the underlying variables to be measured are called the item difficulty and the respondent ability. In food insecurity studies, the ability of corresponds to the severity of the food insecurity experienced by the respondent household, and difficulty is the severity of food insecurity that imply by an affirmative response to the survey question (Opsomer et al., 2002) A critical assumption underlying all item response models is that ability is an unobservable (also called *latent*), one-dimensional and continuous trait, which all respondents possess to varying degrees. At least conceptually, the model implies the existence of a continuous "scale" on which the items can be placed based on their difficulty levels and on which individuals can be placed based on their ability levels. The main objective of item response models is to estimate where individuals (and sometimes, items) fall on that scale (Nord, 2014; Opsomer et al., 2002). Each individual responds to the dichotomous FIES question according to his/her latent ability: the more ability the individual has, the larger the probability that he/she will give a positive response. The Rasch model provides a convenient framework in which to simultaneously estimate the individual ability and the item difficulty parameters, based on a set of questions administered to a group of individuals. Rasch model assumes that the trait to be measured is unobservable but can be assessed by a set of questions whose likelihood of answering "correctly" (or affirmatively) is related directly to the strength (or severity) of that trait (Opsomer et al., 2002).

$$\frac{\text{Exp}\,(\theta n-\delta i)}{1+\ \text{Exp}\,(\theta n-\delta i)}\ \frac{e^{\theta \text{h}-\beta \text{i}}}{1+e^{\theta \text{h}-\beta \text{i}}}\ \frac{\text{Pr}\,(\text{Pi},\text{V})}{1\ -\ \text{Pr}\,(\text{Pi},\text{V})}\ \frac{1}{\theta \text{v}}\ \frac{exp(\theta \text{V}\ -\ \beta \text{i}\,)}{1+exp(\theta \text{V}\ -\ \beta \text{i}\,)}$$

Therefore, using this model, the food insecurity and severity level of households of *prosopis* invaded and non-invades sites was analyzed and determined. Households with positive Rasch

model estimated values was classified as food secure while those with negative Rasch model values was classified as food insecure households (Owino et al., 2014).

1.8.9.2 Propensity Score matching approach

P**ropensity Score Matching (PSM)** is developed by (Rosenbaum & Rubin, 1983) and is an econometric model to measure impact estimation. To estimate the effect of invasion on outcome variables (annual household expenditure, a good proxy for income/food security), PSM was used (Rosenbaum & Rubin, 1983). PSM is a statistical technique used in treatment effect model estimations to reduce bias and mimic a randomized controlled trial (RCT) when analyzing observational data (Jema & Abdu, 2013; Zeray et al., 2017a).

Invasion by *P. juliflora* will not be randomized. Consequently, we used PSM to assess if invasion by *P. juliflora* has a significant negative impact on the food security of the invaded communities. PSM uses a statistical model to calculate propensity of invasion based on the set of observable characteristics. Invaded and non-invaded households are matched on the basis of probability or similar propensity scores (Jema & Abdu, 2013). The PSM methodology aims to locate control observations, specifically non-invaded households, with initial observable characteristics akin to those of the invaded households. These selected control observations function as reliable proxies for the missing counterfactuals, representing unobserved outcomes (Jema & Abdu, 2013; Khandker, 2009; Zeray et al., 2017b).

The average effect of *P.juliflora* invasion is calculated as the mean difference in outcomes across households of invaded and non-invaded groups. The validity of PSM depends on two conditions: (a) conditional independence (namely, that unobserved factors do not affect participation in our case invasion by *P.juliflora*) and (b) sizable common support or overlap in propensity scores across the participant and nonparticipant samples (Jema & Abdu, 2013) i.e invaded and non-invaded sample households.

PSM model was used to answer the question what the income would be generated from crop and livestock production of the invaded households, had these households not been invaded by *P. juliflora.* The study tried to answer this question and also assessed the livelihood of households in both area through measuring the income and consumption expenditures per year (see list of variables in Appendix I).

1.8.10. Climate Variability and Trend Analysis

To measure the local climate variability and trend analysis- climatic trend data of the past forty years was collected and properly used during the analysis. All climatic and other related data was analyzed using appropriate tools.

Trend analysis is used to investigate whether the trend is upward, downward, or no trend in data value points. The most frequently used non-parametric test for identifying trends in climate variability is the Mann-Kendall (MK) test (DH Burn, 2002; Ermias, 2018; Girma et al., 2020; Hirsch, 1982; Yue et al., 2002). The Mann-Kendall (MK) test can be complemented with Sen's slope estimation to determine the magnitude of the trend (Girma et al., 2020; Yadav, 2014). Hence, for this study, Mann-Kendall test was used for the trend analysis. Mann-Kendal (MK) is a widely used nonparametric method and was applied to identify statistically significant trends in temperature and precipitation for the period of 1990–2021, using both observed and satellite climate dataset.

To quantify the magnitude of detected trends, a frequently used nonparametric method, the Sen's slope method (Sen, 1968) which was extended by (Hirsch, 1982) was applied in the study. This method is robust against outliers in a time series (Buma et al., 2016; Kumar et al., 2009; Mahmood & Jia, 2017).

1.8.11. Land use land cover change analysis

The effects of *prosopis* invasion on climate changes was analyzed using NDVI (Normalized Difference Vegetation Index) satellite imagery over time scenarios and through field level sample survey and analysis (Mao, 2010). An increase of annual maximum NDVI is directly related with an increase of vegetation condition of the area (Ning, 2015).

Landsat pre-processing was conducted and landsat images was atmospherically corrected using Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (Aramde , 2016; Masek, 2013). Pre-processing was done before the main data analysis and extraction of information in order to correct distorted data and create a more realistic representation of the original scene. Thus, Landsat images was atmospherically corrected, and a Dark Object Subtraction (DOS) was performed to correct for additive noise caused by aerosols (Masek, 2013; Zhu, 2012).

The land use land cover classification and change detection for the changes in land cover between 1983 and 2021 was determined using a supervised classification method based on a combination of Landsat 5 TM (Thematic mapper) and Landsat 8 OLI-Operator Land Imager (maximum likelihood algorithm), (Aramde, 2016; Mohajane, 2018) with the information generated from ground control points and based on local peoples' knowledge of field observation information about vegetation types particularly related to the Prosopis expansion in the study area.

The accuracy assessment was carried out using ground control points from field observations as the major sources of reference data and google earth points generated to assess accuracy. The accuracy of classification was carried out by means of overlaying of the classified maps and the test samples. For each land cover class, a contingency matrix was generated and the overall accuracy, the Kappa statistic, and the producer and user accuracy for each class is calculated (Rwanga, 2017). Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement.

1.9. Ethical consideration

The researcher took the protection of human subjects very seriously in conducting the research work and held the data collectors and supervisors to the same standard. All research activities comply with the *Common government Policy for Protection of Human Subjects.* Actions to protect ethical issues included a clear statement of informed consent with every survey, training for all data collectors on survey and research ethics and de-identifying all results data. Access to data is password protected and only the researcher and supervisors have access to the raw data.

1.10. Structure of the Dissertation

This dissertation is organized into six chapters. This chapter one presented background of the study, problem statement and the rationale, objectives, research questions, significance of the study, scope and limitation of the study, review literature, and methodology part of the study. Chapter two deals with the dynamics of Land Use and Land Cover Changes (LULCC) in the study area. It presents the analysis on the spatiotemporal effects of *P. juliflora* invasion on LULCC) in *Amibara* and Awash-Fentale Districts. Chapter three presents the effect of *P.*

juliflora invasion on local climate variability and climate extremes. Chapter four examines the impacts of P. juliflora invasion on food (in)security of the households in the study region. Chapter five focuses on determining the status and severity of food insecurity of households in *P. juliflora* (Swartz DC.) invaded and non-invaded areas in Afar Region. Finally, chapter six presents the synthesis of major findings, along with conclusion, and implications based on the finding of the study.

CHAPTER 2: DYNAMICS OF LAND USE AND LAND COVER CHANGES IN *AMIBARA* AND A*WASH-FENTALE* DISTRICTS, ETHIOPIA[2]

Abstract

This study focuses on detecting LULC changes in Amibara and Awash-Fentale districts from 1985 to 2021. We utilized five sets of Landsat data (Landsat 5 TM for 1985, 1995, 2002, and Landsat 8 OLI for 2015 & 2020) and applied supervised maximum likelihood classification. Accuracy assessments revealed overall accuracies ranging from 88.9% to 95.3% for Amibara and 89.5% to 93.2% for Awash-Fentale. Both districts exhibited six main LULC classes: agriculture, bare land, built-up, mixed forest, shrub land, and water bodies. In Amibara LULC changes from 1985 to 2021 revealed significant shifts, maintaining its primary bare land characteristic, concentrated agriculture, and expanding Prosopis-dominated shrub land due to livestock-mediated seed dispersal. Conversely, in Awash-Fentale bare land dominance decreased from 92.28% to 67.02%, while agriculture, built-up areas, and shrub land expanded. Water bodies emerged between 2015 and 2021 which is associated with the construction of Kesem Kebena dam for sugar cane farm production. The net gains were observed in shrub land (12.9%), agriculture (5.8%), mixed forest (4.1%), water bodies (1.5%), and built-up areas (0.9%), with bare land experiencing a loss of 25.3%. In conclusion, Amibara and Awash-Fentale underwent both comparable and distinct LULC shifts, featuring prevalent bare land and central agriculture, alongside Prosopis-driven shrub land expansion. While mixed forest exhibited fluctuations, built-up areas and water bodies remained limited. Notably, Awash-Fentale showed higher LULC variability. The study underlines the multifaceted implications of land-use and land-cover changes in Amibara and Awash-Fentale, emphasizing the prevalence of bare land, agriculture, and Prosopis-driven shrub land expansion. These shifts necessitate the development of strategic sustainable land management strategies.

Keywords: Agricultural expansion, Land management, Prosopis-dominated shrubland

[2] Journal of Remote Sensing Applications: Society and Environment (Published)

2.1. Introduction

Land use and land cover (LULC) change detection analysis is essential for comprehending environmental transformations and effectively managing natural resources (Munthali et al., 2019; Rawat et al., 2013). The escalating alterations in LULC, especially in developing nations, have resulted in the depletion of critical resources such as water, soil, and vegetation (Sankhala & Singh, 2014). Primarily spurred by anthropogenic activities, these changes bear both local and global implications, significantly impacting natural resources on a broad scale (Foley et al., 2005; Minale, 2013). Recognizing the importance of LULC assessment, researchers, policymakers, and planners have utilized LULC growth patterns to monitor changes in natural resources (Adeel, 2010; Twisa & Buchroithner, 2019). Changes in LULC have been identified as key factors affecting various applications, including hydrology, agriculture, forest, environment, geology, and ecology (Weng, 2001). Notably, the invasion of *Prosopis juliflora* in certain regions has disrupted ecosystem service values, affected human health, and reduced livestock productivity (Haregeweyn et al., 2013; Hailu Shiferaw et al., 2019).

Therefore, the assessment of LULC changes is crucial for understanding environmental costs and the driving forces behind such alterations. As the world's forest area diminishes and Africa experiences the highest net loss of forest area, accurately tracking LULC changes is essential for informed decision-making (FAO, 2020). In this regard, remotely sensed data and geographic information systems (GIS) technologies offer valuable tools for efficiently assessing the dynamics of LULC at various temporal and spatial scales (Lambin, 1997).

In the specific context of the Afar region in Ethiopia, where this study is conducted, climate-induced droughts have been a major cause of displacement, adversely impacting water resources, biodiversity, and ecosystem services (Yigzaw & Abitew, 2019). The spread of exotic flora, like *Prosopis Juliflora*, has further affected livelihoods in the region. In this regard, monitoring LULC changes in Afar is vital for environmental restoration and resilience measures, addressing climate change, conserving biodiversity, and improving water resources management.

Therefore, the objective of this study was focused on detecting and analyzing land-use and land-cover (LULC) changes in Amibara and Awash-Fentale districts from 1985 to 2021, as well as comparing these changes between the two districts, particularly considering Awash-Fentale's proximity to Awash National Park. The aim is to provide valuable insights for

sustainable environmental resource management, food security, and livelihoods in the Afar region and beyond.

2.2. Materials and Methods

2.2.1. Study Areas

The study areas under investigation encompass the adjacent districts of *Amibara* and Awash-Fentale, located within Zone 3 of the Afar Region in Ethiopia. Geographically, these districts lie between 8° 50' to 9° 49’ latitudes and 39° 48’ to 40° 26' longitudes. *Amibara* district covers a substantial area of 2,016 km^2 and exhibits altitudinal variations ranging from 668 meters to 1,353 meters above sea level. On the other hand, Awash-Fentale encompasses an area of approximately 1,049 km^2, with altitudes varying from 725 meters to 1,394 meters above sea level. Both districts are situated in the middle Awash valley, which is part of the larger Awash River basin.

Amibara district shares borders with Awash-Fentale district to the southwest, while the Awash River acts as a natural boundary, separating it from Dulecha and Semurobina-Gelano districts to the west. To the north, *Amibara* district is adjacent to Gewane district. Furthermore, it shares boundaries with the Maeso district in the part of Somali region to the east and the Meiso district in the part Oromia region to the south-east. In the south-eastern region of *Amibara* district, a portion of the Alledeghi wildlife reserve is also situated, adding to the biodiversity of the area.

Likewise, Awash-Fentale district is bordered by other districts, including Fentale in the Oromia region to the south-west, Berehet in the Amhara region to the north-west, Dulecha in the north, and *Amibara* in the north-east. Notably, a significant portion of Awash-Fentale district is encompassed by the Awash National Park, making it a significant part of the region's conservation efforts (Figure 2.1).

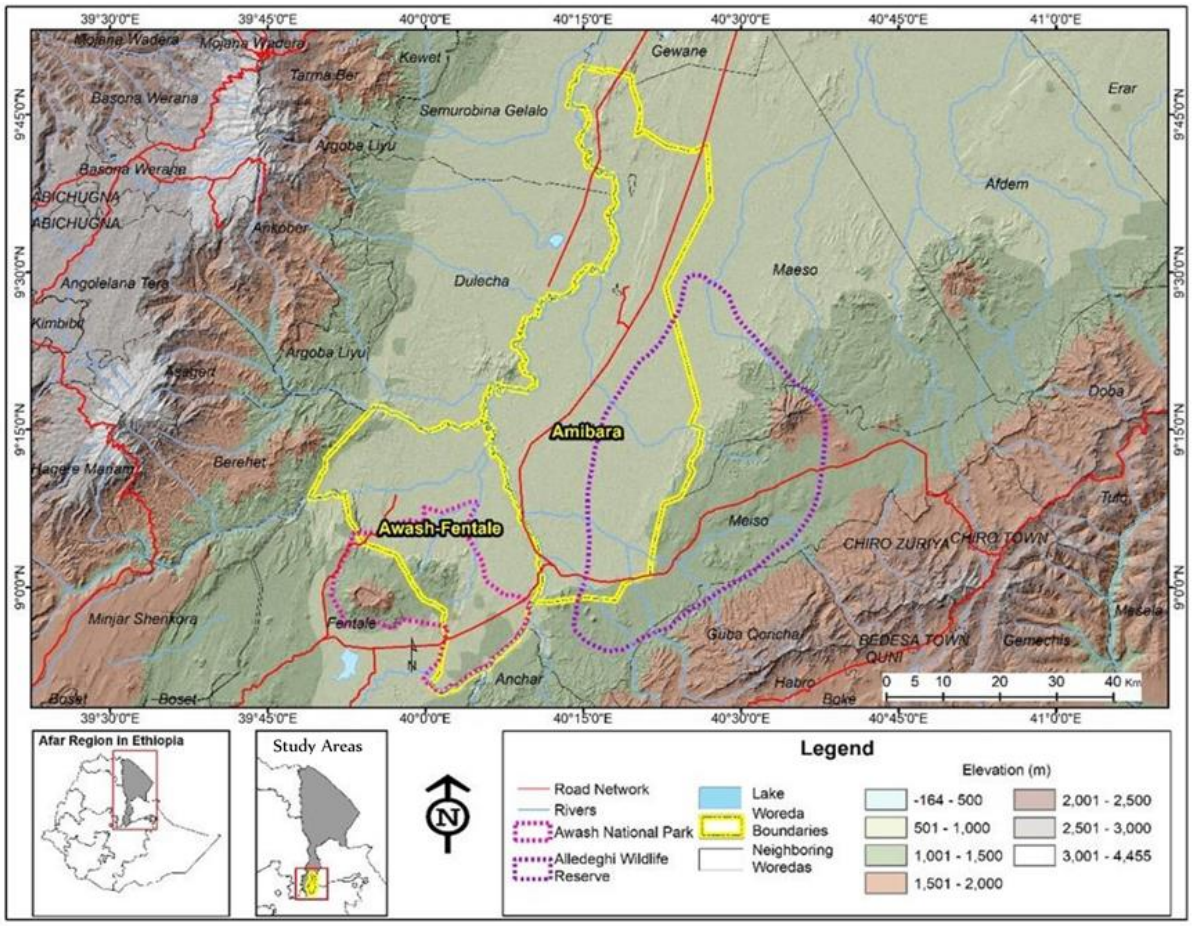

Figure 2.1: Location map of the study area (*Amibara* and *Awash Fentale* Districts) with geographical features

The climate in Awash-Fentale and *Amibara* districts is characterized by hot to warm moist conditions, with the mean annual temperature of 27˚C, and 26.8˚C, respectively (Shiferaw et al., 2022a). The same source reported that the annual precipitation of *Awash Fentale* and *Amibara* districts was 490 mm and 416 mm, respectively (Shiferaw et al., 2022a). Other source also showed that the annual rainfall in the region was between 200 mm-600 mm (Bekele, Haji, et al., 2018a). According to data from the Central Statistical Agency of Ethiopia in 2013, *Amibara* district is estimated to be home to approximately 110,427 people, with 61,175 males and 49,252 females. On the other hand, Awash-Fentale district is inhabited by around 55,708 individuals, including 28,778 males and 26,930 females (Wollie Asmare, 2022).

The dominant production system in both districts is transhumance pastoralism, which involves the rearing of cattle, camels, goats, and sheep. This production system plays a central role in the local economy and livelihoods of the residents (Haregeweyn et al., 2013).

2.2.2. Data Acquisition and Preparation

In order to comprehensively evaluate alterations in land use and land cover (LULC), the analysis effectively utilized Landsat imagery. Satellite imageries were collected for different time periods (1985, 1995, 2002, 2015, and 2021) to capture the spatial representation of the landscape. The selection of observation dates was contingent upon a range of criteria, encompassing considerations such as data quality, availability, and alignment with the dry season. These specific images were obtained through the USGS Earth Explorer Viewer (https://earthexplorer.usgs.gov) and were acquired using precise Path/Row parameters. For the *Amibara* district, these parameters were 167/53 and 167/54, while for the Awash-Fentale district, the parameters were 167/54 and 168/54 all images with the spatial resolution of 30 meters (See Table 2.1).

Table 2. 1: Detailed metadata of Landsat images used in the study area

Year	Landsat	Sensor	District and acquisition date	
			Amibara	Awash-Fentale
1985	Landsat 5	TM	18-Jan-85	02-Jan-85
1995	Landsat 5	TM	24-Feb-95	23-Jan-95
2002	Landsat 5	TM	27-Feb-02	27-Feb-02
2015	Landsat 8	OLI	14-Jan-15	05-Jan-15
2021	Landsat 8	OLI	14-Jan-21	21-Jan-21

The initially planned decadal analysis interval faced an obstacle due to the absence of quality imagery of 2005 for the study area in the same season. As a result, the 2002 imagery was adopted for the analysis in place of the absent 2005 data. These obtained datasets formed the basis for creating precise LULC maps, which were subsequently integrated into a Geographic Information System (GIS).

For the technical implementation, two essential software packages played pivotal roles: ERDAS Imagine 2014 and ArcGIS 10.8. These tools were harnessed at various stages of the analysis to ensure comprehensive and accurate results. It is noteworthy that while the spatial resolution of all images remained consistent at 30 meters, variations existed in terms of the sensors utilized across different Landsat satellites and the specific times of data acquisition. Therefore, to ensure uniformity, rigorous image pre-processing was carried out for each scene. This included correction for atmospheric effects, radiometric variations, and geometric

distortions. This ensures that the images are suitable for accurate analysis. Subsequent steps encompassed mosaicking and image sub-setting, which were executed in alignment with the distinct study areas under consideration. By meticulously addressing these preparatory steps, the analysis laid the groundwork for robust and insightful assessments of LULC changes over the specified timeframes.

To overcome challenges posed by disruptions stemming from the COVID-19 pandemic and civil conflicts during the study period in the area, we implemented innovative data collection strategies, utilizing mobile survey platforms using Kobo Toolbox and conducting structured phone interviews. These measures not only ensured real-time data collection but also prioritized respondent safety amid the constraints posed by the external disruptions.

2.2.3. Land-use and Land-cover Classification

In the context of land-use and land-cover (LULC) analysis, the classification process was conducted in two stages: an initial unsupervised classification followed by a supervised classification to delineate the LULC classes. Previous studies (Xiao & Weng, 2007) have shown that the hybrid classification approach yields superior results compared to purely supervised or unsupervised methods. Each satellite image is classified into different land use and land cover categories using classification algorithms. Spectral and spatial characteristics of pixels in the images are used to assign them to specific classes.

For the unsupervised classification, the ISODATA algorithm in ERDAS Imagine software was utilized to analyze the study area. This algorithm relies on spectral distance and iterative reclassification of pixel values to gradually identify spectral patterns and produce 36 classes through 10 iterations. The subsequent supervised classification employed the maximum likelihood technique to further categorize the 36 LULC classes obtained earlier. By correlating the spectral signatures of all 36 classes, considering the research objectives and the primary data source, a hybrid classification scheme based on both Level-I and Level-II classification approaches, as proposed by (Anderson et al., 1972), was adopted to determine the six LULC classes as agriculture, bare land, built-up, mixed forest, shrub land, and water bodies (Table 2.2).

Table 2.2: Land-use and land-cover (LULC) classification scheme

Class	Descriptions
Agricultural	This category represents areas used for cultivation and agricultural activities. Changes in agriculture can reflect shifts in cropping patterns, intensification, or abandonment of farmland.
Bareland	Bareland indicates areas with minimal or no vegetation cover. Changes in bareland might result from deforestation, urbanization, or changes in natural conditions like drought.
Built-up	This category encompasses urban and built environments, including infrastructure and residential areas. Changes in built-up areas reflect urbanization, construction, and land development.
Mixed Forest	Mixed forests include areas with a diverse composition of tree species. Changes in mixed forests can indicate deforestation, afforestation, or natural succession processes.
Shrubland	Shrublands consist of areas dominated by shrubs and other woody vegetation (indigenous & exotic species, e.g., *Prosopis juliflora* invasion). Changes in shrubland might relate to land management practices, wildfires, or ecological changes.
Water Body	This category includes natural and artificial water bodies such as lakes, rivers, and reservoirs. Changes in water bodies can result from water management, climate variations, or anthropogenic activities.

In order to enhance the accuracy of the supervised algorithm, an analysis of reference data from the Google Earth image viewing platform, combined with local knowledge, was integrated into the study. Training samples were selected by defining polygons around representative sites, resulting in the establishment of 100 training areas per study region to generate spectral signature files for the derivation of the LULC types.

2.2.4. Accuracy Assessment

The accuracy assessment of Land Use and Land Cover (LULC) classification for five observation years in both the *Amibara* and Awash-Fentale districts was conducted to evaluate the reliability of the classification results. In order to maintain the integrity of the assessment, a total of 418 and 265 points were randomly utilized for the LULC maps of *Amibara* and

Awash-Fentale districts, respectively. This allocation was deliberate, ensuring an adequate and proportionate representation of ground-truth data that corresponded to the unique spatial scopes of the two districts. This approach aimed to avoid any spatial bias in the accuracy evaluation process. For each observation year, a stratified random sampling approach was employed. This method ensured representative samples for each of the LULC classes within the study areas. It aimed to encompass the diversity of land cover types and mitigate potential bias in the accuracy assessment. The accuracy assessment was carried out using primary metrics of User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA) and The Kappa index of agreement (Congalton, 2001; Fung & LeDrew, 1988). The UA gauges the proportion of correctly classified pixels for a specific LULC class. It measures the accuracy of the classification from the perspective of the user. The PA, on the other hand, calculates the proportion of correctly classified pixels for a given land cover class. It provides insight into the accuracy of the classification process from the perspective of the data producer. The Kappa Index of Agreement was utilized to assess the agreement between the classified LULC maps and the ground-truth data (Rosenfield & Fitzpatrick-Lins, 1986).

2.2.5. Change Detection

The classified land cover maps of different time periods are compared using change detection algorithms. These algorithms highlight areas where land cover changes have occurred. The field of change detection encompasses a range of techniques tailored to uncover transformations in landscapes. Diverse methodologies, such as image differencing, principal component analysis, and post-classification comparison, have been developed to this end (Lu et al., 2004). The land use and land cover change detection analysis for the study sites of *Amibara* and Awash-Fentale involves examining how the distribution and composition of various land use and land cover categories have changed over the specified time periods. In the context of our study, the post-classification change detection method was carefully chosen due to its capacity not only to identify alterations in the extent and distribution of changed areas—whether positive or negative—but also to quantify the proportional changes between different land cover classes within each transition.

The analysis focuses on two specific study sites, *Amibara* and Awash-Fentale. These sites likely represent geographical areas with unique characteristics, such as natural ecosystems, human settlements, and economic activities. By studying changes in land use and cover in these specific sites, researchers can uncover localized trends and factors influencing these changes.

The data for land use and land cover change is presented for five distinct time periods: 1985-1995, 1995-2002, 2002-2015, 2015-2021and 1985-2021. These intervals allow us to observe changes and trends across both short and relatively longer durations. Analyzing changes over these time frames provides insights into both immediate and cumulative effects on land use and land cover.

The cornerstone of the change detection analysis was the computation of the Land Use and Land Cover (LULC) change-transition matrix. This matrix was constructed using the overlay technique within the ArcGIS platform. Its primary function was to quantitatively depict the conversion of land from one LULC class to another over the study period. By calculating the changes across four discrete time intervals (1985-1995, 1995-2002, 2002-2015, and 2015-2021), we harnessed the cross-tabulation method. This technique facilitated the comparison between the classified images of different dates, thereby revealing the dynamic transitions occurring within the landscape.

Detected changes are visualized on maps, showing how each land use and land cover type has evolved. Visual interpretation is crucial to validate the changes identified by the algorithms and to understand the nature of these changes. The algorithms quantify the changes, providing information about the magnitude and direction of change for each land use/cover category. This includes the number of ha or pixels that have transitioned from one category to another. In practical terms, the LULC change-transition analysis was executed by assigning unique values to areas that experienced transitions in land cover classes. This approach enabled a visual representation of alterations within each distinct LULC class. Consequently, the transformation dynamics were effectively communicated, offering valuable insights into the evolution of the landscape over time.

2.3. Results

2.3.1. Land Use and Land Cover Classification

The transformation of Land Use and Land Cover (LULC) in *Amibara* and Awash-Fentale districts over the span of 1985 to 2021 is depicted in Figure 2.2 and Table 2.1.

Amibara Study Site:

Throughout this period, the majority of the *Amibara* retained its bare land characteristics. Agricultural land, primarily consisting of government-operated cotton and sugarcane farms, was concentrated in the central western part of the study area. The distribution of mixed forest

exhibited temporal variations. In 1985, it was present in three patches within the *Alledeghi* wildlife reserve, while by 1995, it was confined to the northern part of the district. Subsequently, from 2002 to 2021, mixed forest coverage dominated around the government farm's northern region and the banks of the Awash River.

Shrub land, mainly dominated by *Prosopis*, initially flanked the main road in 1985. Over the following years (2015 and 2021), shrub land exhibited axial expansion along the main road and encroached into the *Alledeghi* wildlife reserve.

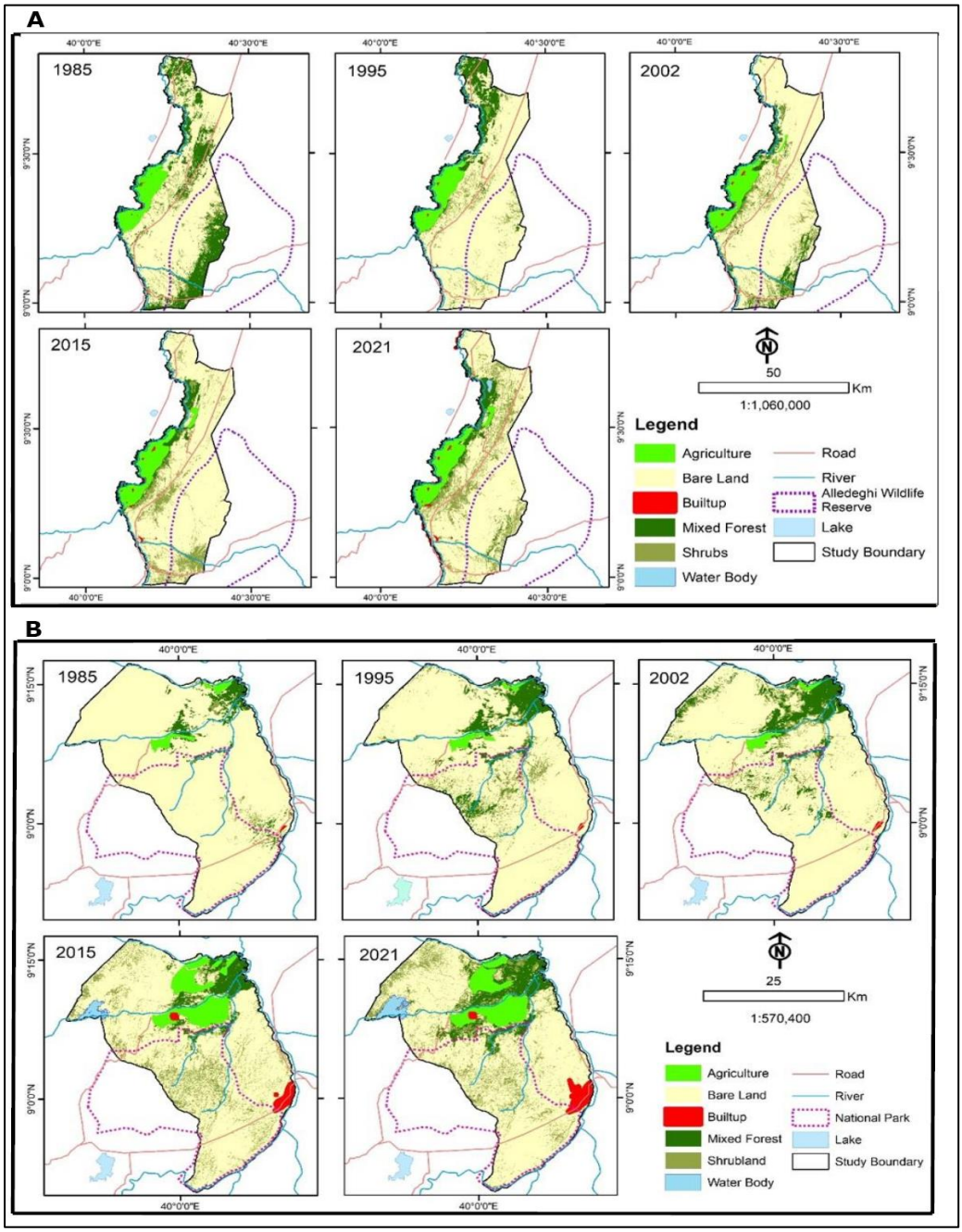

Figure 2.2: LULC classification (A) *Amibara* District; (B) Awash-Fentale District

A rising trend of shrub land (mainly *Prosopis*) was evident from the study's commencement to its conclusion. In 1985, bare land covered 62.96%, mixed forest covered 25.01%, while agricultural land spanned 7.69%. The temporal changes in LULC during the five observation years (1985, 1995, 2002, 2015, and 2021) revealed fluctuations. Agriculture peaked in 2015, while bare land reached its apex in 1995. Built-up areas expanded, with the highest coverage in 2021, and mixed forest had its zenith in 1985. Figure 2.2, along with Table 2.1, offer a comprehensive view of LULC trends in *Amibara* district. By 2021, bare land dominated (65.77%), followed by shrub land (17.66%), both potential areas for *Prosopis* expansion. Throughout the period (1985-2021), agriculture, built-up areas, and shrub land expanded, while mixed forest dwindled. Agriculture increased by 1.03%, bare land by 2.82%, built-up by 0.43%, shrubs by 13.42%, and water bodies by 0.31%. Conversely, mixed forest decreased by -18%.

Awash-Fentale Study Site:

The trajectory of LULC changes in Awash-Fentale from 1985 to 2021 is also summarized in Figures 2.2, accompanied by Table 2.3, based on six LULC categories. In 1985, the landscape composition, as a percentage of total area, was primarily bare land (92.28%), followed by mixed forest (4.84%), agriculture (1.55%), and built-up (0.04%). LULC changes were noted in 1995, 2002, 2015, and 2021, with agriculture, built-up, and shrub land expanding, while bare land decreased. Mixed forest exhibited variations over these years. Water bodies emerged in 2015 and 2021. By 2021, the landscape was dominated by bare land (67.02%), followed by shrub land (14.17%), mixed forest (8.95%), agriculture (7.38%), water bodies (1.47%), and built-up (0.99%).

Throughout the study (1985–2021), agriculture expanded from 1.55% to 7.83%, built-up from 0.04% to 0.99%, shrub land from 1.29% to 14.17%, water body from 0.0% to 1.47%, and mixed forest exhibited fluctuations, reaching its peak at 10.35% between 1985 and 2002, decreasing to 6.06% in 2015, and rising again to 8.95% in 2021. Bare land decreased from 92.28% to 67.02%, while mixed forest exhibited both increases and decreases. The net gains were highest in shrub land (12.9%), followed by agriculture (5.8%), mixed forest (4.1%), water body (1.5%), and built-up (0.9%), while bare land experienced a net loss of 25.3%.

2.3.2 Accuracy Assessment

The accuracy levels for *Amibara* ranged from 88.9% to 95.3%, while for Awash-Fentale, they ranged from 89.5% to 93.2%. Similarly, the Kappa values showed variation across the five observation years, ranging from 0.85 to 0.94 for *Amibara* and from 0.86 to 0.91 for Awash-Fentale (Table 2.4).

Table 2.3:The area coverage (ha) of different LULC in 1985, 1995, 2002, 2015 & 2021 of *Amibara* and Awash-Fentale districts

		Land use/Land cover types						
Year	Study Site	Agriculture	Bare land	Built-up	Mixed Forest	Shrub land	Water Body	Total
1985	*Amibara*	15513	126927	190	50425	8540	12	201607
	Awash-Fentale	1624	96777	45	5075	1354	0	104875
1995	*Amibara*	15802	149503	298	25246	10758	0	201607
	Awash-Fentale	1476	86896	118	9431	6954	0	104875
2002	*Amibara*	15671	148278	538	18255	18860	5	201607
	Awash-Fentale	1360	86415	186	10857	6057	0	104875
2015	*Amibara*	17606	143481	826	11337	28351	6	201607
	Awash-Fentale	8312	74379	712	6355	14126	991	104875
2021	*Amibara*	17581	132602	1069	14116	35602	637	201607
	Awash-Fentale	7742	70284	1040	9385	14884	1540	104875

2.3.3. Land Use and Land Cover Changes

The study examines several key land use and land cover types, namely Agriculture, Bare land, Built-up Areas, Mixed Forest, Shrub land, and Water Bodies. A comprehensive overview of how land use and land cover have changed over different time intervals within two study sites, *Amibara* and Awash-Fentale. is presented in Table 2.5. The table's numerical values represent the net change (in ha) for each land use/cover type during the specified time intervals. Positive values indicate an increase in that land use/cover type, while negative values suggest a decrease.

Table 2. 4: Accuracy assessment of the LULC classification at *Amibara* and Awash-Fentale districts

Year	Study Site	Land use/Land cover types												Overall Accuracy (%)	Kappa Index
		Agriculture		Bare land		Built-up		Mixed Forest		Shrub land		Water Body			
		PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA		
1985	*Amibara*	75	100	100	75.5	85	100	100	86.7	87	100	NA	NA	89.5	0.86
	Awash-Fentale	88.6	91.2	100	63.9	73.7	100	91.5	91.5	77.7	100	NA	NA	89.5	0.86
1995	*Amibara*	78.3	100	100	84.8	80.5	100	100	86.1	81.9	100	NA	NA	89.8	0.87
	Awash-Fentale	90.5	90.5	100	87.2	66.7	100	90.5	90.5	81	100	NA	NA	90.9	0.89
2002	*Amibara*	87.5	100	100	90.6	81	100	97.6	100	100	100	NA	NA	95.3	0.94
	Awash-Fentale	96	80	98	84.5	64	100	87.8	95.6	100	100	NA	NA	89.8	0.87
2015	*Amibara*	97.6	97.6	100	70.6	66.3	100	96.4	94.4	90	70.6	80	100	90	0.85
	Awash-Fentale	96.6	100	100	86.1	76.2	100	100	88	81.3	100	100	100	93.2	0.91
2021	*Amibara*	100	91.7	100	73.5	73.8	66.7	91.2	100	86.8	97.6	86.2	100	88.9	0.85
	Awash-Fentale	93.9	90.2	100	89.5	76.5	100	83.9	89.7	95.8	95.8	100	100	92.1	0.9

PA = Producer's Accuracy (%); UA = User Accuracy (%)

***Amibara* Study Site:**

1985-1995: During this initial decade, the study site exhibited both positive and negative trends in its land use and land cover types. Agriculture expanded significantly, with an increase of 289 ha. There was also a noteworthy increase in shrub land by 2,218 ha. However, the most striking change was the reduction in mixed forest by 25,179 ha. Additionally, water body decreased by 12 ha (Table 2.5).

Table 2.5: Magnitude of LULC change (ha) in *Amibara* and Awash-Fentale districts

Year	Study Site	Land use/Land cover types					
		Agriculture	Bareland	Built-up	Mixed Forest	Shrubland	Water Body
1985-1995	*Amibara*	289	22576	108	-25179	2218	-12
	Awash-Fentale	-148	-9881	73	4356	5600	0
1995-2002	*Amibara*	-131	-1225	240	-6991	8102	5
	Awash-Fentale	-116	-481	68	1426	-897	0
2002-2015	*Amibara*	1935	-4797	288	-6918	9491	1
	Awash-Fentale	6952	-12036	526	-4502	8069	991
2015-2021	*Amibara*	-25	-10879	243	2779	7251	631
	Awash-Fentale	-570	-4095	328	3030	758	549

1995-2002: This interval showed a shift in land use and land cover in *Amibara*. Notable changes include a reduction in bare land by 1,225 ha and a decrease in mixed forest by 6,991 ha. On the other hand, there was an expansion in built-up areas by 240 ha and shrub land increased by 8,102 ha. Agriculture also experienced a decrease of 132 ha, while water body increased by 5 ha.

2002-2015: Over this period, there was a significant increase in Agriculture by 1,938 ha, indicating a shift towards more intensive agricultural activities. There was also growth in built-up areas by 288 ha and shrub land by 9,491 ha. However, the trend of decreasing forest cover continued with a decrease in mixed forest by 6,918 ha. Water body experienced an increase of 1 hectare.

2015-2021: During this recent timeframe, agriculture experienced a slight decline of 25 ha, possibly reflecting changes in land use practices. Bare land also decreased by 10,879 ha, indicating

possible shrub expansion by *Prosopis* invasion since there was an increase in shrub lands by 7,251 ha, and increase of built-up area by 243 ha suggesting changes in land management. Both mixed forest and water body increased by 2,779 and 631 ha, respectively.

Awash-Fentale Study Site:

Over the span of several decades, the Awash-Fentale region underwent significant transformations in its land use and land cover patterns.

1985-1995: The period between 1985 and 1995 revealed noteworthy changes, with a reduction in agricultural activity by 148 ha while bare land declined significantly by 9,881 ha. Built-up areas also increased by 73 ha, indicative of urbanization trends. Notably, mixed forest cover saw a positive change of 4,356 ha, possibly due to reforestation efforts, while shrub land expanded by 5,600 ha.

1995-2002: Subsequently, from 1995 to 2002, agriculture and bare land experienced further diminutions, while built-up areas continued to grow. The landscape saw contrasting dynamics in mixed forest and shrub land, with the former expanding by 1,426 ha and the latter shrinking by 897 ha.

2002-2015: The period spanning 2002 to 2015 showed substantial shifts in land use, highlighted by a considerable increase in agricultural areas by 6,952 ha and a significant reduction in bare land by 12,036 ha. Shrub land expanded dramatically by 8,069 ha, potentially due to natural succession or land management practices.

2015-2021: During the relatively recent timeframe, the Awash-Fentale region underwent notable alterations in its land use and land cover patterns. One prominent change was the visible expansion of mixed forest cover, which increased by 2,779 ha over these six years. Furthermore, an interesting transformation unfolded in terms of water bodies within the region. The water body area experienced an expansion of 631 ha during this period. The combined expansion of mixed forest cover and water bodies within this timeframe reflects the intricate interplay between environmental dynamics and human activities.

Over the entirety of the study period, the Awash-Fentale region experienced a cumulative growth in agriculture, shrub land and built-up areas. However, bare land showed a considerable decrease, and mixed forest cover underwent a net loss. These changes collectively underscore the complex interplay between human activities, natural processes, and conservation efforts that have shaped the region's landscape over the years.

2.3.4. Land use and land cover change matrix

1985-1995

Table 2.6 offers a comprehensive LULC (Land Use and Land Cover) conversion matrix, shedding light on the dynamic changes that unfolded within the *Amibara* and Awash-Fentale districts during the transformative period from 1985 to 1995. This matrix serves as an invaluable tool for analyzing and understanding the shifts in land utilization and environmental conditions over the decade. The table is organized with the LULC types in 1985 listed vertically on the left-hand side and the LULC types in 1995 listed horizontally across the top. The cells of the matrix contain the corresponding hectare values for each specific LULC conversion. This thoughtful arrangement allows for a systematic exploration of how each specific LULC type evolved and transitioned within the given time frame.

For this specific study, it becomes apparent that the conversion data encapsulates a multitude of alterations. In the *Amibara* region, for instance, the table reveals that a significant expansion of 14,980.6 ha, originally classified as Agriculture in 1985, maintained its identity as such in 1995. Remarkably, a portion of bare land spanning 102.2 ha in 1985 transformed into agriculture in the subsequent decade. This shift could potentially indicate agricultural expansion or land reclamation efforts.

However, the matrix also illustrates more diverse transitions. Notably, built-up areas showed limited changes in the *Amibara* district, with a mere 190 ha converting from other land categories. Similarly, a portion of mixed forest encompassing 390.7 ha in 1985 evolved into Agriculture, reflecting potential deforestation or land clearance for agricultural purposes. Moreover, shrubs underwent noteworthy transformations, with 8,066.1 ha in this category in 1985 undergoing shifts, primarily into Agriculture.

Table 2. 6: LULC conversion matrix of the *Amibara* and Awash-Fentale District between 1985 and 1995

LULC Type in 1985 (ha)	Study site	LULC Type in 1995 (ha)						
		LULC Class	Agriculture	Bare Land	Built-up	Mixed Forest	Shrub land	Water Body
	Amibara	Agriculture	**14980.6**	102.2	87.2	289.9	56.6	0
		Bare Land	437.3	**115869.2**	17.4	8118	2484.1	0
		Built-up	0	0	**190**	0	0	0
		Mixed Forest	390.7	33529.4	3.1	**16351.9**	147.1	0
		Shrub land	0	0	0	473.8	**8066.1**	0
		Water Body	0	0	0	8.4	4	**0**
	Awash-Fentale	Agriculture	**1282.4**	60.8	0	244.9	39.8	0
		Bare Land	73.7	**83773.5**	73.1	5043.2	8371.1	0
		Built-up	0	0	**44.8**	0	0	0
		Mixed Forest	123.3	711.5	0	**4044**	196.6	0
		Shrub land	0	630.1	0.3	98.4	**63.5**	0
		Water Body	0	0	0	0	0	**0**

In the Awash-Fentale District, a different pattern emerges between 1985 and 1995 where the result highlights two primary changes: shifts in the agriculture and bare land areas, indicating alterations in their classifications and transitions to other land cover types. Agriculture underwent changes, with 1282.4 ha retaining their classification over the ten-year period, meaning these areas remained under agricultural use. This implies that this specific area continued to be used for farming and related agricultural activities while a small fraction (60 ha) shifted to bare land, (244.9 ha) to mixed forest, and (39.8 ha) to shrub land. Additionally, bare land areas showed alterations, with 73.7 ha transitioning to agriculture which indicates that some areas previously characterized as bare land were converted to agricultural use, likely through land clearing and cultivation and 73.1 ha to built-up which suggests that portions of the bare land were converted to built-up areas, reflecting urbanization or infrastructure development.

1995-2002

The Land Use and Land Cover (LULC) conversion matrix for the *Amibara* and Awash-Fentale districts spanning 1995 to 2002 presents dynamic changes in various LULC classes within these study sites. This matrix reveals the transition of LULC categories over the specified timeframe,

including Agriculture, Bare Land, Built-up areas, Mixed Forest, Shrubs, and Water Bodies (Table 2.7).

In the *Amibara* district, the transformation of LULC classes from 1995 to 2002 is noteworthy. Agriculture, which encompassed 14,802.5 ha in 1995, evolved into multiple classes by 2002, including bare land (141.4 ha), built-up areas (202.4 ha), mixed forest (458.2 ha), and shrub land (193.9 ha). Similarly, 132,348.1 ha bare land, which occupied 1995 remained stable, while a significant change underwent, converting into agriculture (594.7 ha), built-up areas (27.3 ha), mixed forest (9325.8 ha), and shrub land (7205.5 ha). Built-up areas remained stable at 298 ha. Mixed forest transformed into various classes, including agriculture (251.8 ha), bare land (15786.7 ha), built-up areas (26.9 ha), shrub land (1317.2 ha), and even a small water body portion (4.9 ha) while (7863.7 ha) mixed forest remained unchanged. Shrub land shifted to mixed forest (613.6 ha) and a dominant shrub land area (10,144.4 ha) remained unchanged.

Table 2. 7: LULC conversion matrix of the *Amibara* and Awash-Fentale district between 1995 and 2002

	Study site	**LULC Class**	**LULC Type in 2002 (ha)**					
			Agriculture	Bare Land	Built-up	Mixed Forest	Shrub land	Water Body
LULC Type in 1995 (ha)	***Amibara***	Agriculture	**14802.5**	141.4	202.4	458.2	193.9	0
		Bare Land	594.7	**132348.1**	27.3	9325.8	7205.5	0
		Built-up	0	0	**298**		0	0
		Mixed Forest	251.8	15786.7	26.9	**7863.7**	1317.2	4.9
		Shrub land	0	0	0	613.6	**10144.4**	0
		Water Body	0	0	0	0	0	**0**
	Awash-Fentale	Agriculture	**1187.5**	123.5	0	110.4	59.8	0
		Bare Land	65.9	**80082.3**	68.8	2884.8	3792.3	0
		Built-up	0	0	**118.1**	0	0	0
		Mixed Forest	67	2078.8	0	**6631.9**	652.4	0
		Shrub land	45.2	4125.6	0.6	1228.9	**1551.2**	0
		Water Body	0	0	0	0	0	**0**

In the Awash-Fentale district, a similar pattern emerged. Agriculture expanded into Agriculture (1,187.5 ha), Bare Land (123.5 ha), Mixed Forest (110.4 ha), Shrubs (59.8 ha), and Water Bodies in 2002 from its 1995 state. Bare Land transformed into Agriculture (65.9 ha), an increased Bare Land area (80,082.3 ha), Built-up areas (68.8 ha), Mixed Forest (2884.8 ha), and Shrubs (3792.3 ha). Built-up areas experienced modest growth to 118.1 ha. Mixed Forest shifted into Agriculture

(67 ha), Bare Land (2,078.8 ha), Mixed Forest (6,631.9 ha), Shrubs (652.4 ha), and Water Bodies. Shrub land also transformed into Agriculture (45.2 ha), Bare Land (4,125.6 ha), a small mixed Forest area (0.6 ha), while (1,228.9 ha) shrub land remained unchanged.

2002-2015

Table 2.8 presents the Land Use and Land Cover (LULC) conversion matrix for the *Amibara* and Awash-Fentale districts during the period from 2002 to 2015. This matrix meticulously documents the changes in hectares across distinct LULC categories, offering a comprehensive overview of the transformations that unfolded within these study sites.

The *Amibara* district showed a series of notable alterations in its landscape over the examined period, as evidenced by distinct shifts in land use categories. About 15,623.91 ha of agricultural land remained stable between 2002 and 2015. In a contrasting but equally significant conversion, agricultural land was transformed into other LULC, contributing to a noteworthy augmentation of 6.4 ha for bare land, 29.5 ha for built-up, 177.5 for mixed forest and 0.5 for shrub land.

Moreover, the district experienced a significant shift from bare land to built-up areas, encompassing 170.7 hectare, which is a clear reflection of urbanization trends and the expansion of infrastructure. Additionally, the dynamic transformation of mixed forest into bare land, covering an extensive area of 5,917 ha, points towards a substantial degradation of forest resources.

In the Awash-Fentale district, the LULC conversion matrix between 2002 and 2015 outlines significant transitions in land cover types. About 1,173.2 ha of agricultural land remained stable during this period. However, significant area is converted into other LULC. For instance, 21.2 ha of agricultural land is transformed into bare land, 25.4 ha into built-up, 125 ha into mixed forest and 39.4 into shrub land. On the other hand, bare land contributed to agricultural land accounts for an expansion of 4261.2 ha, indicating a deliberate focus on increasing agricultural productivity. There was a shift from bare land to mixed forest amounting 654.8 ha, 10,607 ha into shrub land and 924.6 into waterbody. Notably, the conversion from shrub land to Agriculture results in a transformation spanning approximately 1363.2 ha, possibly signifying the conversion of shrub land into arable land. The transition from shrub land to mixed forest encompasses an expansion of 866.1 ha.

Table 2. 8: LULC conversion matrix of the *Amibara* and Awash-Fentale district between 2002 and 2015

	Study site	LULC Class	LULC Type in 2015 (ha)					
			Agriculture	Bare Land	Built-up	Mixed Forest	Shrub land	Water Body
LULC Type in 2002 (ha)	*Amibara*	Agriculture	**15623.91**	6.4	29.5	177.5	0.5	0
		Bare Land	1090	**134207.7**	170.7	2635	18458.9	5.5
		Built-up	0	0	**538**	0	0	0
		Mixed Forest	535.2	5917	29.2	**6907**	4871.6	0.72
		Shrub land	364.1	3348.9	48.4	1616.6	**5019.8**	0.01
		Water Body	0	0	0	3.9	0.96	**0**
	Awash-Fentale	Agriculture	**1173.2**	21.2	25.4	125	39.4	0
		Bare Land	4261.2	**69464.6**	484.1	654.8	10607	924.6
		Built-up	0	0	**186**	0	0	0
		Mixed Forest	1538.6	2347.6	2	**4708.7**	2208.1	48.1
		Shrub land	1363.2	2544.8	14.9	866.1	**1248.5**	17.9
		Water Body	0	0	0	0	0	**0**

Source: Own calculation

2015-2021

Table 2.9 depicts the evolving landscape of the *Amibara* and Awash-Fentale Districts over a six-year span from 2015 to 2021. This matrix reveals the intricate transitions within the Land Use and Land Cover (LULC) categories, shedding light on how LULC shifted among various classes.

In the *Amibara* district, the Agricultural land retained its 17,570.61ha extent between 2015 and 2021while conversion other categories like bare land, mixed forest, shrub land, and water body were absent. However, a small portion of Agricultural land (32.1 ha) converted into built-up area. A substantial portion of the initial 120,042.7 ha of bare land persisted within the same class, while some converted to mixed forest (2,219.1 ha), shrub land (21,107.9 ha), and built-up areas (108.1 ha). During this period, minor growth in built-up areas and significant expansion in mixed forest and shrub lands were observed, possibly originating from conversions of bare land and other classes.

Meanwhile, in the Awash-Fentale district, the 7,765.84 ha agricultural land remained nearly consistent, while the initial 62,648 ha bare land remained stable whereas, major portion of bare land is transformed into other LULC partially into shrub land (8,652.9 ha), mixed forest (2,280.2 ha), built-up area (328.6 ha) and water body (469.1 ha).

Table 2. 9: LULC conversion matrix of the *Amibara* and Awash-Fentale District between 2015 and 2021

	Study site		LULC Type in 2021 (ha)					
		LULC Class	Agriculture	Bare Land	Built-up	Mixed Forest	Shrub land	Water Body
LULC Type in 2015 (ha)	*Amibara*	Agriculture	**17570.61**	0	32.1	0	0	0
		Bare Land	0	**120042.7**	108.1	2219.1	21107.9	2.7
		Built-up	0	0	**826**	0	0	0
		Mixed Forest	0	615.8	14	**9320.4**	1234.8	155
		Shrubs	0	11939.3	94.4	2581.4	**13257**	479.5
		Water Body	0	3.2	0	2.9	0.01	**0.08**
	Awash-Fentale	Agriculture	**7765.84**	8.7	0	450.2	110.7	0
		Bare Land	0	**62648**	328.6	2280.2	8652.9	469.1
		Built-up	0	0	**712.4**	0	0	0
		Mixed Forest	0	460.6	0	**5090.3**	798.1	5.6
		Shrubs	0	7148.7	15.3	1563.9	**5299.1**	76.1
		Water Body	0	1.26	0	0	0	**989.4**

About 5,090.3 ha of mixed forest remained stable during the study period, whereas 460.6 ha of mixed forest converted into bare land due to deforestation, 798.1 ha into shrub land and 5.6 ha into water body. Notably, a substantial 989.4 ha of water body remained stable whereas, 1.26 ha of water body is converted into bare land. As indicated in table 2.10 there is an increase of agricultural land in both Woredas specifically high rate of expansion in Awash Fentale this might be due to the establishment of Kesem Kebena dam and expansion of irrigation-based farming activities. The bareland is dominate land use type in both Woreda however significant conversion of bare land into agriculture land observed in Awash Fentale compared with Amibara. There is an increasing trend of shrub land with decreasing trend of bare land and mixed forest in both Woredas specifically high rate of increase in Awash Fentale which might be due to expansion of *P. juliflora* in both areas.

Table 2. 10: **Summary of LULC Gross Changes between the years (1985 -2021)**

		1985GC		2021GC		LULC Change (1985 - 2021)	
Woreda	Class	Area [Ha]	Area [%]	Area [Ha]	Area [%]	Change Area [Ha]	Change From Total Area [%]
Amibara	Agriculture	15,512	7.7%	17,583	8.7%	2,071	1.0%
	Bare Land	126,927	63.0%	152,448	75.6%	25,521	12.7%
	Built-up	190	0.1%	1,063	0.5%	873	0.4%
	Mixed Forest	50,425	25.0%	14,126	7.0%	-36,299	-18.0%
	Shrubs	8,540	4.2%	16,021	7.9%	7,481	3.7%
	Water Body	12	0.0%	372	0.2%	360	0.2%
	Total Area [Ha]	201,606	100.0%	201,613	100.0%		
Awash Fentale	Agriculture	1,624	1.5%	7,742	7.4%	6,118	5.8%
	Bare Land	97,338	92.8%	74,760	71.3%	-22,578	-21.5%
	Built up	45	0.0%	1,040	1.0%	995	0.9%
	Mixed Forest	5,076	4.8%	11,951	11.4%	6,875	6.6%
	Shrubs	792	0.8%	7,928	7.6%	7,136	6.8%
	Water Body	0	0.0%	1,452	1.4%	1,452	1.4%
	Total Area [Ha]	104,875	100.0%	104,873	100.0%		

2.4. Discussions

2.4.1. LULC Classification and Change Detection

The results of the study indicate noteworthy transformations in land use patterns influenced by factors such as urbanization, agricultural expansion, reforestation initiatives, and the presence of invasive species like *Prosopis*. The observed shifts, as discussed in detail, reveal a complex interplay between natural processes and human interventions, emphasizing the multifaceted dynamics shaping the regions over the specified timeframe. These alterations in land cover categories, including changes in bare land, shrub land, mixed forest, and built-up areas, provide valuable insights into the intricate relationship between environmental changes and human activities in the *Amibara* and Awash-Fentale districts. The examination of Land Use and Land Cover (LULC) alterations in the *Amibara* and Awash-Fentale districts spanning the period from 1985 to 2021 yields significant findings that offer key perspectives on the changing landscapes and their potential consequences for the local communities involved (Haregeweyn et al., 2013; Mekuyie et al., 2018; Seid et al., 2020a; Shiferaw et al., 2019; Wudad & Abdulahi, 2021).

In the *Amibara* district, bare land remained predominant throughout the study period, with concentrated agricultural activities related to cotton and sugarcane farming (Haregeweyn et al., 2013; Shiferaw et al., 2019). The mixed forest cover exhibited fluctuations, influenced by government-run farms and the presence of the Awash River. Shrub land, mainly occupied by *Prosopis*, expanded notably, encroaching into wildlife reserves due to livestock-dung-mediated seed dispersal (Seid et al., 2020b; Shiferaw et al., 2019). These changes align with previous studies, indicating an increase in farmland and *Prosopis*, leading to a decrease in woodland and bare land (Haregeweyn et al., 2013; Shiferaw et al., 2019). It is also reported that in the period (1974-2014), in the Awash national park, there was a reduction in the size of the grassland units with most of it replaced with shrubs such as *Prosopis* and *Acacias* (Chernet & Consult, 2015; Tezera, 2015).

Similarly, in the Awash-Fentale district, bare land dominance shifted, giving way to expansions in agriculture, built-up areas, and shrub land (Mekuyie et al., 2018). Fluctuations were observed in mixed forest cover, hinting at dynamic reforestation efforts or environmental changes (Wudad & Abdulahi, 2021). Noteworthy was the emergence of water bodies during specific years, suggesting potential alterations in hydrological patterns (Shiferaw et al., 2004). These changes, consistent with previous studies, emphasized the intricate interplay between human activities and environmental factors (Mekuyie et al., 2018).

Analyzing the patterns and magnitude of LULC changes revealed intriguing findings (Hailu Shiferaw *et al*., 2019). *Amibara* shown a net expansion of shrub land cover slightly exceeding Awash-Fentale, yet its annual expansion rate was more than double. Bare land in *Amibara* increased modestly, while Awash-Fentale experienced a substantial reduction (Shiferaw et al., 2019). Agricultural land cover increased slightly in *Amibara* compared to Awash-Fentale's substantial expansion, growing nearly three times faster (Hailu Shiferaw et al., 2019). Both districts showed growth in built-up land cover, with Awash-Fentale's expansion being twice that of *Amibara* (Mekuyie et al., 2018*)*. Water body cover and its growth rate were substantially higher in Awash-Fentale, with a nearly five-fold overall increase and an annual growth rate around two and a half times higher (Shiferaw et al., 2004). The emergence of water body in the latter years at *Awash Fentale* could be associated with the construction of Kesem Kebena dam for sugar cane farm production. The mixed forest cover in *Amibara* experienced a significant reduction, whereas Awash-Fentale saw a slight increase (Wudad & Abdulahi, 2021).

These findings have critical implications for local communities. In *Amibara,* the reduction of mixed forest and expansion of *Prosopis* led to a shortage of pasture land, affecting Afar pastoralists' livelihoods and food security (Seid et al., 2020b). The differences between the districts highlight the complexity of shaping landscapes in distinct regions, emphasizing the need for tailored and context-specific land management strategies (Shiferaw et al., 2019).

Examining specific periods reveals further insights. During the first period (1985-1995), *Amibara* experienced a substantial loss of forested areas and a noteworthy increase in bare land and a slight growth in built-up areas alongside a minor increase in shrub land, accompanied by a substantial decrease in mixed forest cover. In contrast, Awash-Fentale showed a substantial increase in both shrub land and mixed forest, corresponding to a substantial decrease in bare land and a notable decrease in agricultural land. These observations in *Amibara* might be attributed to large-scale deforestation of mixed forests for domestic fuel sources like fuelwood and charcoal, while Awash-Fentale's mixed forest increase could be attributed to environmental conservation activities. Furthermore, the expansion of *Prosopis* in the early 1980s might explain the growth of shrub land in both districts.

In the second period (1995-2002), *Amibara* showed an increase in shrub land at the expense of mixed forest cover, alongside a slight decrease in bare land. In this period, the decrease in agricultural land continued in Awash-Fentale. Conversely, *Amibara* experienced a decrease in bare land, coupled with an increase in built-up areas. The most striking change was observed in mixed forest, where Awash-Fentale showed an increase in mixed forest cover, suggesting potential reforestation or natural forest regeneration. There was also a slight increase in water bodies in *Amibara*.

Moving to the third period (2002-2015), *Amibara* showed substantial growth in agriculture and further expansion of shrub land, causing additional deforestation of mixed forest cover and utilization of bare land. *Amibara* showed a decrease in bare land and a modest increase of in built-up areas. Mixed forest in *Amibara* declined, likely due to continued deforestation or land conversion. Shrub land in *Amibara* expanded significantly, indicating changes in land management practices. Similarly, Awash-Fentale experienced substantial expansion of shrub land and agricultural land, resulting in extensive bare land reduction and mixed forest due to deforestation.

This period also showed the emergence of water bodies and built-up areas. Both districts showed the total coverage of shrub land and agricultural land exceeds that of mixed forests. In Awash-Fentale, the establishment of Kesem sugar factory and the construction of an irrigation dam led to considerable changes in land cover (Assefa, 2018; Kedir et al., 2022).

In the fourth period (2015-2021), *Amibara* experienced further shrub land expansion, mixed forest recovery, and water body increase at the expense of bare land. Notably, the mixed forest cover increased during this period. In Awash-Fentale, mixed forest cover expanded over previous bare land, with further growth in built-up areas, shrub land, and water bodies. In this short timeframe, there was a decline in agricultural land in Awash-Fentale, possibly due to shifting agricultural practices or changes in land use priorities. *Amibara* experienced a substantial decrease in bare land and a minor increase in built-up areas. Mixed forest in Awash-Fentale rebounded with an increase area, suggesting potential reforestation efforts or changes in land management practices. The *Amibara* region showed an expansion in its shrub land area, likely attributed to a combination of natural vegetation progression and the invasion of *Prosopis*. Additionally, there was an observable rise in water bodies within the same area.

Over the entire period from 1985 to 2021, while both *Amibara* and Awash-Fentale experienced changes in land use and land cover, their specific trends and patterns differed. The reasons behind these differences could include variations in land management practices, natural environmental conditions, urbanization rates, and local development priorities.

During the study period, the expansion of Prosopis was notable. Previous studies have quantified the expansion of *Prosopis* along the Afar region. For instance, in the Middle Awash area of Ethiopia, the invasive Prosopis has severely impacted Afar pastoralists' essential rangelands, occupying vast areas (Mehari, 2015b). Other studies showed rapid expansion, with *Prosopis* invading 1.17 million hectares in the Afar region (Shiferaw et al., 2019), leading to significant forage grass depletion (Shiferaw et al., 2019b; W. Shiferaw et al., 2019; Wakie et al., 2014). Dispersed by wildlife and livestock, *Prosopis* invaded areas increased by 965,000 hectares between 1986 and 2017, at a rate of 31,127 hectares per year (Shiferaw et al., 2019). District-specific data indicated substantial expansion in *Amibara* and Awash-Fentale, emphasizing the urgent need for tailored management strategies (Shiferaw et al., 2018). The invasion's extensive

reach, covering 1.17 million hectares in Afar, underlines the pressing challenges (W. Shiferaw et al., 2021). These studies highlight the necessity for further research and effective management against *Prosopis* invasion in the region.

2.4.2. Accuracy Assessment

The findings discuss the profound implications arising from a meticulous accuracy assessment carried out within the *Amibara* and Awash-Fentale districts. Accuracy assessment plays a pivotal role in the realm of remote sensing and geospatial analysis, particularly when dealing with the classification of land use and land cover (Congalton, 1991; Rwanga & Ndambuki, 2017)

The results, spanning an accuracy range of 88.9% to 95.3% for *Amibara* and 89.5% to 93.2% for Awash-Fentale, underscore the precision with which the classification process identifies and categorizes diverse land use and cover types. These percentages indicate how well the classification process correctly identified and labelled different land use and land cover categories within the study area. Reinforcing the credibility of the classification outcomes, the computation of Kappa indices of agreement adds an extra layer of validation (Jenness & Wynne, 2007). These Kappa values, ranging from 0.85 to 0.94 for *Amibara* and 0.86 to 0.91 for Awash-Fentale across multiple observation years, substantiate the robustness of the classification results by quantifying the agreement between actual and expected classifications. The fact that these Kappa values consistently exceed 0.85 demonstrates a high level of agreement and accuracy in the classification outcomes, meeting the minimum threshold and indicating a robust foundation for subsequent analyses. Thus, these findings highlight the importance of considering both accuracy levels and Kappa values to comprehensively evaluate the reliability and consistency of data collected from different geographical locations over multiple years.

The noteworthy results of this accuracy assessment hold significant implications for the study. By establishing a strong foundation of reliability, the assessed accuracy levels and elevated Kappa indices provide a platform for more intricate and comprehensive analyses pertaining to evolving land use and cover patterns within the targeted study area. This assurance of data precision, stemming from the high agreement demonstrated by the Kappa values, lays a dependable framework for delving into the dynamics of land use and cover transitions over the designated timeframe. Moreover, the temporal consistency implied by the multi-year assessment encourages

researchers to confidently explore changes over time, while also fostering informed decision-making in domains such as natural resource management planning, environmental management, and policy formulation.

2.4.3. Land use and land cover change matrix

The detailed examination and comparison of land use and land cover (LULC) changes in the *Amibara* and Awash-Fentale Districts have illuminated the distinct developmental paths these regions have taken (Abebe et al., 2022; Shiferaw et al., 2019). These divergent trajectories emphasize the influence of local conditions, priorities, and challenges on guiding their land use patterns. The study period from 1985 to 2021 revealed significant shifts in LULC categories, reflecting responses to a myriad of socio-economic, environmental, and land management practices.

During the period from 1985 to 1995, the *Amibara* district showed significant expansions in the agricultural sector, indicating a deliberate focus on agricultural development and possibly responding to growing food demands (Abebe et al., 2022). Shifts from mixed forest to agriculture highlighted a balance between preserving natural ecosystems and utilizing land for productive purposes. In contrast, the Awash-Fentale district focused on alterations within agriculture and bare land sectors, potentially reflecting adjustments to socio-economic factors or changing strategies (Shiferaw et al., 2019b).

Between 1995 and 2002, the *Amibara* district displayed diverse changes within the agricultural sector, adapting and diversifying land use practices to achieve sustainability and development goals. Urbanization pressures were evident through conversions from bare land to built-up areas, indicating the district's efforts to accommodate a growing population. In comparison, the Awash-Fentale district demonstrated a strategic approach, concentrating on bolstering agricultural productivity to align with economic objectives (Shiferaw & Demissew, 2022).

From 2002 to 2015, the *Amibara* district witnessed a stable agricultural focus but faced challenges such as potential forest degradation due to shifts from mixed forest to bare land. This reflected a complex interplay between economic pressures and environmental preservation. The Awash-Fentale district showed adaptability in land use practices, focusing on agricultural productivity and

ecological sustainability by transforming shrub land into agriculture and mixed forest (Haregeweyn et al., 2013; Seid et al., 2020b; Shiferaw & Demissew, 2022).

In the period spanning from 2015 to 2021, the *Amibara* district demonstrated a compelling dichotomy, balancing agricultural stability with urbanization pressures and dynamic land utilization strategies. The Awash-Fentale district maintained a steady agricultural focus while diversifying bare land into mixed forest and shrub land, indicating a thoughtful approach to land management (Haregeweyn et al., 2013; Seid et al., 2020b; Shiferaw & Demissew, 2022).

In summary, the conversion matrices have provided invaluable insights into the intricate transformations within the *Amibara* and Awash-Fentale districts. The persistent prevalence of bare land cover in both the *Amibara* and Awash-Fentale districts between 1985 and 2021 can be attributed to various interrelated factors. Initially, historical evidence points to the regions being characterized by extensive sand dunes (Hagos et al., 2016), which limited the establishment of vegetation, resulting in a prevalent bare land landscape. Both districts are situated in regions that might experience low annual rainfall, characteristic of arid or semi-arid environments with erratic rainfall patterns, posing challenges for sustaining vegetation cover. The susceptibility of both districts to low annual precipitation of *Awash Fentale* and *Amibara* districts which was reported as 490 mm and 416 mm respectively has likely constrained vegetation growth, making it challenging for the land to transition from bare areas to more vegetated cover (Shiferaw et al., 2022a). Additionally, human activities, including deforestation for charcoal production and agricultural expansion, may have further exposed bare land areas, disrupting natural vegetation cover. Changes in land management practices over time, such as the concentration of agricultural activities like cotton and sugarcane farming in *Amibara*, contribute to increased water demand, potentially limiting vegetation expansion due to salinity and associated factors).

The combination of low annual rainfall, formation of sand dunes and land management practices collectively contributes to the observed prevalence of bare land cover in both districts during the specified period. Shaped by distinct socio-economic and environmental circumstances, these districts navigate the complex relationship between changing land use and the pursuit of sustainable development. By capturing shifts in categories such as agriculture, bare land, and built-up areas, these matrices serve as indispensable tools for unravelling the interplay between human

activities and environmental dynamics. These insights offer a clearer understanding of the evolving landscape and its potential implications for striking a harmonious balance between developmental progress and environmental sustainability.

The study, while offering valuable insights into the dynamics of land use and land cover changes in the *Amibara* and Awash-Fentale districts, presents certain limitations that merit acknowledgment for future research endeavors. Firstly, the study's temporal scope spanning from 1985 to 2021 might not adequately capture short-term fluctuations, underscoring the need for more frequent and yearly time series data. Secondly, disruptions arising from the COVID-19 pandemic and civil conflicts significantly impacted data collection activities, posing challenges in engaging with respondents. The utilization of mobile survey platforms and structured phone interviews effectively resolved these issues, ensuring real-time data collection without compromising respondent safety. Thirdly, limited stakeholder engagement due to civil unrest impeded interactions with local communities. To counter this obstacle, the research team made repeated visits to the study area, providing training to local individuals to act as intermediaries, thereby facilitating a continuous flow of information. Lastly, ethical considerations, particularly in conflict-affected areas, introduced complexity to the research process, potentially constraining the study's scope and depth. Despite these challenges, the study successfully employed mobile survey platforms, structured phone interviews, capacity-building initiatives within the local community, and meticulous ethical considerations. These strategies ensured a comprehensive analysis of land use changes in the specified study districts.

2.5. Conclusions

The analysis of land use and land cover (LULC) changes in the *Amibara* and Awash-Fentale districts spanning the years 1985 to 2021 has provided valuable insights into the dynamic interactions between human activities and the environment. In both study sites, distinct shifts in LULC categories have been observed, driven by factors such as agricultural expansion, urbanization, *Prosopis* invasion, and environmental dynamics. These changes have significant implications for the need to have sustainable land management and development in the region.

Throughout the study period, the *Amibara* district displayed a consistent dominance of bare land. Agriculture, built-up areas, and shrub land also underwent notable growth, indicating changing

land use practices and urbanization trends. However, mixed forest experienced a substantial decline between 1985 and 2021, highlighting the vulnerability of forested areas to human activities and environmental pressures. These shifts underline the need for strategies that balance economic development with ecological preservation, particularly in the face of *Prosopis* expansion, which contributes to shrub land growth.

Similarly, the *Awash-Fentale* district perceived transformations in its LULC patterns, with notable increases in agriculture, built-up areas, and shrub land. While mixed forest showed fluctuations, the cumulative loss over the entire study period reflects the challenges of maintaining forest cover in the context of changing land use. The growth of agriculture and shrub land, coupled with a substantial decrease in bare land, indicates changes in land management practices and potential restoration efforts. This highlights the importance of considering land degradation and conservation measures in the context of sustainable development.

Moving forward, effective land management and sustainable development strategies are imperative in light of these observed changes. The observed land cover changes in *Amibara* and *Awash-Fental*e districts have significant implications across environmental, economic, societal, and policy realms. Environmentally, these changes could impact biodiversity, altering local ecosystems and potentially threatening certain species. Shifts in water bodies and erosion patterns might affect hydrology, soil fertility, and agricultural productivity. Economically, changes in agricultural and grazing lands could challenge food security and livestock management, necessitating adaptive strategies. Societally, livelihoods of communities reliant on agriculture and livestock might be directly affected, requiring adjustments in traditional practices. The expansion of built-up areas implies urbanization, demanding infrastructural development. In policy and planning contexts, understanding these changes is critical for conservation, sustainable development, and managing invasive species. Additionally, further research is essential to explore links between these changes and climate changes, emphasizing the need for continued long-term monitoring. Overall, the study's implications highlight the complexity of these transformations, offering valuable insights for informed decision-making and sustainable development efforts in these districts.

CHAPTER 3: SPATIOTEMPORAL CLIMATE VARIABILITY AND EXTREMES IN MIDDLE AWASH AFAR REGION ETHIOPIA: IMPLICATIONS TO PASTORALISTS AND AGRO-PASTORALISTS FOOD SECURITY[3]

Abstract

This study examines the phenomenon of climate variability and its implications to pastoralists and agro-pastoralists food security in Amibara and Awash Fentale districts, Afar region, Ethiopia. The study relied on meteorological records of temperature and rainfall in the study area between the years 1988 - 2018. Besides, literature on the topic were reviewed to make caveats on the literal picture that comes from quantitative data and that is the fresh contribution of this study to the existing debate on climate change and variability. Spatiotemporal trend was determined using Mann-Kendall test and Sen's slope estimator, while variability was analyzed using Coefficient of Variation (CV) and Standardized Anomaly Index (SAI). And SPI/SPEI were applied to determine the drought frequency and severity. Results revealed that the mean seasonal rainfall varies 111.34mm to 518.74mm. Although the maximum and minimum rainfall occurred in the summer and winter seasons, respectively, there has been a decrease in seasonal and annual rainfall at the rate of 2.51mm per season 4.12mm per year, respectively. The study sites have been experiencing high seasonal rainfall variability. The drought analysis result confirms that a total of nine agricultural drought ranging from moderate to extreme years were observed. Overall, the seasonal and annual rainfall of the Amibara and Awash Fentale districts showed a decreasing trend with the highest temporal variations of rainfall and ever rising temperatures and frequent drought events which in turn mean that the climate situation of the area could adversely affect pastoral and agro-pastoral households' food security. However, analysis of data from secondary sources reveals that analyzing precipitation just based on the meteorological records of the study area would be misleading. That explains why flooding, rather than drought, is becoming the main source of catastrophe to smallholder livelihoods. Therefore, it is argued that analysis of temperature and rainfall dynamics in the Afar Region, hence the inception of all development interventions, must take the hydrological impact of the neighboring regions which appears to be useful direction to future researchers.

Keywords: Climate variability, Afar, livelihoods, food security, drought, flood

[3] International Journal of Climate Change Strategies and Management (published)

3.1. Introduction

Climate patterns and extreme events have become subjects of paramount importance due to their significant impacts on ecosystems, human societies, and economies (Birkmann et al., 2022). Understanding the spatiotemporal trends and variability of climate phenomena, including drought frequency, magnitude, and extreme events as well as risks, is crucial for informed decision-making and developing effective mitigation and adaptation strategies (IPCC, 2019).

The climate variables such as temperature, precipitation, and humidity are inherently characterized by spatiotemporal variations (IPCC, 2023). These variations and associated impacts on the livelihood and food security of the exposed community could be explained by spatial (local, regional, and global) and temporal (daily, seasonal, and annual) scales (Niang, 2014). Drought is among the most recurring hydro metrological hazards characterized by extended periods of deficient precipitation and water scarcity. Drought frequency, duration, and intensity could vary significantly across regions and over time. The severity of drought and its effect could be aggravated by climate extremes heat waves, dry spells, wet spells, rainfall intensity, and storms. It seems clear that understanding how these variables change across seasons and years is essential for discerning long-term climate trends for adequate and proper intervention (Birkmann et al., 2022; IPCC, 2019).

Cognizant of this reality, this study examines the spatiotemporal trends, distributional behavior, and drought situation using observational data. The temporal aspect of climate variability has been reconstructed at seasonal and annual scales. The spatial aspect of climate variability has been reconstructed based on metrological data throughout *Amibara* and *Awash Fentale* districts. Drought frequency and magnitude were also examined using established drought indices and investigated the patterns of various climate extremes. In so doing, the study attempts to contribute to a deeper understanding of climate variability in a localized setting and its real impacts and potential implications for ecosystems, societies, and economies.

3.2. Methodology

3.2.1. Description of the study area

The study area is located in Afar administrative region (Zone 3), latitude between 9°06' and 9°69' N and longitude of 40°10' and 40°46' E (Fig 3.1), with areas of 1,046.41 km^2 and 2,007.05 km^2, respectively (Adnew et al., 2019). The topography of this area is generally flat, with a maximum altitude of up to 1,342m above sea level.

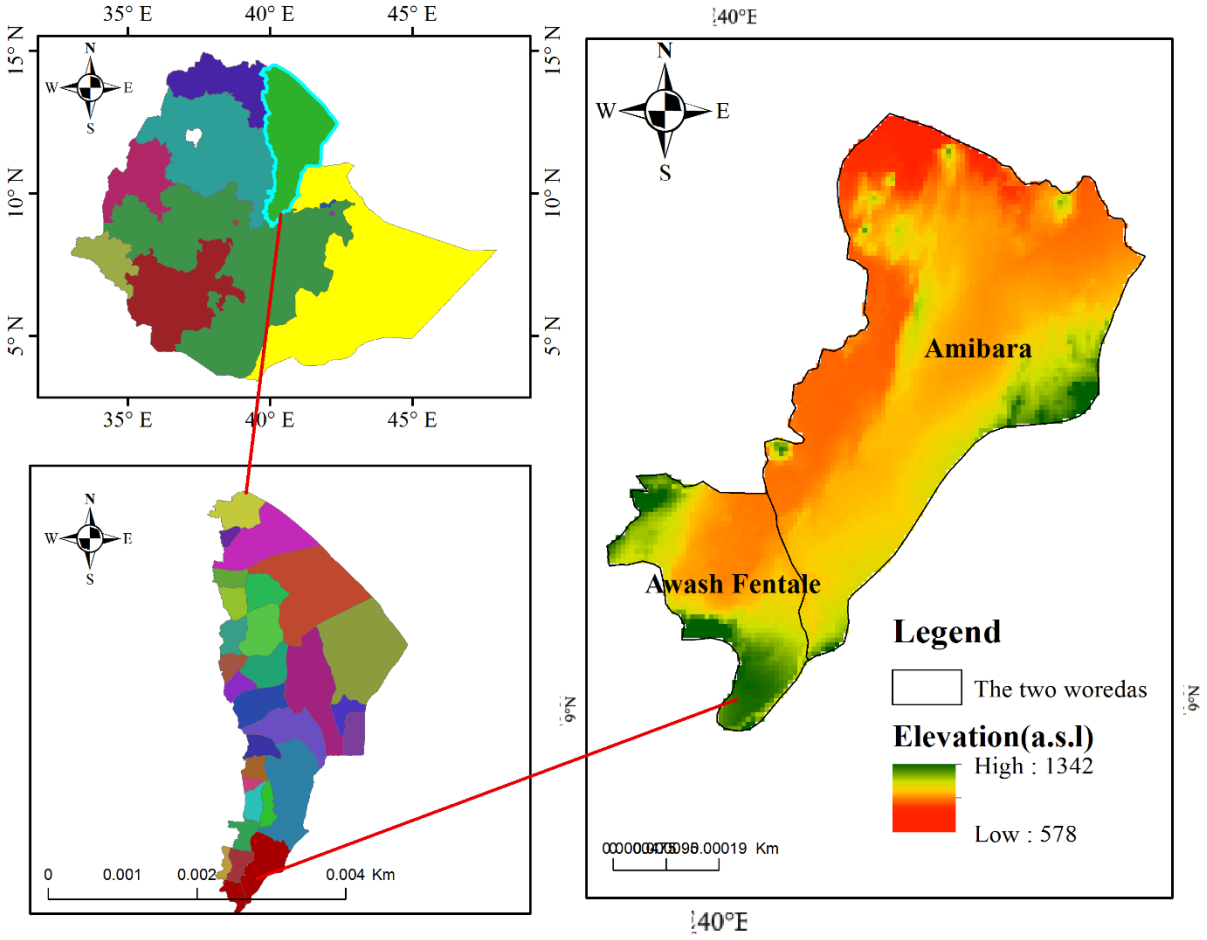

Figure 3.1: The location of study area relative to regional divisions of Ethiopia (left-top); the whole districts of Afar region (left-bottom); and *Awash Fentale Woreda* and *Amibara Woreda* Awash in Afar region (right)

The climate of the area is hot and semi-arid. The mean annual temperature is estimated at 26.64^{o}C. The mean annual rainfall is 468.69mm. Precipitation is generally little, irregular, and unpredictable and seems to follow a bimodal pattern in February-April and July-August (Fig 3.2).

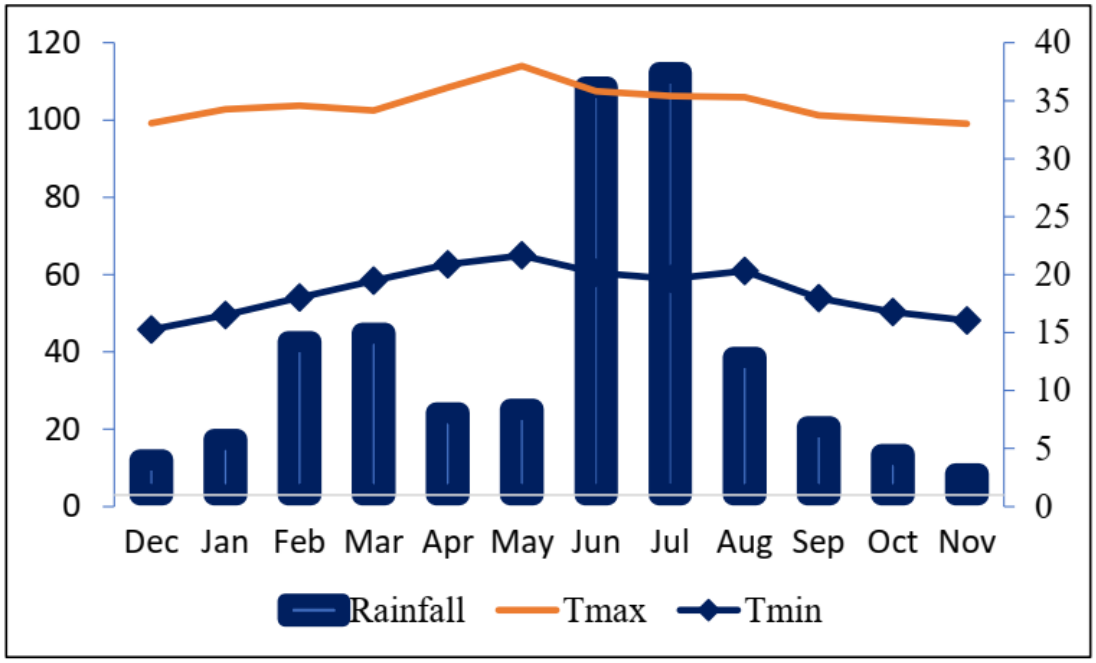

Figure 3.2: Mean monthly rainfall, mean monthly Tmax and mean monthly Tmin of the study area.
(NB: Tmax = Temperature Maximum; Tmin = Temperature Minimum)

3.2.2. Statistical variability test

The spatiotemporal trends and variability of rainfall and temperature could be best understood by combining the observational data and climate models. Historical climate data collected through meteorological stations, satellites, and remote sensing offer insights into past climate patterns. Additionally, climate models simulate past and future climate conditions, allowing scientists to analyze trends and variability within a controlled environment. Statistical techniques, such as time series analysis and spatial interpolation, are often used to identify patterns and quantify changes in climate variables. Thus, in this research several statistical techniques have been used to analyze the climate data, which generally fall into variability and trend analysis categories (Kiros et al., 2016; Koudahe et al., 2017). As such, mean, standard deviation, median, kurtosis, Skewness, range, and Coefficient of Variance (CV) were used. The latter, CV can be calculated as follows:

$$CV = {}_{\sigma}\,{}_{\mu} \times 100$$

Where σ is the standard deviation, and μ is the mean. And it is noted that CV<20 indicates less variability, 20<CV<30 indicates moderate variability and CV beyond 30 shows high variability (Asfaw et al., 2018; NMA, 1996).

3.2.3. Standard Anomaly Index (SAI)

The standard anomaly index (SAI) was used to compute negative and positive rainfall and temperature fluctuation anomalies in the study area. The SAI indicates the distance between the data and its mean value (Alemayehu & Bewket, 2017). It is calculated using the equation (1):

$$SAI = \left(\frac{x-\bar{x}}{\sigma}\right) \quad (1)$$

Where: x is the rainfall or temperature data, $\bar{x}$ and σ are the mean and standard deviation of the data, respectively.

3.2.4. Temporal and spatial trend analysis of climate variables

Different types of tests are available to detect and estimate trends of climate variables. Trend detection can be performed using parametric and non-parametric methods. An example of the parametric method is the linear regression test, and non-parametric (also called rank-based) methods include the Mann-Kendall test (Kendall, 1948; Mann, 1945). The linear regression model was used to measure the pattern or trend of variables over a long period (Kiros et al., 2016). It is calculated using equation (2).

$$Y = a + bx_t \quad (2)$$

Where, Y indicates the trend value, a is the intercept, b is the slope of the trend, and x_t is the time point.

Mann-Kendall or nonparametric test is applied to analyze the trends of the climate variables. The tests are distribution-free and can tolerate data outliers (Kendall, 1948; Mann, 1945; Yue et al., 2002). The mathematical equations for calculating Mann-Kendall statistics (S) and standardized test statistics Z are as follows (Equations 3-6):

$$S = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} sgn(x_j - x_i) \quad (3)$$

$$sgn(\theta) = \begin{cases} 1\ if\ (x_j - x_i) > 0 \\ 0\ if\ (x_j - x_i) = 0 \\ -1\ if\ (x_j - x_i) < 0 \end{cases} \quad (4)$$

$$V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{k=1}^{g} t_k(t_k-1)(2t_k+5)\right] \quad (5)$$

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} S > 0 \\ 0,\ S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}\ S < 0 \end{cases} \quad (6)$$

Where, N is each number of data points, assuming (x_j - x_i) = θ, the value (θ) was computed as the sign functioning, which is the number of data points, g is the number of tied groups (a set of data having the same value), and t_k is the number of data series in the k_{th} group. Z is the standard statistics test Z. The statistical significance level of the trend variation was evaluated using Z_s value. A positive Z_s value indicates an increasing trend, while a negative Z_s shows a decreasing trend. The null hypothesis H_0 should be rejected if $|Zs| > (1\text{-}\alpha_2)_t$, the α = 0.05 level of significance (Du et al., 2013). However, time-series climate data has positive autocorrelation, increasing the probability of significant output that indirectly leads to a false trend (Lisa V. Alexander Xuebin Zhang et al., 2009 ; Sa'adi et al., 2019). Thus, this study applied autocorrelation tests of the time series before using the MK trend test.

3.2.5. Sen's slope Estimator

Sen's slope (Sen, 1968) estimator was used to predict the magnitude of the trend. The nonparametric method can evaluate the change per unit of time. This technique assumes a linear trend in the time series. The slope (Q_i) of all pairs of data x can be calculated as

$$Q_i = \frac{x_j - x_k}{j-k}, i = 1,2, \ldots N, j > k \quad (7)$$

Where x_j and x_k are data values of time j and k, respectively. If there are n values in the time series, then as many as N = n (n-1)/2 slop estimates Q_i. The Sen's slope estimator is defined as the median of the N values of Q_i. The values of slopes are ranked from the smallest to the largest, and Sen's slope estimator Q_i is calculated as:

If N is an odd observation: $Q_i = Q_{(N+1)/2}$ (8)

If N is even observation: $Q_i = \frac{1}{2}\left(Q_{N/2} + Q_{(N+2)/2}\right)$ (9)

In this study, each climate variable was analyzed based on four seasons. These are spring that runs from March to May, summer runs from June to August, autumn runs from September to October, and winter runs from November to February**.**

3.2.6. Test for single change point (Pettiti test)

The Pettitt test has been used in several climate studies to detect abrupt changes in the mean distribution of the variable of interest. It is applied to detect a single change point in climate series with continuous data and gives information about the location of the shift. The test statistic $U_{t,T}$ is evaluated for all random variables from 1 to T; then, the most significant change point is selected where the value of $\lfloor U_t \rfloor$ is the largest (Jaiswal et al., 2015). To identify a change point, a statistical index U_t is defined as follows:

$$U_{t,T} = \sum_{i=1}^{t} \sum_{j=1}^{T} Sgn(x_i - x_j), 1 \leq t \leq T \quad (10)$$

Where similar to the MK test,

$$Sgn(\theta) = \begin{cases} +1 & \theta > 0 \\ 0 & \theta = 0 \\ -1 & \theta < 0 \end{cases} \quad (11)$$

The most probable change point is found where its value is when the break occurs in year k. The test statistic K_n and the associated probability (P) used in the Test are given as.

$$K_{t_0} = \max_{1 \leq y \leq n} \left| U_{t,T} \right| \quad (12)$$

and the significance probability associated with the value K_t is evaluated as

$$p_{(t_0)} = 2exp\left[\frac{-6k_{t_o}^2}{T^3 + T^2}\right] \quad (13)$$

Where: t_0 is concluded as a significant change point when $Pt_0 \leq 0.5$. The value is then compared with the critical value (Pettitt, 1979). Given a certain significance level α, if $p < \alpha$, we reject the null hypothesis and conclude that x_t is a significant change point at level α (Du et al., 2013).

3.2.7. Drought indices

Studying droughts involves assessing their historical occurrence and projected changes in a changing climate. Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the Soil Moisture Anomaly Index (SMAI) are widely used to quantify the severity,

frequency, and spatial extent of drought events at different scale. Moreover, advanced techniques like remote sensing and machine learning are increasingly being employed to monitor and predict drought conditions. Different drought indices have been used to analyze drought characteristics in different areas (Morid et al., 2006). This is because a single index does not provide a complete picture of the spatiotemporal distribution of the drought characteristics of the area (Alsafadi et al., 2020; Ellis et al., 2010; Tefera et al., 2019; Temam et al., 2019). In this study, the two multi-scalar (i.e., multiple timescales) drought indices, including the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) in 3, and 12-month time scales, were used to investigate the occurrence of drought and wet events in the area. The SPI index, the two-parameter Gamma distribution, has been suggested (McKee et al., 1993). The SPEI index is calculated with the three-parameter log-logistic distribution (Vicente-Serrano et al., 2010). Table 3.1 is used to categorize the dry and wet values of the indices.

3.2.8. Standardized Precipitation Index

The SPI evaluates drought in precipitation deficit, impacting groundwater availability, soil moisture streamflow, and reservoir storage (McKee et al., 1993; WMO, 2012) developed the Standardized Precipitation Index (SPI) to analyze precipitation departures from the average precipitation for a particular month or determining time scale. The SPI index is based on the cumulative probability of the considered precipitation. The SPI calculation consists of adjusting the Gamma probability density function to the frequency distribution of the precipitation of each of the rainfall stations. The Gamma probability density function is given by the Equation 20.

$$f(x) = \frac{1}{\beta^{\alpha} \mathrm{r}(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \qquad \text{x>0} \tag{14}$$

Where $\alpha > 0$ is the shape of the parameter, $\beta > 0$ is the scale parameter, x > 0 is precipitation and $\mathrm{r}(\alpha)$is the Gamma function, defined as Eq.20.

$$\mathrm{r}(\alpha) = \int_0^{\infty} x^{\alpha-1}\, e^{-x} dx \tag{15}$$

The parameters $\alpha \; and \; \beta$ of the probability density function are estimated for each station by maximum likelihood (Wilks, 2011).

$$\hat{\alpha} = \frac{1}{4A}1 + \sqrt{1 + \frac{4A}{3}} \quad (16)$$

$$\hat{\beta} = \frac{\hat{x}}{\hat{\alpha}} \quad (17)$$

$$A = ln\bar{x} - \frac{\sum_i^n x_i}{n} \quad (18)$$

The resulting parameters are then used, and the cumulative probability of the occurrence of a precipitation event for the given month and time scale at the station is considered. The cumulative probability is given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\gamma}\mathrm{r}(\gamma)_0}\int_0^x x^{\gamma-1}\, e^{-\frac{x}{\beta}}dx \quad (19)$$

Where α > 0 is the shape parameter, β > 0 is the scale parameter, x is the precipitation, and Γ (α) is the Gamma function, defined as

$$G(x) = \frac{1}{\mathrm{r}(\gamma)}\int_0^x t^{\gamma-1}e^{-t}\, dt \quad (20)$$

Because the gamma function is undefined for x=0 and the precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x) = q + (1-q)G(x) \quad (21)$$

Where q is the probability of zero precipitation. $H(x)$ is then converged into the standard normal SPI variable following approximation (Abramowitz & Stegun, 1965). The normal standardized distribution with null average and the unit variance was then obtained from the transformation of

$$\text{SPI}=\begin{cases} -\left(t-\frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_2t^3}\right) \; for\; 0<H(x)\leq 0.5 \\ t=\sqrt{ln\left(\frac{1}{H(x)^2}\right)} \\ +\left(t-\frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_2t^3}\right) \;\; for\; 0.5<H(x)\leq 0.1 \\ t=\sqrt{ln\left(\frac{1}{1-H(x)^2}\right)} \end{cases} \quad (22)$$

$H(x)$ is the cumulative probability of observed precipitation. The coefficient $C_0, C_1,\ C_2\ and\ d_1, d_2, d_3$ are given as follows: $C_0 = 2.515517,\ C_1 = 0.802853,\ C_2 = 0.010328,\ and\ d_1 = 1.432788,\ d_2 = 0.189269,\ d_3 = 0.001308.$ The SPI values are symmetrical and can identify both dry and wet conditions. The drought begins when the SPI value becomes negative and ends while returning to a positive value (wet events) (McKee et al., 1993).

3.2.9. Standardized Precipitation Evapotranspiration Index

The SPEI is multi-scalar and used to evaluate different types of global droughts (Labudová et al., 2017; Wang et al., 2014; Yang et al., 2019). The SPEI algorithm is mathematically similar to SPI, but it includes the effect of temperature in addition to precipitation. The SPEI is computed using precipitation (P) and potential evapotranspiration (PET) as input variables, resulting in the climate water balance (P-PET) outputs (Vicente-Serrano et al., 2010). Including the widely used Penman-Monteith (PM) method, there are several methods introduced to calculate (PET) (Allen et al., 1998). However, the PM method requires complete meteorological data, which is challenging in many parts of the world. Thus, the PET can be estimated using the Hargraves method(Hargreaves & Samani, 1985), which has a similar output as PM (Beguería et al., 2014). Hargraves method needs only precipitation, minimum, and maximum temperature and is extraterrestrial radiation (Senay et al., 2011). Hence, in this study, the Hargraves method was used to calculate the PET.

$$PET_{HG} = 0.0023 \times (T_{mean} + 17.8) \times \left(\sqrt{T_{max} - T_{min}}\right) \times Ra \quad (23)$$

Where: PET_{HG} is potential evapotranspiration of the Hargreaves method (mm/day), Ra is the extraterrestrial radiation (mm/day), calculated theoretically as a function of latitude, T-mean is the average temperature (°C), and T-max and T-min are the maximum and minimum temperature (°C), respectively. Once PET was estimated, the water balance equation was used to calculate the monthly deficit (Di)

$$D_i = P_i - PET_i \quad (24)$$

Where: D_i is climatic water balance (CWB) in a given period (mm), P_i is monthly precipitation in a given period (mm), $PET_i$is the monthly potential evapotranspiration (mm). The accumulated difference between P and PET in different time scales can be calculated as

$$D_n^k == \sum_{i-0}^{k-1}(P_{n-i} - PET_{n-i}) \quad (25)$$

Where n≥ k, k is a different time scale, and n is the number of calculations.

The function of logistic distributions gives better results than other distributions for obtaining SPIE series in standardized D with a mean of zero and standard deviation of one (Potop et al., 2012; Vicente-Serrano et al., 2010). The cumulative distribution function (x) is given by:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1 + \left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \quad (26)$$

Where: α, β, and γ are scale, shape, and location parameters, respectively, for D values in the range ($\gamma < D < \infty$). The probability distribution function of the D series, according to the log-logistic distribution, is given by

$$F(x) = \frac{\beta}{\alpha}\left[1 - \left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \quad (27)$$

The SPEI can be obtained as the standardized values of $f(x)$.

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 - d_1 W + d_2 W^2 + d_2 W^3} \quad (28)$$

$$W = \sqrt{-2\ln(p)} \text{ for } p \leq 0.5 \quad (29)$$

Where p is the probability of exceeding a determined D value, p=1-F (x), if p>0.5, then p is replaced by 1- p, and the sign of the resultant SPEI is reversed; the constants are C_0 = 2.515517, C_1 = 0.8022853, C_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, and d_3 = 0.001308. Detailed computing of SPEI has been widely described in (Vicente-Serrano et al., 2010).

Table 3. 1 Classification of the severity of dry /wet events on the calculation of SPI/SPEI

Categories	SPI/SPEI Values
Extreme drought	Less than -2.
Severe drought	-1.99 to -1.50
Moderate drought	-1.49 to -1.00
Near Normal	-0.99 to 0.99
Moderately wet	1.00 to 1.49
Severely wet	1.50 to 1.99
Extremely wet	More than 2

Sources: (Li et al., 2015; Woldegebrael et al., 2020)

SPI/SPEI can be calculated on different time scales such as 1-3, 6-12- and 24-months and more (Mathbout et al., 2018). These time scales interpret the different effects of drought on the various types of water resources (McKee et al., 1993; Vicente-Serrano et al., 2010). This study calculated the SPI and the SPEI indices using a 3-12-month time scale. The 3 - months' time scale, which is essential to knowing agricultural drought events and the 12- and 24 - months' time scales are used entirely to analyze the hydrological drought events or annual water deficit (Alsafadi et al., 2020; Di Giuseppe et al., 2019; Giuseppe, 2019; Potop et al., 2012).

3.2.10. Assessing drought characteristics

Drought characteristics can be expressed by the following essential features: duration, frequency, intensity, severity, and spatial and temporal extent (Alamgir et al., 2015; Andreadis et al., 2005). The study evaluated the drought occurrence across months whereby measurements that fall between SPI/SPEI≤ -1 are further categorized as moderate, severe and extreme drought events.

In this research assessment of mild drought values was excluded since the variation from the normal level is very slight. The duration, severity, intensity and frequency of the drought events were calculated based on (Table 3.1).

I. The frequency is the number of months in which the SPEI value meets a set value (Table 3.1) divided by the number of months in the entire series (Wang et al., 2014).

$$F = \frac{n}{N} \times 100 \qquad (30)$$

Where n is the number of months of drought events (SPI/SPEI <-1) that, an index value meets a set drought criterion divided by the number of months in the entire series (N). Drought frequency (F) was used to assess the drought prevalence during the study period.

II. Duration is monthly or more length drought episodes. Magnitude (M) is the cumulative sum of the index value based on the duration of drought occurrence.

$$M = \sum_{i=1}^{Duration} Index \quad (31)$$

III. The intensity of a drought event is the magnitude divided by the duration. Events that have a shorter duration and higher severities will have larger intensities.

$$I = \frac{\text{Magnitude}}{\text{Duration}} \quad (32)$$

The inverse distance weighting (IDW) method was used in order to visualize the spatial patterns of climate variability and change.

3.3. Results and Discussions

3.3.1. Temporal trend of mean seasonal and annual analysis of climate variables

Table 3.2 depicts the mean seasonal and annual climate variability statistical description and the trend analysis of the study area from 1988 and 2018. The mean seasonal rainfall of the area ranges from 111.34mm to 518.74mm. The maximum and minimum rainfall occurred in the summer and winter seasons, respectively. However, in the area seasonal and annual rainfall has been decreasing at the rate of 2.51mm per season and 4.12mm per year for the last three decades. Relatively the highest amount of rainfall reduction was observed in the winter season. The rainfall distribution behavior was characterized by high fluctuations all year round. For instance, rainfall distribution was highly variable in spring (CV=48%), summer (37.95%), autumn (63.75%), and winter (81.96%) (Table 3.2).

The seasonal and annual maximum and minimum temperatures is also variable. Both seasonal and annual minimum and maximum temperatures increased significantly. The mean seasonal maximum temperature variability ranges from 33.440C to 36.400C. The mean seasonal minimum temperature ranges between 15.94^0C to 20.48^0C. Generally, according to Table 3.2, the seasonal and annual rainfall of the *Amibara* and *Awash Fentale* districts observed a decreasing in amount

and highly variable in distribution means it could affect soil moisture and hence, water and pasture availability of the study sites.

Table 3.2: Statistical summary of Seasonal and Annual (rainfall, Maximum and Minimum Temperature

Statistics	Season	Mini	Max	Mean	SD	Kendall's tau	Sen slop	P-Value	CV*100
Rainfall	Spring	29.42	218.20	111.85	54.58	-0.02	-0.18	0.92	48.00
	Summer	120.90	518.74	246.04	92.39	-0.23	-2.51	0.07	37.9455
	Autumn	19.53	251.08	72.81	46.42	-0.01	-0.12	0.95	63.75
	Winter	3.95	111.34	37.98	30.87	-0.40	-1.61	0.00	81.96
	Annual	220.66	939.61	468.69	133.70	-0.23	-4.12	0.08	28.52
T-max	Spring	27.57	39.99	34.95	2.18	0.24	0.07	0.06	Very high
	Summer	32.89	39.27	36.40	1.47	0.38	0.08	0.00	>>
	Autumn	30.22	36.33	34.13	1.36	0.24	0.05	0.06	>>
	Winter	31.42	36.14	33.44	1.22	0.02	0.00	0.92	>>
	Annual	32.00	37.39	34.73	1.11	0.20	0.03	0.11	>>
T-min	Spring	15.45	23.44	19.46	2.02	0.45	0.15	0.00	>>
	Summer	14.51	24.33	20.48	2.68	0.38	0.15	0.00	>>
	Autumn	13.52	22.28	18.35	2.03	0.43	0.10	0.00	>>
	Winter	12.70	18.29	15.94	1.47	0.18	0.04	0.15	>>
	Annual	15.49	21.50	18.56	1.76	0.38	0.13	0.00	>>
T- mean	Annual	23.78	28.84	26.65	1.22	0.37	0.07	0.00	>>

3.3.2. Standard Anomaly Index (SAI)

In this study, analysis of the Standardized Anomaly Index (SAI) of hydroclimate data shows the reference line bars above the mean (zero) as positive (surplus), and those below the line mean are negative (deficit) anomalies (Koudahe et al., 2017). The calculated value of (SAI) obtained was plotted against the year (1988-2018) for annual mean rainfall and maximum and minimum temperatures. Accordingly, in Fig 3.3, the mean annual rainfall anomaly depicts a negative trend and the coefficient of determination (R_2) of 0.011. Both the mean minimum and maximum temperatures reveal an increasing trend R_2 0.13 and 0.33, respectively.

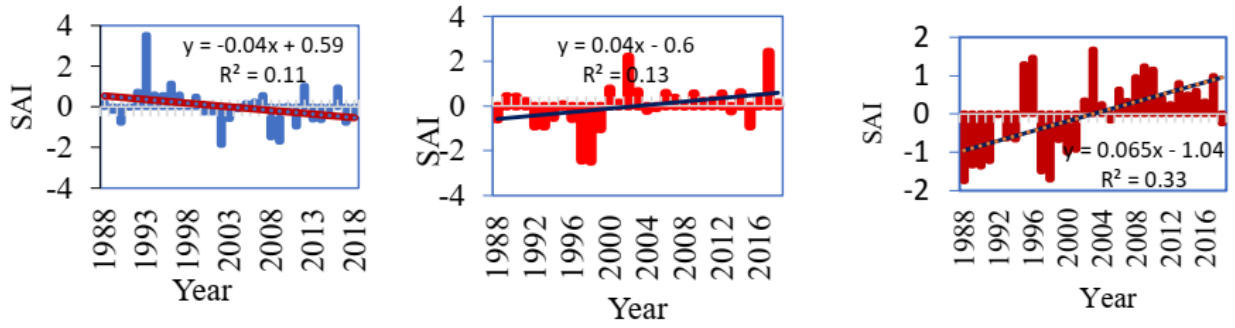

Figure 3.3: Standard Anomaly Index of mean annual rainfall and temperature from 1988 to 2018 of the study area

3.3.3. The spatial trend of mean seasonal analysis of climate variables

The Kriging method is widely used for spatial analysis using geographic information systems (GIS). In this study, spatial analysis was applied using the distance-weighting approach through interpolating the data by including information from specific locations. Fig. 3.4 shows a spatial analysis MK trend test using the Z-value. Accordingly, in the spring, the rainfall decreased in the northern part of *Amibara* district and the increasing trend was observed in *Awash Fentale* district (Fig. 3.4). The spatial analysis result shows that rainfall has been significantly decreasing in summer season throughout the study sites. However, the summer season rainfall reduction was most pronounced in the southern most of *Awash Fentale* district and northwest of the *Amibara* district for the last three decades.

Fig. 3.4 shows the study sites have experienced a mix of increasing and decreasing autumn seasonal rainfall. For instance, the southwestern part of the *Amibara* district received an increase in autumn rainfall while slight rainfall increment recorded in the southeastern part of the *Awash Fentale* district. However, it is important to note that except for the southwestern of *Amibara* and the southeastern part of *Awash Fentale*, the rest parts of the study sites experienced a decrease in rainfall.

The winter season rainfall also observed a significant decreasing rate ($Z < -1.96$) throughout the study sites. In the winter season, the magnitude of the decreasing rainfall is very significant in the southern part of *Awash Fentale* district. The spatial seasonal rainfall trend analysis (depicted Fig. 3.4) reveals that rainfall has been increasing throughout *Awash Fentale* and the southern part of

Amibara district in the spring season. The northern part of *Amibara* district has been experiencing a remarkable reduction in rainfall in the spring season (see Fig. 3.4).

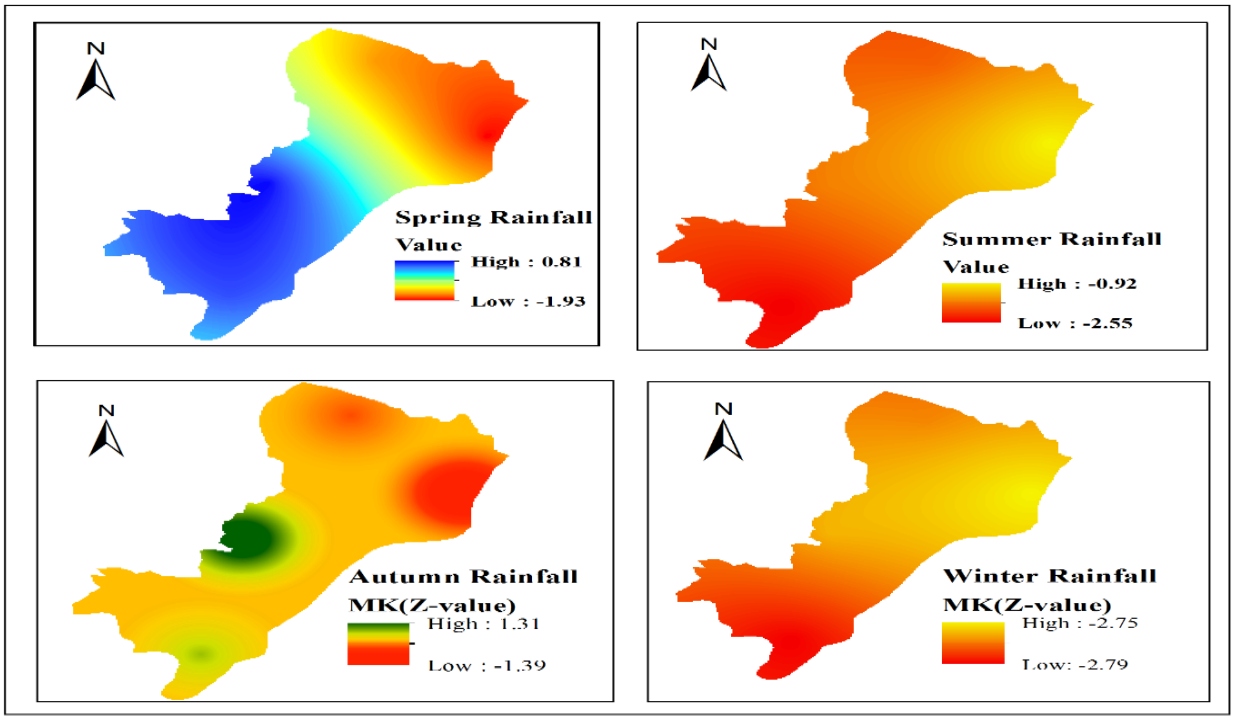

Figure 3.4: The spatial trend of seasonal rainfall in the study area from 1988 to 2018

Fig. 3.5 shows the spatial trend of seasonal maximum temperature increased for the last three decades except in the southwest and northeastern parts of the *Amibara* district. In the southwest and northeast parts of *Amibara* district during the winter season, maximum temperature exhibited reduction. Hence, the lowest and pick spring season maximum temperature increment was observed in the southern part of *Awash Fentale* and the northern part of *Amibara* district, respectively. The spatial analysis confirms that during spring and summer seasons' maximum temperature increased from the south to the northern part of the study sites. Whereas maximum temperature increased from north to south during autumn season. Thus, during the autumn season a pick maximum temperate was recorded in the southern part of *Awash Fentale* district. The highest winter season maximum temperature was observed in northern *Amibara* and the southern part of *Awash Fentale* districts (Fig 3.5).

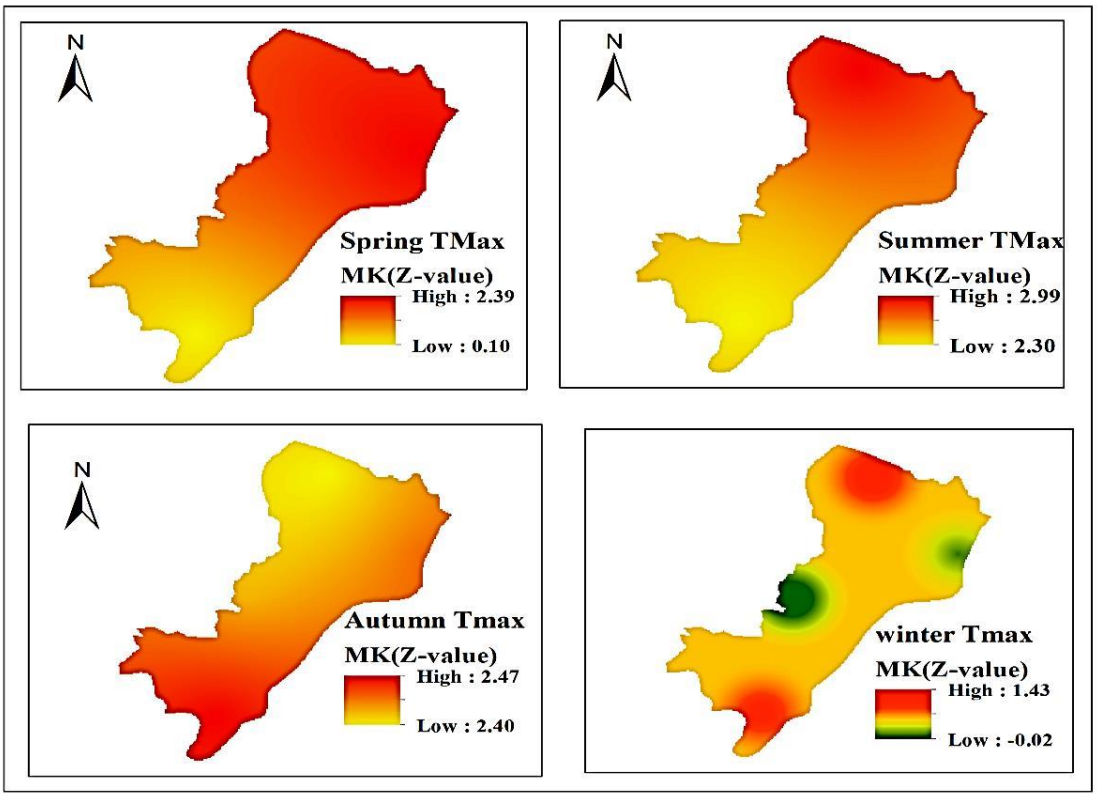

Figure 3.5. The spatial trend of seasonal maximum temperature in the study area from 1988 to 2018

Fig. 3.6 depicts the nature of spatial variations in the seasonal minimum temperature trend of the study area from 1988 to 2018. Seasonal minimum temperature has been increasing in the four seasons at different scale. During the spring season, the pattern of minimum temperature has been increasing from south to north of the two districts. However, unlike the maximum season temperature increment, the autumn season minimum temperature increased from north to south while it lacks a pattern during the summer and winter seasons. The spatial minimum temperate pick of the summer season was observed in the southern part of *Awash Fentale* and the northeastern part of *Amibara* district. The slow minimum temperature increment rate of the summer season was exhibited along the northern and southern tips of *Awash Fentale* and the southern part of *Amibara* districts temperature lack pattern (Fig. 3.6). Overall, however, the data leads to the unmistakable conclusion that the entire study area experienced an increasing trend in the minimum temperature across all seasons due to reinforcing factors including expansion of agricultural land, settlement, and invasive species.

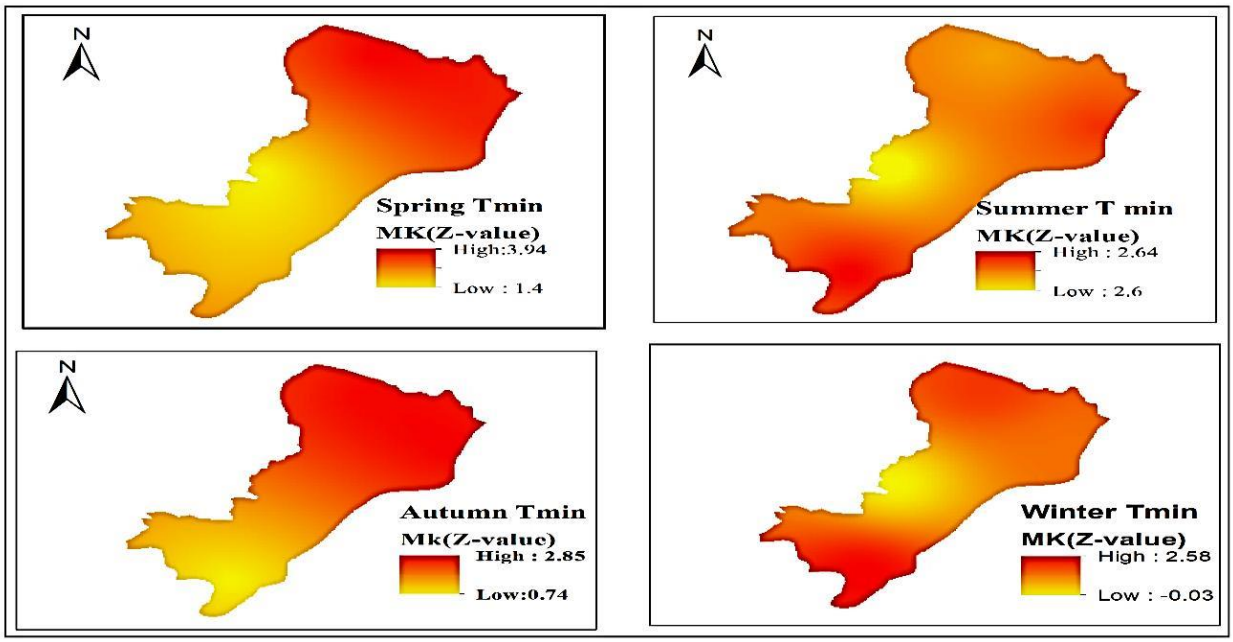

Figure 3.6: The spatial trend of the seasonal minimum temperature of the study area from 1988 to 2018

3.3.4. A Change Points (PETIT) test

Recognizing change points is a statistical technique that plays a vital role in spotting climate jumps in the climatological data period (Palaniswami & Muthiah, 2018). This study used the Pettitt test method to detect the possible change point position and evaluate its statistical significance. The Pettitt test was applied to the annual mean rainfall, minimum temperature, and maximum temperature. Accordingly, Fig. 3.7 revealed that the mean annual rainfall experienced a significant decrease in 1999 (P=0.037). The mean annual maximum temperature showed a significant increment in 2001 (P=002). And the mean annual T-min had its significant mean change at the year of 1999 (P=0.012).

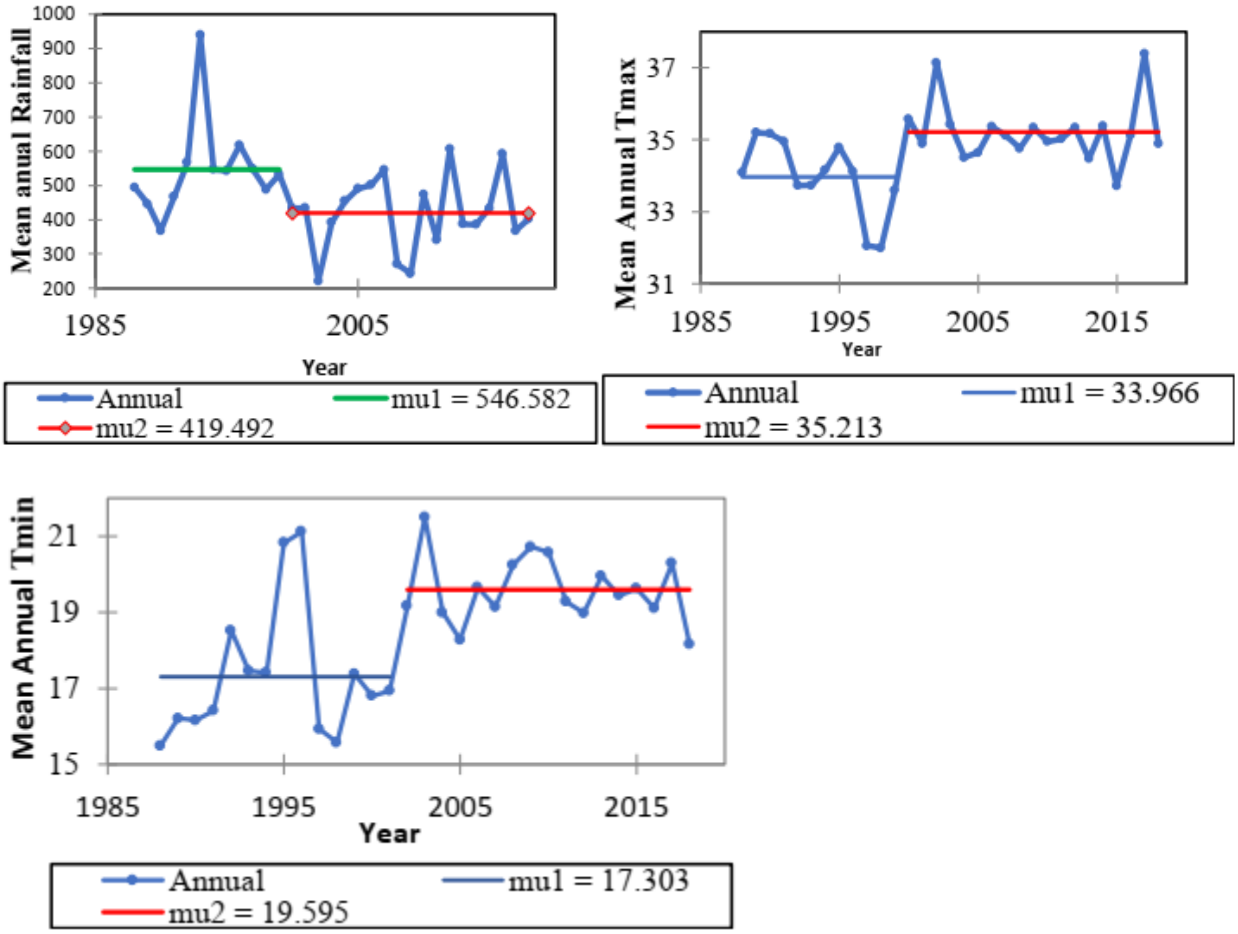

Figure 3.7: The Changing point and the mean variation for mean Annual rainfall, maximum and minimum temperature from 1988 to 2018

3.3.5 The frequency, distribution, and the magnitude of drought events

This study calculated the frequency of the drought events from moderate to extreme drought value based on the threshold value (SPI/SPEI ≤ -1) for the whole study period. From the table below, it is evident that during the study period, the two *Woredas* experienced 13% to 37% moderate and above seasonal drought (SPI_3 and SPEI_3-months) frequency. For SPI_12 and SPEI_12 months, the area experienced severe hydrological drought frequency events from 43% to 47%. The peak extreme drought events were observed in all seasons except in the summer of SPI_3.

Table 3. 3: The drought events frequency, magnitude, and peak value in Awash *Awash Fentale* and *Amibara* districts (1988 to 2018)

	Tim scale	Duration	Frequency(%)	Magnitude	Peak value
Seasonal drought	Spring	SPI_3	13	-19.5	-4.24
		SPEI_3	23	-34.5	-2.08
	Summer	SPI_3	20	-30	-1.82
		SPEI_3	37	-55.5	-2.11
	Autumn	SPI_3	14	-21	-4.14
		SPEI_3	20	-30	-2.27
	Winter	SPI_3	15	-22.5	-2.83
		SPEI_3	27	-40.5	-2.57
Hydrological drought	Annual drought SPEI_4	SPI_12	43	-64.57%	-3.67
		SPEI_12	47	-70.5	-2.71

Source: Own calculation

3.3.6 The mean temporal evaluation of drought events

Fig 3.8 below shows the temporal distribution of drought occurrence over the study area. To evaluate the temporal variation of drought events in the area, which are consecutively less than a threshold value (SPI/SPEI≤-1) and have more than two months duration has been selected. Accordingly, in the basin for agricultural drought (SPI_3), categorized from moderate to extreme droughts occurred in 1999, 2000, 2001, 2007, 2008, 2011, 2013, 2014 and 2017. For agricultural drought (SPEI_3), moderate to extreme droughts were found in 1999, 2001, 2003, 2007, 2008, 2011, 2012, 2014 and 2017. For hydrological drought (SPI_12), moderate to extreme droughts were found in 1988, 1989, 1999, 2000, 2001, 2002, 2003, 2007, 2008, 2010, 2013, 2016 and 2017. Hydrological drought events (SPEI-12) were identified in 1988, 1989, 1999, 2000, 2001, 2002, 2007, 2008, 2010, 2012, 2013, 2016 and 2017. Generally, in the study period, extreme drought was observed in 1989, 2000, 2001, 2002, 2007, 2010, 2012, 2014 and 2017. In sum, the data analysis on drought events (Fig 3.8.) revealed the occurrence of seasonal and hydrological drought events at a significant level.

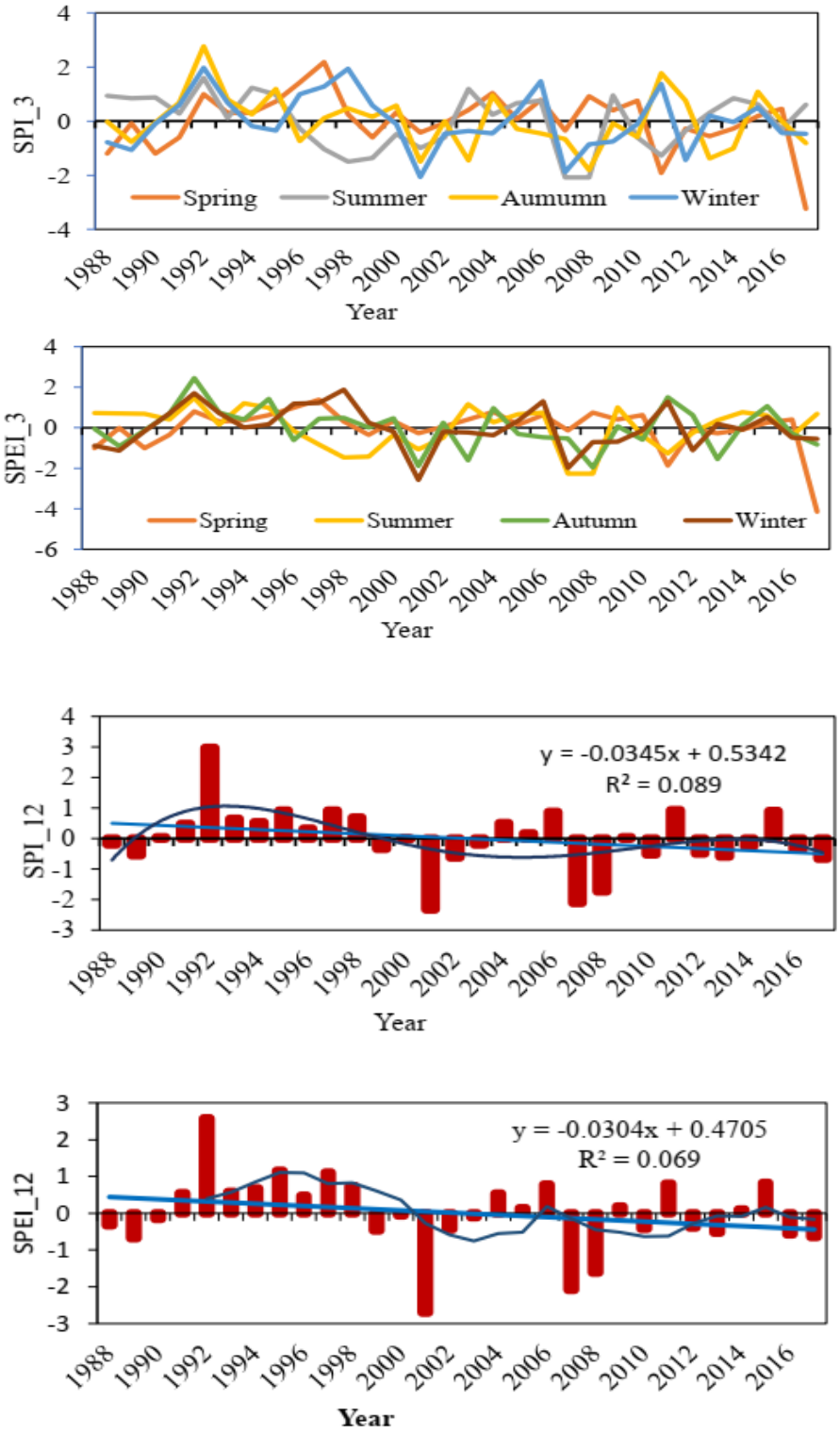

Figure 3.8: The trend and variation of different time-scale drought events in the study area for SPI_3. SPEI_3 represents seasonal/agricultural drought, and SPI_12 and SPEI_12 represent annual/hydrological drought in the study period from 1988 to 2018.

3.3.7. Implications of climate variability and extremes to food security

From the discussion of the climate data, it has been clearly pointed out that the study area has undergone climate variability which varied from moderate to extreme levels. That in turn reveals that the ecological setting suitable to the age-old agronomic practices has been disrupted. The fluctuation behavior of rainfall and temperature as well as drought severity would certainly affect agricultural calendar, soil moisture and pasture availability as well as livestock production and productivity and hence, food security. In sum, the climate variability discerned from metrological data isn't something abstract phenomenon but a potent reality that has environmental, socioeconomic, as well as cultural manifestations being observed in the study area. Therefore, it is of a paramount importance to demonstrate the catastrophic impacts of climate variability on people and the physical environment they inhabit.

For a long time, the Afar region rangeland has been characterized by a vegetation cover markedly dominated by different Savanna bush, grass and open savannas, and woody savannas. Studies reveal that the LULC in Afar region is characterized by 58% Barren land/wasteland (11,501, 000 ha), 3% Grass lands (644, 000 ha), 8% Rain-fed-SC-croplands (1,493,000 ha), 6% Irrigated-SC-croplands (1,263,000 ha), and 23% Forest/shrub lands/grasslands (4,531,000 ha) (Gumma et al., 2022). The character of the Afar region rangeland relates to the dominance of open and woody savannah grasslands ideally suitable for grazing and crop cultivation, mainly maize, sorghum and vegetables. That pattern is the norm in the entire lowlands of the Afar Region while a few high altitudes exhibit connected woodlands. Therefore, the long established ecological condition had been exploited by the Afar people both for crop cultivation and animal husbandry (Belete, 2018).

However, in recent decades, the Afar pastoralists and agro-pastoralists are confronted with the phenomenon of vegetation cover dynamics which has stark correlation with the patterns of climate variability. In the same vein, climate variability characterized by increasing temperature trends has made the occurrence of drought events more frequent and devastating. Not surprisingly, studies in the lowlands of Eritrea, which have a similar ecological setting with the lowlands of the Afar, revealed a similar trend of alarming trend of loss of vegetation cover, as analyzed based on seasonal and annual time scales. Analysis of NDVI (Normalized Difference Vegetation Index) showed decreases in the LULC shares of croplands and shrub lands. The same study attributed to the phenomenon to low moisture caused by drought conditions in the semiarid region. As is the

case elsewhere, the northeast African region is undergoing considerable alteration of vegetation cover and the relative distribution of different species induced by climate variability that favors the incidence of drought which disturbs the regeneration and growth pattern of plants (Measho et al., 2019).

The scientific literature concurs on the conventional view that one of the driving factors for the dwindling of natural habitats and biodiversity has to do with the emergence in and colonization of a given environment by invasive plant species. For instance, the glaring disappearance of shrub land biomes is attributable to the invasive plant known as mesquite or prosopis (Shiferaw et al., 2021). As far as such a phenomenon is the result of natural processes, it has a lot to do with human induced factors. Strikingly, the occurrence of a devastating invasive plant in the study area and its astonishing expansion is found to be the result of climatological and environmental enabling environment as well as human activities. In this regard, the most peculiar invasive plant prevalent in the study area is known as *Prosopis juliflora*.

To start with, it would be misleading to argue that the origin and expansion of *Prosopis juliflora* in the study area is the result of a spontaneous environmental reaction triggered by the arid environment and decline of rainfall and ever rising temperatures. Originally, the plant was introduced by human intervention meant to be the best solution to alter bare landmass with lash green vegetation cover in the mid-1970s. The plant was introduced to cover bare lands with green vegetation, to produce firewood, to increase livestock feed, and for the purpose of enhancing soil stability (Adnew et al., 2019). In retrospect, however, the measure undertaken without feasibility study proved to be a catalyst for compounding a preexisting problem of water scarcity. This is because the plant exhausts surface and ground water throughout the years, especially during the dry season. The unintended effect of introducing *Prosopis juliflora* to the Afar region is that it has posed a formidable threat to the achievement of sustainable development and climate change adaptation(Shiferaw et al., 2021).

Although the appearance of *Prosopis juliflora* in the Afar region has never been a natural response to climate variability, its rapid expansion is attributable to increasing trends of temperature and moisture stress. For a long time, the global concern on the impact of *Prosopis juliflora* has been limited to South America, Central America, South Europe, North Africa, and the Caribbean region

dominated by savannahs grasslands (Kyuma et al., 2016). This study found that the environmental setting that allowed the fast spread of *Prosopis juliflora* in those regions exists in the study area and in a more permissive scale. This is because the minimum temperature and frost weather condition that is contributing to arrest the expansion of *Prosopis juliflora* in those regions doesn't exist in the study area. In fact, the typical weather condition in Afar, high temperature and little precipitation, has provided the most suitable ecological conditions for the *Prosopis juliflora* to thrive and expand beyond expectations. The ecological contrast between North African countries and the Afar region explains the sharp contrast about the nature of the problem posed by *Prosopis juliflora*. Whereas *Prosopis juliflora* in North African countries is limited to the original place of plantation (Dakhil et al., 2021), the climatic and environmental factor in the Afar region has offered the plant the right condition for its unfettered expansion.

The invasion of the Afar region by *Prosopis juliflora* is attributable to the mutually reinforcing factors intrinsic to the nature of the plant itself as well as the enabling ecological and climatological scenarios. The plant tolerates high temperature. Its deep reaching roots enable the plant to overcome moisture stress at the expense of underground water. It is naturally endowed with high efficient water-use. Its wide canopies prevent other vegetation types from accessing sun light. *Prosopis juliflora* increases soil fertility by augmenting fine soil particles useful for its expansion. The allelochemicals produced by the plant undermine the survival of other species by diminishing their seed germination as well as growth.

The rapid expansion of *Prosopis juliflora* in the Afar region is assisted by domestic animals. When domestic animals consume the fruit of *Prosopis juliflora*, the seeds carried in the droppings of animals will be dispersed to long distances and everywhere they are dropped the plant grows. Moreover, the nature of climate variability characterized by seasonal and annual temperature increases coupled with the alkaline nature of soil in the study area has created the right condition for the unmitigated expansion of *Prosopis juliflora*. Hence, the region is confronted with rapid shrinking of savannah grasslands and bush forests that for long constituted the right ecological condition on which the erstwhile pastoralist livelihood of the Afar people depended (Dakhil et al., 2021).Therefore, the findings of the study neatly tally with a previous finding in Kenya which argues that a climate variability characterized by erratic and dwindling rainfall coupled with

increases in the annual mean temperature nurtures the expansion of *Prosopis juliflora* thereby exacting the feed resource available to the livestock population (Kyuma et al., 2016).

There is an emerging discussion about policy response towards *Prosopis juliflora*. As part of that effort the pros and cons of the plant are being sorted out. On the positive side, the plant is a good source of food for humans and animals especially during periods of food and feed stress. It is a good source of firewood, biofuel energy, charcoal, and timber production (Adnew et al., 2019; USAID, 2018). Reports show that local people use the plant to construct their houses and sheds. The plant is also positively evaluated for its benefit regarding flood protection, carbon sequestration, windbreak, treatment for soil salinity, and landscape greening. To the contrary, the plant has damaging aspects: undermining the ecosystem services, fostering food insecurity by reducing the volume of milk and meat production. The more *Prosopis juliflora* depletes animal pasture, animals loose body weight and their market price gets smaller (Adnew et al., 2019). The livestock health is being affected by plant which causes a disease local people 'Armko' which arises when animals consume the raw seeds of *Prosopis*. On balance, the adverse effects of the *Prosopis juliflora* on ecological resources, socio-economic conditions, development projects, urban areas, and national parks outweigh its controversial benefits (Adnew et al., 2019).

Apparently, there seems to be a contradictory argument in the literature about chronic shortage of precipitation on the one hand and the recurrent problem of flooding. As discussed above, the analysis climatic data discussed in this study spanning thirty years offers a compelling argument for climate variability characterized by increment of temperature and decrement of precipitation. Our argument is that the temperature and rainfall measurements in metrological stations offer a misleading impression about the water resources available in the Afar Region. For a balanced assessment of water resources available to the Afar region, one must look at the fact that the lowlands of Afar are natural absorbents of heavy rainfall water from the Amhara, Tigrai and central Ethiopia (USAID, 2018). As a result, the Afar region is naturally bound to be a victim or beneficiary of climate phenomena in the Ethiopian highlands. For instance, the massive flooding that occurred in 2010 had damaged considerable crops, infrastructure, irrigation systems, and livestock. About 67, 000 people were affected by the flood in 46 *Kebeles* of the region (UN-OCHA, 2011). Similarly, a 2020 flooding has been responsible for affecting 67,885, displacing 40,731 people, leaving 32,839 people at risk, evacuation of 4, 915 people, the destruction of 100

education and health centers, and killing 16,626 livestock (UN-OCHA, 2020). That flooding, and not drought is the chief cause of crop damage in Afar region than other regional states can be surmised from the following table.

Table 3. 4: Crop damage by geographic area and source

Region	Dominant hazard in crop land damage	Seasonal dynamic of hazard	Dominant hazard contributing to loss of cattle
Amhara	Hail - 100%	August-September corresponding to Kiremt season	Hailstorms
Oromia	Fire - 82%, Floods - 14%	Fires- September Flood: March and September	Drought
SNNPR	Drought-13% Flood -12%	Floods: September to December	Flood
Afar	Drought: 13% Floods: 47%	Drought: March and September Floods: July-November	Floods
Tigray	Drought - 58%, Floods - 35%, Hailstorm - 8%	Drought- September Floods: June December Hailstorm-July-December	Hailstorm

Source: (USAID, 2018)

Finally, the impact of climate variability and the expansion of *Prosopis juliflora* need to be discussed in light of the strong drive of the government to make the Afar region a vital target of food security through wheat production. In view of the growing demand for wheat the policy direction of the government to substitute wheat import through local production, the government has made Afar region one of the priority areas for irrigation-based wheat production. The land covered with wheat production in 2019/20 was about 21,000 ha which increased to 187,000 ha in 2020/21, and then reached more than 400,000 ha 2021/22 all over the country. Because of inspiring results in wheat production, the government is trying to cover 1.5 million hectares in the coming 5 years with wheat production (Tadesse et al., 2022). In view of the clear danger posed on this ambitious project by the *Prosopis juliflora* invasive plant, the need to overcome the threat of climate variability on food security requires an all-inclusive approach.

3.4. Conclusions and Recommendations

The study has established the characteristics, manifestations, trends, and magnitude of climate variability as witnessed in *Awash Fentale* and *Amibara Weredas* of the Afar National Regional State. The two main sources of data were measurements of temperature and precipitation taken with the span of over thirty years of temporal horizon. For analysis of the impact of climate variability, the study investigated contemporary reports of pertinent organizations and published articles. Based on analysis of statistical results and periodic reports, it is concluded that the study areas have witnessed extreme climate variability where the main patterns show no substantial and directional increase or decrease in measurements of temperature and rainfall. Rather the peculiar feature of climate variability in the two *Weredas* is erratic and highly unpredictable temperature and precipitation. The erratic and unpredictable characteristics of climate variability has been further compounded by the indelible impact of weather conditions in northern and central Ethiopia on the lowlands of the Afar region. Since the Afar region geographically situated to be on the receiving end of excess precipitation in central and northern Ethiopian highlands, analysis of precipitation merely based on meteorological records is proved to superficial.

From the above conclusion, it is recommended that policy design and implementation about the management of climate variability while ensuring food security best suited to the Afar natural ecological landscape and the traditional livelihood practices must take elements and conditions of the weather phenomenon on the entire north Ethiopian region. Because the Afar region gets more precipitation from the flow of flood in central and north Ethiopia, agronomic technologies are better from application of flood water technologies rather than propagation of rainfall based agricultural technologies. Therefore, the ongoing policy drive for irrigation-based wheat production is highly commended to take in to the hydrological impacts of the neighboring regions. Lastly, it should be pointed out that the prospect of harnessing climate change friendly livelihoods for an ideal level of food security requires the concerted and coordinated efforts of all stakeholders towards the eventual elimination of the invasive plant called *Prosopis juliflora.*

CHAPTER 4: IMPACTS OF *PROSOPIS JULIFLORA (*SWARTZ DC.) INVASION ON FOOD SECURITY OF PASTORAL AND AGRO-PASTORAL COMMUNITIES IN MIDDLE AWASH, AFAR REGION OF ETHIOPIA[4]

Abstract

This study examined the impact of Prosopis juliflora invasion on the food security and welfare of pastoralist communities by taking two Woredas (as treatment and control group) in Afar regional state, Ethiopia. The study used a total of 438 randomly selected samples of households (224 from Amibara - invaded area) and (214 households from Awash Fentale - non-invaded area). Descriptive statistics and econometric methods using alternative Propensity Score Matching (PSM) model specifications were employed to estimate the effect of Prosopis juliflora invasion on the food security in the study area. Econometric results indicated that households in Prosopis juliflora invaded areas were more likely to have lower number of livestock assets, less access to veterinary and government support services. They are also less likely to have better access to marketplaces to sell their livestock/agricultural produces compared to those in non-invaded areas However, they are more likely to be older and married households compared to those in non-invaded areas. Results from Average Treatment Effect estimation indicated that households in invaded areas (on average) have 1,167 Birr lower annual consumption expenditure compared to those in non-invaded areas. Hence, it is important for the regional and local administration to understand the adverse impact of P.juliflora expansion on sustainable development of the rangelands of the area and related livestock productivity and consider the policy implications of the findings and follow some of the recommendations derived from this study.

Keywords: Food Security, Prosopis juliflora, Invasion, Amibara, Awash Fentale

[4] Journal of Sustainable Development in Africa (Published)

4.1 Introduction

The impact of *Prosopis juliflora* invasion/ecological expansion on the sustainable development of pastoralists' livelihoods in the Afar Region of Ethiopia can be significant and multifaceted. *Prosopis juliflora* is recognized as one of the most invasive alien plant species in the world and has been introduced in the past 200 years and is now widespread in various parts of the world (Holmgren, 2003; Pasiecznik et al., 2001). Although the exact date of introduction of *Prosopis juliflora* into Ethiopia and particularly in the Afar Region is not well known and documented, most of the local people and different institutions of the area agreed that the species was introduced to the region during the early 1970s (Ayanu et al., 2015a; Haregeweyn et al., 2013; Shiferaw et al., 2004; Sintayehu et al., 2020b; Tessema, 2012). Since then it has been expanding and increasingly invaded large areas of communal rangelands (Birhane et al., 2017). In 2006, a total of 490,000 ha (5.2% of the region) of land in Afar was invaded by *Prosopis juliflora* and then after, has covered an area of more than a 1.17 million ha (12.33% of the region) in Afar (Shiferaw et al., 2019) and more than 12,000 hectares in Dire Dawa Administration (Jema & Abdu, 2013) and it has also invaded many rangelands in a different part of Ethiopia (Hundessa & Fufa, 2016; Lemma & Mohammed, 2016; Sintayehu et al., 2020b; Wakie et al., 2014).

Studies indicated that *Prosopis* has pros and cons, and many countries utilize *Prosopis juliflora* for different purposes such as its pods having nutritive value as food for humans and feeds for animals, its wood for different wooden products and its positive effect on soil amelioration in arid and semi-arid regions (Alves et al., 1990; Harden & Zolfaghari, 1988). It is also used for firewood and charcoal and has high timber quality, its wood is used for making parquet/ wooden floors, furniture and turnery items, fence post (Adodo & Iwu, 2020; Feleker & Bandurski, 1979; Pasiecznik et al., 2001; Roy, 2011).

On the other hand, *Prosopis juliflora* has been creating problems to the ecosystems, biodiversity, health, socio-economics, and several aspects of human welfare (Pasiecznik et al., 2001). The most ecological impacts of *Prosopis juliflora* is due to its dense canopy cover and related influences on light transmission to the ground which in turn results in changes and suppression of the undergrowth species or vegetation (Hussain et al., 2021; Zeila, 2011) as a result it affects the sustainable productivity of the livestock in the area due to lack of enough pasture in the *Prosopis*

invaded rangelands. In highly *Prosopis juliflora* invaded areas, it is found that the growth of native grass, herbaceous plants and tree diversity is suppressed (Ilukor et al., 2016a; Kahi, 2004). In line with this some other study also indicated that if the optimal invasion dose (intensity) of *Prosopis juliflora* is above 22.23%, it will create a negative impact on the biodiversity as well as the income of the households (Haji, et al., 2018a). As local elders in Afar indicated, *Prosopis juliflora* has been killing a larger number of cattle than those killed by drought, and which indicates how much *Prosopis juliflora* potentially leading and significantly affecting the pastoralism livelihood system and sustainable development of rangelands in the area. The Afar region boasts a cattle population of roughly 1.6 million, with approximately 131,000 of these cattle residing in the Amibara District. The primary purposes for keeping livestock in this region are for milk and meat production, as well as generating income (Ilukor et al., 2016b).

On the other hand, a study on climatic suitability model analysis for Prosopis indicated that more than 95% of the country was non-suitable for *Prosopis juliflora* growth are now becoming highly suitable (Sintayehu et al., 2020b). In 2050, both moderately and highly suitable area for *Prosopis juliflora* is expected to be increased (Bogale & Tolossa, 2021; Sintayehu et al., 2020b). This revealed that the climatic suitability for *Prosopis juliflora* invasion will increase and create a conducive environment for *Prosopis juliflora* expansion and threaten the livelihoods of the community (Dakhil et al., 2021). Key adverse consequences of climate variability in Ethiopia encompass food insecurity due to droughts and floods, disease outbreaks, and land degradation caused by heavy rainfall (Bogale & Tolossa, 2021). Moreover, *Prosopis juliflora* quickly invades pasture lands and severely affects households' income from livestock production (Wakie et al., 2016; Zeray et al., 2017a). It is also indirectly increasing household health expenditure (Ayanu et al., 2015a; Haji, et al., 2018a; Haregeweyn et al., 2013) due to creating severe injuries to the hooves of animals and have equally affecting human health.

Some community-level discussions revealed that there is a conflict of interest between pastoralists and urban dwellers in Afar on *Prosopis juliflora*, in a way that all pastoralists viewed *Prosopis juliflora* as no advantage whereas those community groups engaged in firewood and charcoal production considered as useful tree and means of income through sale of firewood and charcoal. A study indicated that the sales from charcoal and fire woods constitutes around 26% of the

average annual income of the households (Jema & Abdu, 2013). An increase in *Prosopis juliflora* invasion resulted in the loss of indigenous grasses and other plant species which in turn contributed to the substantial reduction of the number and productivity of livestock in Afar (Herrie, 2014; Yosef et al., 2013). Livestock populations especially cattle and camel in the Amibara declined at a rate of 36% and 20%, respectively, between 1997 and 2011 (Haregeweyn et al., 2013; Ilukor et al., 2016a). Many of previously rich pastoralists with having large number of livestock in Afar are started living under food insecurity (Rettberg, 2010) due to loss of their livestock. The rising global demand for livestock products is driven by the continuous improvement of living standards over time. Furthermore, climate change poses a significant threat to the sustainability of livestock production, affecting the quality of feed crops and forage, the availability of water, animal and milk production, livestock health, animal reproduction, and biodiversity (Rojas-Downing et al., 2017). Animal-based products play a vital role in the nutrition, food security, livelihoods, and resilience of hundreds of millions of people worldwide.

The number of livestock is declining from time to time due to many factors but also as households are selling off animals to buy food items, and about 64% of the rural Afar households are consuming less than three food groups out of seven (Ethiopia & Headquarters, 2014; Ilukor et al., 2016a). In Ethiopia, Afar region, has the households with the highest food expenditure and malnutrition as well as the lowest household food stock per capita (1 kg/person) (WFP, 2009).

Many pastoralists are moving into sedentary life within the last 20 years and engaging into different alternative income-generating activities (Ilukor et al., 2016b; Rettberg, 2010; Rettberg & Müller-Mahn, 2012). There are limited livelihood diversification and sustainable development options or alternatives in Afar to cope with this food insecurity challenges. Some of the studies conducted so far in Afar related to *Prosopis juliflora* primarily focus on its expansion/coverage, ecological and environmental impact, and means of utilization as a useful resource; some of them have dealt with the biological characteristics that promote its invasive ability and its impact on ecological services. However, studies that examine the impact of *Prosopis juliflora* invasion on the pastoralists' and agro-pastoralists' food security are rare. Hence, this study examined the impact of *Prosopis juliflora* invasion on food security using alternative estimation strategies to check the robustness of the results from PSM estimation.

4.2 Conceptual and Analytical Framework

Basic concepts

The concept of food security gradually broadened during the 1980s a move from global and national-level issues into food security concerns at local, household, and individual levels. The 1996 World Food Summit adopted the following definition that is more complex: *"Food security at any level is defined as physical and economic access by all people at all times to enough, safe, and nutritious basic food to meet their dietary needs and food preferences for an active and healthy life"(FAO, 1996)*. Then later the concept of social access was introduced in the definition, and it became, *"Food security is a situation that exists when all people, at all times, have physical, "social" and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life*" (Cafiero et al., 2016; FAO, 2009; Pinstrup-Andersen, 2009). It involves the availability, accessibility, utilization, and stability of food. On the other hand, *Food insecurity* is a situation in which individuals do not have physical or economic access to the nourishment they need, and they have no access to resources to produce food or cash. A household is also considered food insecure if its dietary intake is less than 80% of the daily minimum recommended allowance (MRA) of caloric intake required for an individual to be active and healthy (Owino et al., 2014).

Analytical Framework

As per the thematic focus of empirical and theoretical reviews conducted; the impact of *Prosopis juliflora* invasion on food security/insecurity is interconnected with various factors and dimensions such as demographic, socio-economic characteristics and other institutional settings that are directly and indirectly affecting the communities, livelihood and local climate and land use and land cover changes. The study tried to identify how some of the socio-economic factors related to the changing of food security/insecurity situation of the communities of the study areas. The following conceptual framework is developed to show how some of the key issues under each factor (demographic, socioeconomic, and institutional) linked with and contributed to show the impact of the *Prosopis* invasion on the welfare and food security/insecurity of the communities in the areas (Figure 4.1).

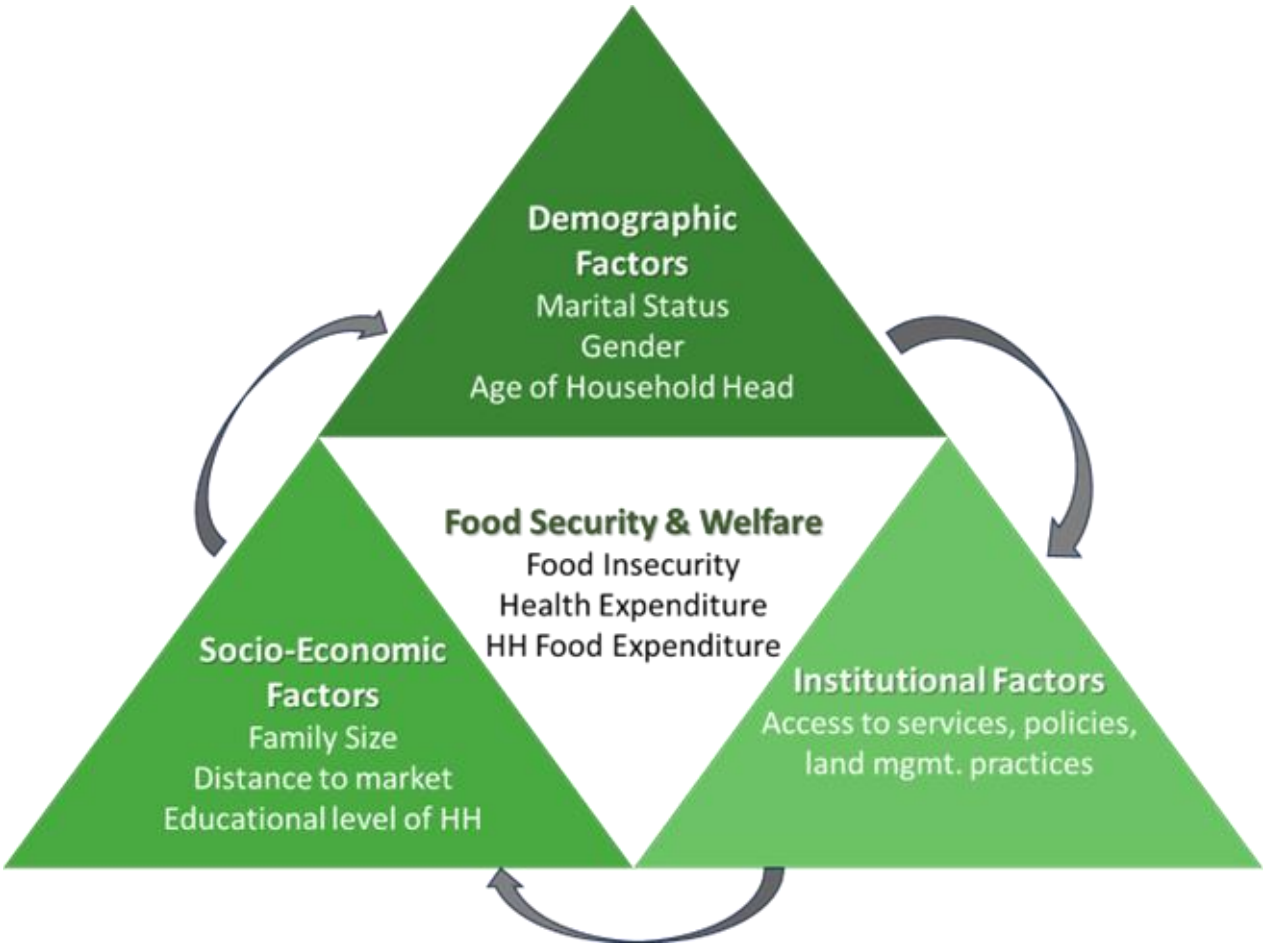

Figure 4. 1: Conceptual Framework-impacts of *Prosopis juliflora* invasion on Food Security

Livestock assets ensure food security for pastoralists in the Afar Regions. The consumption of milk, meat, and other livestock products provides essential nutrients and sustenance for the community. During periods of drought or crop failure, when agricultural production is limited, livestock products serve as a reliable source of food. For instance, the Afar people heavily rely on camel milk, which is rich in nutrients and can be consumed even in times of water scarcity. Livestock assets contribute to the resilience of pastoralists, enabling them to withstand food shortages and maintain their livelihoods.

4.3 Methodology

Study sites

The study is carried out in Afar Regional State (ANRS), Awash Fentale, and Amibara Woredas (40°08'- 40°12'E and 09°16'- 09°21' N) and which is located 160 and 250 km from Addis Ababa respectively (Figure 4.2). The altitude of these study sites is between 740 and 820m above sea level(CSA, 2021).The Afar National Regional State is part of the Great Rift Valley of East Africa.

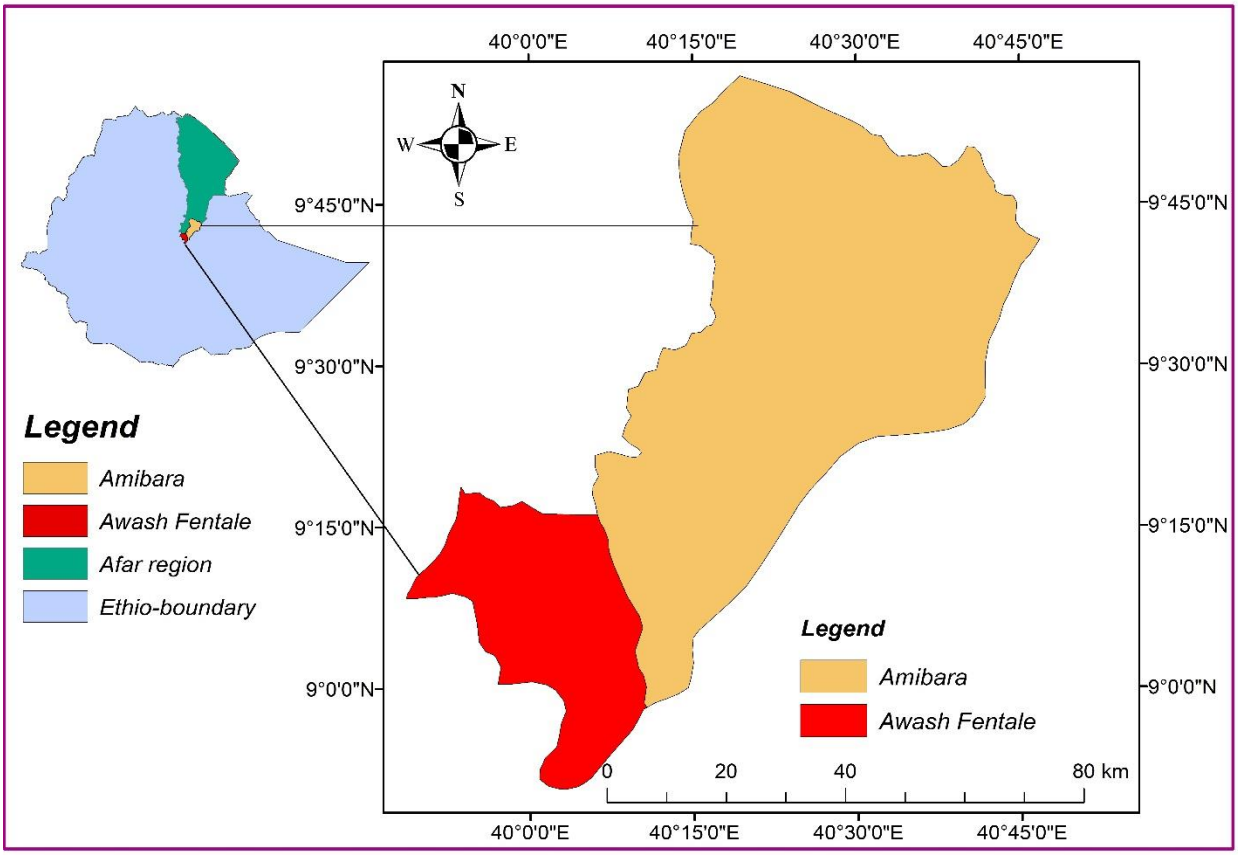

Figure 4. 2: Map of the study sites, Afar

The southern part of the region covers 6.67 million ha which is about 10% of the total areas of Ethiopia and about 29% of pastoral lowlands (Shiferaw et al., 2019). It is arid and semi-arid with a mean annual temperature of 31 °C having erratic rainfall with annual precipitation between 200 and 600 mm. The region has about 1.99 million population (CSA, 2021). The livelihood system of the region is mainly dependent on pastoralism (more than 90%) and agro-pastoralism (less than

10%) engaged in small-scale irrigation activities around the rivers. Most of the river in the areas are invaded by *P. juliflora* (Ayanu et al., 2015a; Ilukor et al., 2016a).

Shrublands, riverine forests, grasslands, wetlands, Settlements, and bare land are some of the key land use types in the areas. Encroachment of *prosopis* trees on grazing land is forcing pastoralists to move their herds to other areas in search of suitable grazing and water resources (figure 4.3). This can disrupt traditional grazing patterns and lead to conflicts with other communities over limited resources. Forced migration can also result in the loss of social networks and cultural ties, further impacting pastoralists' livelihoods.

Figure 4.3: Cattle in *P. juliflora* invaded rangelands of Afar, Ethiopia

4.4. Study Areas Population and Economic Activities

The total population (urban and rural) of Amibara and Awash Fentale Woredas are 110,427 and 55,708, respectively, of which, the total rural population of Amibara and Awash Woreda are 86,133 (14,355 HHs) and 43,452 (7,242 households) respectively, whereas the average household size is seven (CSA, 2021). The sale of livestock and livestock products, such as milk, meat, and hides, provides them with cash to meet their basic needs and invest in other income-generating activities. For example, the sale of goats or camels can help pastoralists purchase essential items like food, clothing, and medicine. Livestock assets also act as a form of savings, allowing pastoralists to accumulate wealth and cope with economic shocks, such as droughts or market fluctuations.

4.5. Sampling methods

The study used multi-stage sampling procedure to select Woredas and kebeles. First, when it comes to the selection of study region and woreda, Afar region- Amibara and Awash Fentale Woredas are chosen purposively as Amibara is the first most *Prosopis juliflora* invaded Woredas in Ethiopia and Awash Fentale is relatively free from *Prosopis juliflora* invasion. In the second stage, among all rural Kebeles in the two Woredas, *Prosopis juliflora* invaded (*Bedul Ali, Halaydege, Serkamo* and *Worer*) and non- invaded (*Doho, Dudub, Kebena* and *Sabure*) *Kebeles* were selected purposively in Amibara and Awash Fentale Woredas, respectively. Thirdly, a sample number of pastoralist and agro-pastoral households were randomly selected from the list of households obtained from each invaded and non-invaded *Kebeles* administration offices.

The sample households were selected for interview based on probability proportionate to the relative size of households in selected sample kebeles. First, the list of all households was collected from the *kebele* manager/administrator, and the list was used as a sample frame. In the circumstance when any randomly selected household head refused to participate in the interview are replaced by the next household. Data were collected using a pre-tested survey questionnaire. The survey was administered using experienced local language speaker data collectors using Kobo toolbox system in mobile/tablet for data collection. In addition, desk review was conducted and information from different sources was considered as input to develop a comprehensive survey questionnaire.

4.5.1. Sample size

The sample size for the study is determined by employing Yamane (1973) formula to calculate the sample size from each Woredas of the rural population. The sample size calculation considered a 5% acceptable error (e=0.05); a 50% reasonable estimate for the key proportion to be studied (p =0.5); and a 95% confidence level. The formula is given as:

$$n = \frac{N}{(1 + N\ (e2))} \qquad (1)$$

Where:

n = desired sample size

N= total number of population (i.e HHs)

e= the level of precision or the quality of being careful and accurate which is equal to 0.05.

Initially, the sample size for Amibara and Awash Fentale Woredas was estimated to 398 HHs and 397HHs, respectively. An additional 5% HHs were also considered to compensate for those respondents not willing to interview and which makes it a total of 835 HHs to be involved for household survey in both Woredas. However, considering the recurrent ethnic conflicts and security issues in *Zone 3* and the northern war effect in Afar and other related difficulties for field level data collection, the researcher in consultation with supervisors has decided and reduced the sample size, and data were collected from 438 households of the two Woredas (Figure 4.4).

4.5.2 Data collection tools and methods

The study was conducted following a preliminary assessment and review of relevant literature, local information, and observations. The researcher consulted with all relevant sectors and stakeholders during the study. Data collection tools and questionnaires were developed to effectively gather the required information from the field. As a result, the researcher collected both primary and secondary data from all available sources and household surveys. Field level data was collected during the lean season of the area, which was in January and February 2021. For primary data, both quantitative and qualitative surveys were conducted at household/individual level through well-developed survey questionnaires. Participatory community level discussions were employed to generate complementary and reliable data and information from different sectors at different levels. All food security data were collected from the sample *Woredas* and *kebeles*.

4.6. Data Analysis

The data were analyzed using descriptive statistics and econometric methods. Mean comparison tests using t- test and Chi square test were used to test whether there is a statistically significant difference across variables of interest between the two groups. The econometric method used propensity score matching techniques with alternative model specifications as a robustness check.

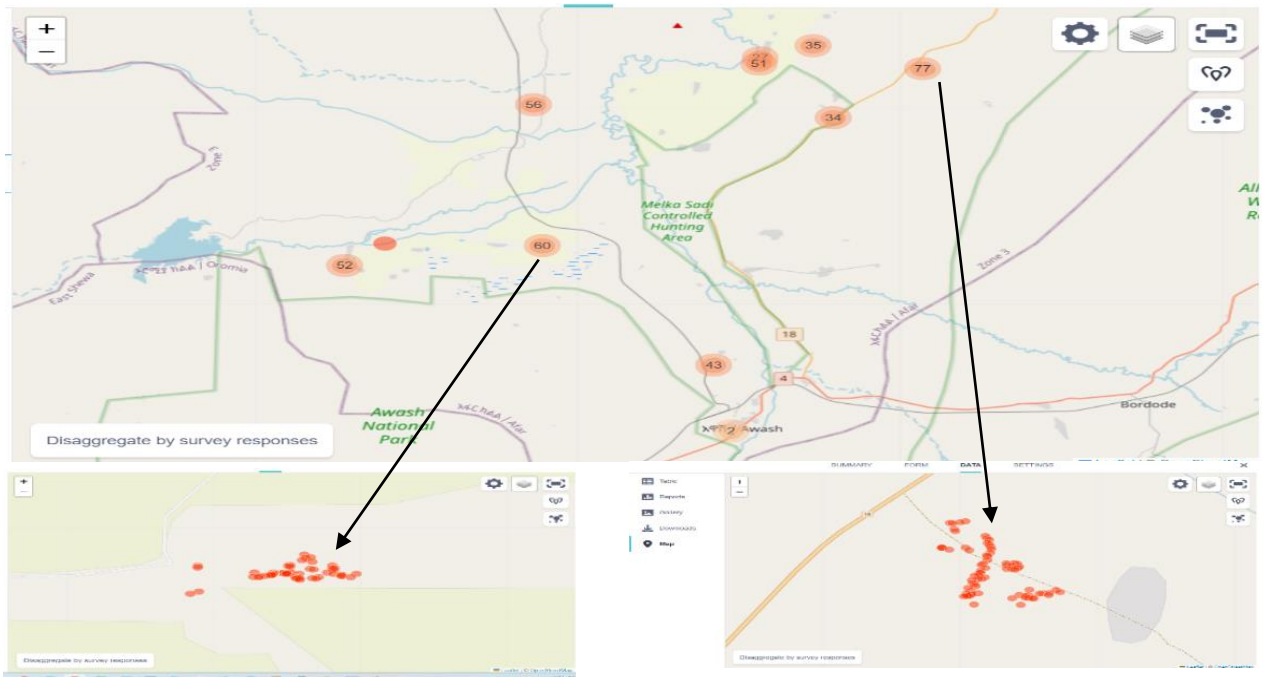

Figure 4. 4: Sample sites and distribution of interviewed households by Woredas

4.6.1. Propensity Score Matching Technique

To estimate the effect of invasion on outcome variables (annual household expenditure, a good proxy for income/food security), propensity score matching technique (PSM) was used (Rosenbaum & Rubin, 1983). Propensity score matching (PSM) is a statistical technique used in treatment effect model estimations to reduce bias and mimic a randomized controlled trial (RCT) when analyzing observational data (Jema & Abdu, 2013; Zeray et al., 2017a). It aims to estimate the causal effect of a treatment or intervention by matching treated (invaded areas) and control units (non-invaded) based on their propensity scores. PSM process often requires the below steps:

1. Define the treatment and control groups: Identify the treatment group (those who received the treatment) and the control group (those who did not receive the treatment) from observational data. 2. Estimate the propensity scores: Propensity scores are the estimated probabilities of receiving the treatment based on observed covariates. A logistic and/or probit regression model may be used to estimate the propensity scores, with the treatment variable as the dependent variable and the covariates as independent variables. 3. Assess covariate balance: Check the balance of covariates between the treatment and control groups after estimating the propensity scores. Covariate balance ensures that the groups are comparable and reduces bias. Common methods to assess balance include standardized mean differences, t-tests, or chi-square tests. 4. Match treated and control units: Match treated units with control units based on their propensity scores. There are different matching methods available, such as nearest neighbor matching, exact matching, or kernel matching. The goal is to create pairs or groups of treated and control units with similar propensity scores. Overall, propensity score matching is a valuable tool in observational studies for reducing bias and improving the validity of causal inference regarding the effects of treatments or interventions. 5. Assess post-matching balance: After matching, reassess the balance of covariates between the treated and control groups. This step ensures that the matching process has successfully reduced bias and achieved covariate balance. Overall, assessing post-matching balance is essential for ensuring the validity, reliability, and interpretability of results obtained from propensity score matching. It allows researchers to evaluate the success of the matching process in creating comparable treated and control groups, thus improving the credibility of causal inferences drawn from observational studies. 6. Estimate treatment effect: Finally, estimate the treatment effect by comparing the outcomes of the treated and control groups. Common methods for estimating treatment effects in PSM include difference-in-differences, regression adjustment, or stratification.

It's important to note that PSM has assumptions and limitations. Assumptions include the confoundedness assumption (conditional independence of treatment assignment given covariates) and the common support assumption (overlap in propensity scores between treated and control units). Careful consideration and evaluation of these assumptions are crucial when using PSM for treatment effect estimation. Results in section 4.7 were presented having the above steps in consideration to improve the validity of observational studies such as in our case.

Relevant socioeconomic, demographic and related factors were hypothesized as factors influencing the probability of treatment assignment and the causal effects (average treatment effect). These includes income (livestock assets which can be measured in tropical livestock unit (TLU), TLU commonly takes 250 kg live weight as a standard of unit, and accordingly, the TLU conversion factor for camels, cattle, and small stocks is 1, 0.7, and 0.1, respectively (Jahnke & Jahnke, 1982)) , age of household head, family size, education, marital status, access to veterinary services, and access to food aid (support services) (Table 4.2). Past studies and our own experience were used to select these covariates/explanatory variables that are expected to influence the probability of treatment assignment and the causal effect of *Prosopis juliflora* tree invasion on pastoralists livelihoods. As a robustness check to our results, alterative propensity scores matching methods have been used using the matched datasets. Once the matching is done, the impact has been computed as follows.

$$T_{ATT}^{PSM} = E_{P(X)\,|\,\mathrm{D}=1}\{E\left[Y(1)\,\middle|\,\mathrm{D}=1,\mathrm{P(X)}\right] - E\left[Y(0)\,\middle|\,\mathrm{D}=0,\mathrm{P(X)}\right]\} \qquad (2)$$

Specifically, psmatch2 and kmatch commands with PSM option in Stata were used to estimate the effect of the explanatory variables on outcome variables (annual household expenditures- as proxy for food security/income) across treated and control groups (Table 4.2). The balance of covariates between the treatment and control groups were confirmed using density and cumulative density plots with distance kernel matching methods (kmatch command in Stata).

4.7. Results and Discussions

4.7.1. Descriptive results

4.7.1.1. Socioeconomic Characterization of the Study area

The study used a total of 438 samples households from both Woredas, 224 from *Amibara* and 214 households from *Awash Fentale* Woredas where these are Prosopis invaded and non- invaded Woredas, respectively. Descriptive analysis on socioeconomic characteristics of the sample households indicate that the proportion of male headed households are 69.6% and 67.8% in invaded and non-invaded areas, respectively. While the average family size is 6.5 and 6.3 persons per household, the average age of household head in Prosopis-invaded and non-invaded kebeles was 38 and 37 years, respectively (Table 4.1, for tests of significant difference between areas).

In addition, by distance from the market, invaded and non-invaded households were 3.23 and 7.69 km away from the market, respectively. As indicated, the non-invaded area is relatively far from the market center which is in line with the fact that areas nearby to market centers have a high likelihood to be invaded as livestock are the main Prosopis disseminating agents. This is line with (Zeray et al., 2017a) who also noted that the average distance of non-invaded households from nearby city and main road is significantly far away than invaded areas.

Table 4.1: Socio-economic characteristics of households by treatment groups

Variables	Amibara (Invaded area)	Awash Fentale (non invaded area)
Family size in numbers	6.473	6.262***
	(0.13)	(0.17)
Age of household head in years	38.071	37.107***
	(0.62)	(0.78)
Distance from Market in km	3.230	7.689***
	(0.24)	(0.82)
Gender (1=Male)	0.696	0.678***
	(0.03)	(0.03)
Marital Status (1=married)	0.996	0.935***
	(0.00)	(0.02)
Assistance (1=Yes)	0.598	0.794***
	(0.03)	(0.03)
Vet-Access (1=Yes)	0.625	0.706***
	(0.03)	(0.03)
TLU (Tropical livestock unit)	21.343	23.705***
	(0.87)	(0.97)
Annual expenditure (ETB)	5247.661	6358.706***
	(123.39)	(227.00)
Income in ETB (monthly)	2513.170	2687.477***
	(88.98)	(142.94)
N	224	214

Note: For mean comparison, t- test was used for continuous variables while Pearson chi2 for dummy/categorical variables. Standard errors are in parentheses. Tests of significance stars are shown on Awash Fentale column values instead of having a separate p-value column.

Results also indicate that households in the non-invaded area have better access to veterinary services, as the average accessibility of veterinary service is 70.6% for non-invaded area - Awash Fentale, while it is 62.5% for invaded area – Amibara (Table 4.1). The difference in access to veterinary service between the groups is statistically significant at 1%. Access to social services including vet service is much better in non-invaded areas mainly because of the difficulty for

livestock and others movement in invaded areas where Prosopis become thick and impossible for livestock and veterinary service providers to move from place to place. The less invaded the area, the more likelihood to provide services for pastoral communities which contributes a lot to enhance productivity of livestock and crops and related increase of incomes from sales of livestock products.

Since almost all households in the area are pastoralists, the invasion of Prosopis has also other implications for households accessing social services, including veterinary services. For one thing, it reduces livestock health management capability of the pastoralists. The difficulty for livestock to move freely in Prosopis-invaded areas may limit their access to regular veterinary check-ups, vaccinations, and treatments. Consequently, livestock health management and disease control measures could be compromised, leading to a higher risk of health issues among the animal population. According to (Mehari, 2015b), invaded household lost about 7 cattle and 6.5 small stocks, on average, due to health threats resulted from the pods of *Prosopis juliflora*.

In addition, it has its own impact on the livelihoods of households. Livestock rearing is often a vital source of income and sustenance for communities in rural areas. The restriction of livestock movement in Prosopis-invaded areas can negatively impact the livelihoods of these communities by limiting their ability to trade, sell, or move livestock to access better grazing areas or markets. The fact that the households in non-invaded area have significantly higher income expenditure from the Table above could support this argument.

Finally, it is also found that households in invaded areas have less livestock number than households in non-invaded area (Table 4.1). This could be due to the impact of the *Prosopis juliflora* invasion on pastureland that support livestock production in the area. This is consistent with (Mehari, 2015b) result that most of the households in the area claimed to have lost more than half of their grazing lands due to the invasion. Figure 5 below shows the differences in the distribution of livestock (in Tropical Livestock Unit) between the invaded and non-invaded area. The test results using two-sample Kolmogorov-Smirnov indicated that there are statistically significant differences in TLU distributions between the treatment groups (combined K-S values at 0.1580; p-value=0.008). Hence, households in invaded region have lower TLU distributions or values than in non-invaded region (Figure 4.5). In this regard, noting the intentional introduction

of the *Prosopis juliflora* in the area, (Seid et al., 2020b) also argued that the plant has become very invasive, and it severely harmed livestock rearing which is the main livelihood strategy of households in the study area.

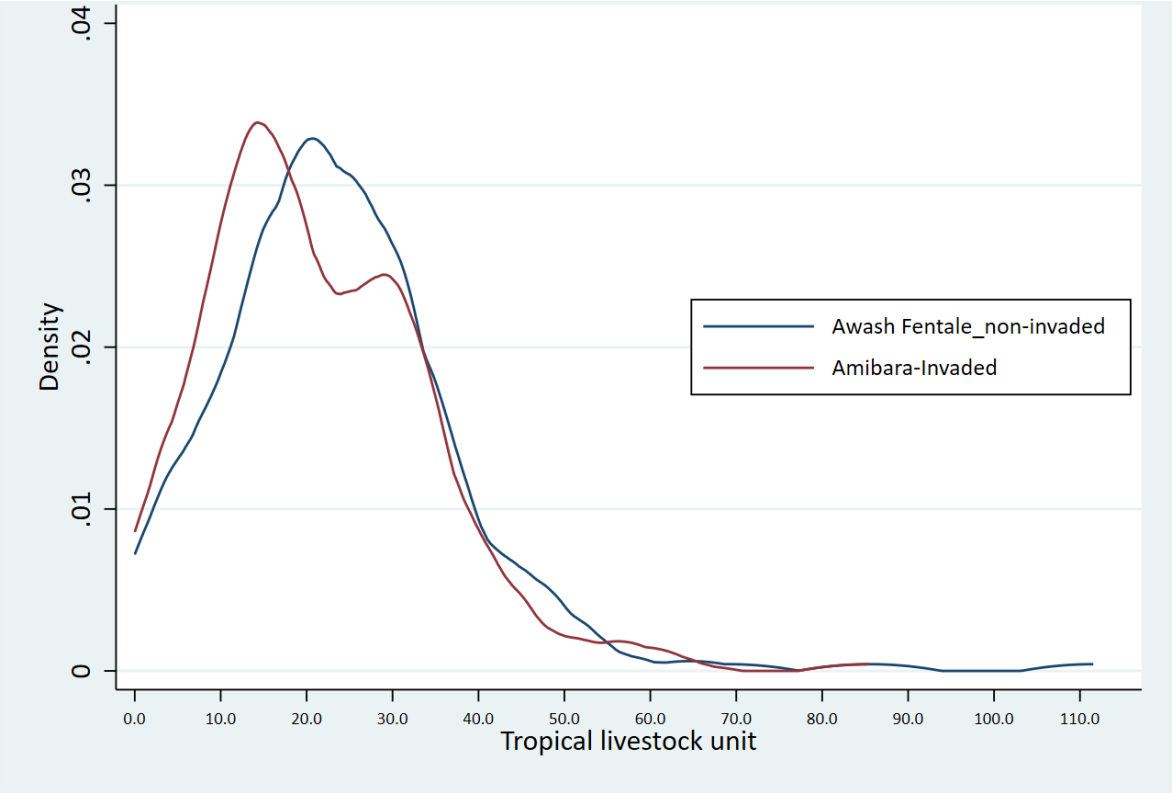

Figure 4. 5: Differences in TLU distribution by Prosopis invasion, Afar Region of Ethiopia

Source: Own data visualization using Stata 17.1 version, 2023

Livestock serve as a source of income, allowing pastoralists to meet their basic needs and invest in other income-generating activities. They also act as a reliable source of food during periods of drought or crop failure. Moreover, livestock assets hold significant social and cultural value, symbolizing wealth, prestige, and fostering social cohesion. Therefore, the preservation and sustainable management of livestock assets are crucial for the well-being and resilience of pastoralists in the Afar Regions.

4.7.2. Econometric Results

4.7.2.1. Probability of Treatment Assignment

The impact of the Prosopis invasive tree species on pastoralists' livelihoods in the Afar Region of Ethiopia can be significant and multifaceted. To identify the net impact of the invasion on the food security of households, the PSM matching technique was used in this study. Since results from PSM estimation are sensitive to the kind of matching methods applied and the underlying assumptions of the model such as no unobserved confounders between covariates and the outcome variable, this study presented estimation results using two alternative model specifications (Table 4.2). The balance of covariates between treatment and control was also checked before estimating the factors contributing to the treatment assignment and the causal effect of Prosopis invasion.

In order to check the quality of matching between the two groups, density balancing plot was used to compare the distribution of the covariates before and after matching, and it indicated that the matched groups have similar distribution after treatment as shown in the figure 4.6. This confirms the accuracy of the matching process that helps to eliminate selection bias in estimating the impact of treatment on outcome variable.

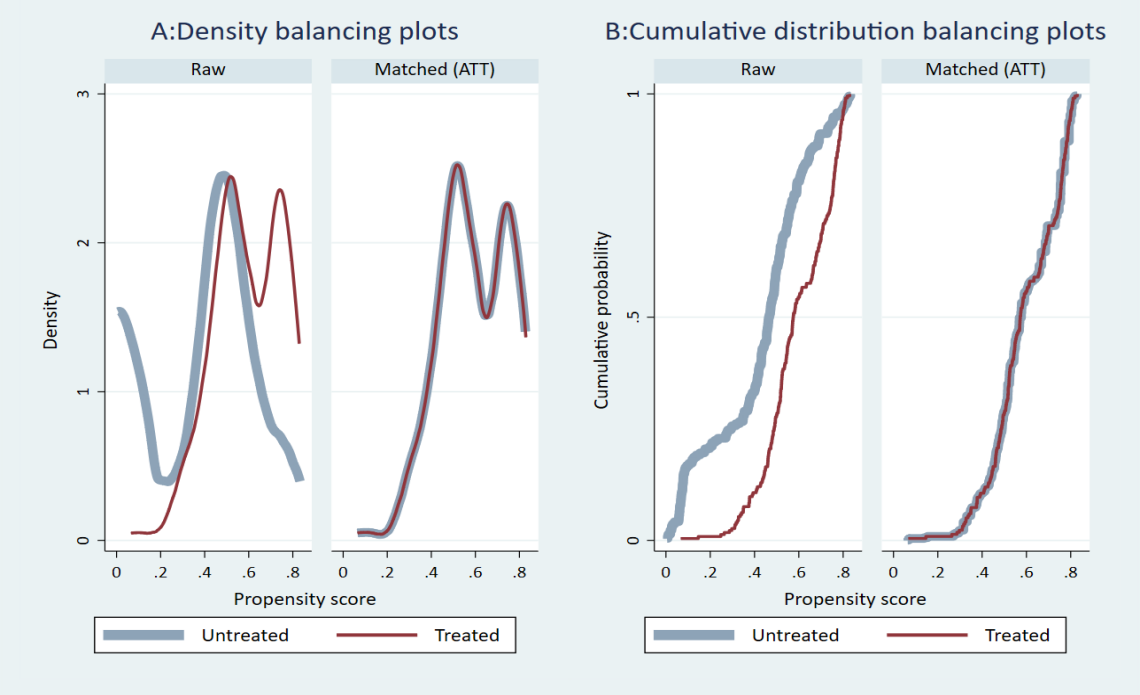

Figure 4.6: Accuracy of the matching process using kmatch graph command

Source: Own data visualization, 2023. See (Jann, 2017) for kmatch command in Stata 17.1.

Consistent results across models were obtained confirming the robustness of our estimation (Table 4.2). Since the overall model fit and standard errors were bootstrapped in kmatch (with probit model option), results from this model will be used and interpreted in this study.

As expected, households in treated areas were more likely to have lower number of livestock assets, less access to veterinary and government support services. They are also less likely to have better access to marketplaces to sell their livestock/agricultural produces compared to those in non-invaded areas. However, they are more likely to be older and married households (Table 4.2). These results support the descriptive results presented and discussed in Table 4.1. It also confirms that *Prosopis* invasion is a threat to pastoralists livelihood strategy-livestock asset. This is because livestock is an asset that provides economic stability, ensures food security, and contributes to the social and cultural fabric, prestige, and fostering social cohesion of the pastoral community. Therefore, the preservation and sustainable management of livestock assets are crucial for the well-being and resilience of pastoralists in the Afar Regions.

Table 4.2: Propensity score matching estimation results

	psmatch2-logit b/se	Kmatch-probit b/se
Treatment equations-household characteristics		
Family size	0.003	0.004
	(0.05)	(0.03)
Male=1	0.067	0.048
	(0.23)	(0.14)
Married	2.419**	1.341**
	(1.08)	(0.53)
Age of household head in years	0.090*	0.055*
	(0.05)	(0.03)
Age of household head squared	-0.001	-0.001
	(0.00)	(0.00)
Education		
2nd cycle (5-8) grades	0.912	0.580
	(0.62)	(0.38)
Has no formal education	0.717	0.440
	(0.52)	(0.32)
High school (9-12) grades	1.116	0.698
	(0.89)	(0.54)
Technical / vocational certificate or diploma	0.663	0.420
	(1.55)	(0.90)
Market distance in km	-0.084****	-0.052****
	(0.02)	(0.01)
Assistance received 1=Yes	-1.067****	-0.641****
	(0.24)	(0.14)
Access to vet. Services 1=Yes	-0.483**	-0.279*
	(0.24)	(0.15)
Tropical livestock unit	-0.017**	-0.010**
	(0.01)	(0.00)
Constant	-3.174**	-1.831**
	(1.49)	(0.83)
Observations	438	438
LR chi2(13)	82.57	83.16
Prob >chi2	0.000	0.0000
Pseudo R2	0.136	0.137
Average Treatment effects estimation results	psmatch2	kmatch
ATT	-1112.6**	-1167.8***
SE-ATT	259.9	273.94
T_Stat	-4.28	-4.26
P_value	0.0000	0.0000

Note: * p<0.10, ** p<0.05, *** p<0.01. Outcome variable is household total expenditure in both models. In both models, regressions are on common supports. Standard errors are bootstrapped for kmatch model. A probit model with Mahalanobis-distance kernel matching (md) through bootstrapping of standard errors was specified for kmatch method.
Source: Own estimation, 2023

4.7.2.2 Average Treatment-Effect (ATT) estimation results

By matching individuals with similar propensity scores, the method aims to create comparable groups and reduce the bias caused by confounding[5] variables. The estimated treatment effect represents the average difference between the potential outcomes for the treated and control groups (Becker & Ichino, 2002). As shown in Table 4.2, alternative PSM matching methods were applied using matched observations. Results from both models indicated that *Prosopis juliflora* invasion signficantly reduced pastoralists annual consumption expenditure although a relatively higher average treatment effect result was obtained from kmatch model compared to psmatch2 model (see Table 4.2, ATT row).

As expected, households in invaded areas (on average) have lower annual expenditure (e.g. 1,168 Birr) compared to those in non-invaded areas (see ATT row of Table 4.2 for kmatch model). Because expenditure is a good measure of food security compared to income measure, it can be inferred that those in invaded areas are more food insecure since they have less amount of money to cover their expenses. Statistically significant Average Treatment Effect (ATT) values from the `kmatch` command in Stata indicate that there is evidence to suggest that the treatment has had a significant impact on the outcome variable of interest. This finding supports previous studies' that examined the effect of this invasive plant on pastoralists livelihoods using mostly descriptive analysis. For example, 84% of pastoral households perceived *Prosopis juliflora* as a harmful bush (Mehari, 2015b), and similarly about 90% of households have negative perception towards effects of *Prosopis juliflora* invasion on the rural community (Seid et al., 2020b). In this study, 60% and 34.5% of the households indicated as *P.juliflora* is harmful, and useful and harmful respectively. Only 5.7% of interviewed households mentioned as it is useful tree. Further discussions on the usefulness of prosopis was conducted separately with both women and male focus groups and the results indicated that 92% of the women focus groups said as it is useful for charcoal whereas 86% of male focus groups members said as it is useful for livestock shed. However, similar with other studies made by (Ilukor et al., 2016a), most households favored whole eradication of the *Prosopis*. 70% percent of interviewed households said that it harmful in degrading the rangeland whereas

[5] Variables that may affect both the treatment variable (indicator) and outcome variable simultaneously that may potentially result in spurious regression results.

62% of the households indicated as it is harmful in relation with its impact on the health of their livestock due to poisonous nature of its thorn.

4.8. Conclusions

This study examined the impact of *Prosopis juliflora* invasion on the food security and welfare of pastoralist communities in *Amibara and* Awash *Fentale* woredas of Afar region. A total of 438 randomly selected samples of households (224 from *Amibara* - invaded area) and (214 from *Awash Fentale* - non-invaded area) were interviewed using structured survey questionnaire with initial pre-testing. Both descriptive and econometric results were presented and discussed to examine the impact of this invasive species on pastoralists food security proxied by total annual expenditure. Unlike previous studies, this study uniquely examined the effect of this invasive tree on pastoralists key assets-livestock and additional covariates to disentangle the casual effects of *Prosopis juliflora* invasion on food security.

Using PSM technique combined with advanced methods for checking covariate matching and diagnostics, the average treatment effect of *Prosopis juliflora* invasion on pastoralists food security was estimated. The results from this matching method indicated that pastoralists in treated (invaded areas) were found to be food insecure (had lower annual income/expenditure) compared to the control groups (non-invaded areas). This may suggest *Prosopis juliflora* invasion, though intentionally introduced in the area, poses important food security and welfare concerns to pastoralists than the potential benefit it accrues from sale of charcoal and firewood for some members of the community.

Results from this study also indicated that pastoralists in invaded areas were more likely to have fewer number of livestock assets that holds significant (economic, social, and cultural values) to pastoralists compared to those in non-invaded areas. In addition, pastoralists in invaded areas were less likely to have access to veterinary and other support services compared to those in non-invaded areas. Limited access to veterinary services would mean pastoralists' ability to control livestock diseases could be compromised, leading to a higher risk of animal health and loss of livestock assets-a key livelihood strategy that contributes a lot for sustainable economic and social

development for pastoral communities in the area. Given livestock rearing, a major means of sustenance for the pastoral community, the restriction of livestock movement in *Prosopis*-invaded areas also tend to limit their ability to trade and access better grazing land, and hence negatively impact the livelihoods and the sustainability of livestock production by pastoral communities.

In addition, as part of sustainable development strategy, an understanding of the impacts of *P. juliflora* invasion enables pastoralists to build resilience against future threats to food security. By implementing measures to control invasive species and diversifying livelihood strategies, communities can become more resilient to environmental changes and disruptions. The study contributes to the development of sustainable livelihood strategies for pastoralists by identifying alternative income sources and land management practices that are compatible with ecosystem conservation and food security objectives.

4.9 Recommendations

The invasion of *Prosopis juliflora* trees in the Afar Region of Ethiopia poses significant challenges to pastoralists' livelihoods, including reduced grazing land, water scarcity, livestock health issues, and displacement. Addressing this invasive species and finding sustainable development solutions is crucial to ensure the resilience and well-being of pastoralist communities in the region. This study unveiled evidences that *Prosopis juliflora* invasion significantly impact the livelihood of the pastoralist community, especially in highly invaded areas of the region. Based on the study results, the following are important recommendations. First, develop methods to contain the spread of this invasive tree species. Such measures may include uprooting seedlings, cutting, and burning and use of modern technologies/machinery such as (e.g., pod and tree crushing machines). The use of modern tree crushing machines may create job opportunities and by products (feed resources).

Second, encourage pastoralists to diversify their livelihood strategies. Since the main livelihood strategy of the households in the area is livestock rearing, anything that affects this huge asset cannot be overlooked. As the plant takes over grazing land, sucks water from soil, and cause harm due to its poisonous thorns, among others, that significantly reduced the number of livestock in invaded area, livelihood diversification strategies may also be sought as complete eradication of the plant may not be possible. Thus, pastoralists in the area may be provided proper agricultural

extension services to combine crop production activities along with their livestock rearing. Additional non-farm income generating activities and initiatives may also be looked at since pastoralists key asset (livestock) is under significant treat by *Prosopis juliflora* invasion.

Third, it is also vital to search for technological options. The invasion of the tree is already an issue on other part of the world including Asia (e.g., India), Latin America and Southern Africa in particular. Collaborative research works may be needed to pull varied experiences and resources together that geared towards coming up with some innovative solutions to deal with the plant.

CHAPTER 5: DETERMINING THE STATUS OF FOOD INSECURITY OF HOUSEHOLDS IN *PROSOPIS JULIFLORA (*SWARTZ DC.) INVADED AND NON-INVADED AREAS IN AFAR REGION. AN APPLICATION OF THE RASCH MODEL[6]

Abstract

Food security in an integral part of sustainable development. This study aimed to assess food security in Prosopis-invaded and non-invaded districts (Amibara and Awash Fentale, respectively) in the Afar region, where the availability and efficient utilization of natural resource is very critical sustainable livelihood of the community. Employing the Rasch modeling approach and using Food Insecurity Experience Scale (FIES), data from 438 randomly selected households collected in 2022 were analyzed. Results indicated that a lower average food security assessment in Amibara (5.168 ± 0.8) compared to Awash Fentale (6.576 ± 3.575), at a 5% significance level. Results also revealed significantly higher food insecurity prevalence in Amibara (Prosopis invaded) compared to Awash Fentale. The analysis also showed 50% and 43% of households as severely food insecure in invaded and non-invaded areas, respectively. Additionally, 47% and 30% of households were moderately food insecure in invaded and non-invaded areas, respectively. Notably, only 3% of the households are food secure in the invaded area, while 28% were food secure in non-invaded areas. Thus, the study underscores the treat the invasion posed and hence urgent on the need for targeted interventions to address the invasion and food insecurity in these communities.

Keywords: Rasch model, severity, prevalence, invaded and non-invaded, food insecurity.

[6] Submitted to Journal of Sustainable Development in Africa (Published)

5.1 Introduction

Food security and nutrition is an integral part of sustainable development (Berry et al., 2015). The environment and the obtainability of natural resources are preconditions for the availability of food as well as the preservation of biodiversity (Berry et al., 2015; Sperling & McGuire, 2012). One of the ecological challenges in arid and semi-arid area in Ethiopia is the invasion of exotic plant species that pose significant threat to natural ecosystems and environmental sustainability, particularly in areas experiencing severe depletion of resources like soils, water, and forests. At first, people are compelled to introduce new exotic plant species, chosen for their ecological adaptability and rapid growth as an effort to reduce desertification. However, research indicates that the adverse ecological and social impacts of many invasive plants often outweigh their benefits (Pasiecznik et al., 2001). Notably, Prosopis juliflora is recognized as one of the most invasive alien plant species, impacting pastoralists and agro-pastoral livelihoods in Ethiopia's Afar Region. This invasion disrupts daily activities, affecting the livelihoods of pastoralists and the broader ecosystem in the region. Despite some potential benefits, the prevailing perception among the local population overwhelmingly leans toward viewing Prosopis juliflora as harmful, often referred to as the "devil tree."

The invasive plant has caused disruptions to ecosystems, biodiversity, health, socioeconomic, and various aspects of human welfare often impacting livestock productivity in the area by limiting pasture availability in invaded rangelands (Pasiecznik et al., 2001). Livestock, crucial for nutrition, food security, livelihoods, and resilience for millions globally, face a decline in numbers as households sell animals to purchase food. For instance, in rural Afar, approximately 64% of households consume less than three out of seven food groups, contributing to a precarious food situation (Ethiopia & Headquarters, 2014; Ilukor et al., 2016a). Notably, the Afar region experiences the highest food expenditure and malnutrition, coupled with the lowest household food stock per capita (1 kg/person) in the country (WFP, 2009).

Globally, 9.7% of the world population (746 million or nearly one in ten people in the world) were exposed to severe levels of food insecurity in 2019, with an additional 16% facing food insecurity at moderate levels (I. FAO, UNICEF, WFP and WHO, 2020). In Ethiopia, the (Ethiopia & Headquarters, 2019) estimate shows that 25.5% of the people experiences food insecurity, with varying levels across regions. Notably, the Amhara region reports the highest percentage of food

insecure households at 36.1%, followed by Afar (26.1%) and Tigray (24.7%). Rural areas exhibit a higher food insecurity rate of 22.7% compared to urban areas at 13.9%. In Afar, the average monthly household expenditure is 775 birr (Ethiopia & Headquarters, 2019). A study by (Hirvonen & Wolle, 2019) in Afar revealed concerning findings: none of the rural children and only 10.1% of urban children met the minimum dietary needs. Additionally, only 11% of households in Afar consumed from more than six food groups, where total calorie declined by 6% between 2012 and 2015. Food insecurity manifests in various stages, from initial concerns about having enough food to dietary changes and prolong food availability. This progression often involves reducing consumption sizes, starting with adults and extending to children (Meroni et al., 2017).

Over the past two decades, an increasing number of pastoralists in Afar have shifted from a pastoral to sedentary lifestyle, engaging in alternative income-generating activities (Ilukor et al., 2016b; Rettberg, 2010; Rettberg & Müller-Mahn, 2012) even though there are limited livelihood diversification options to tackle food insecurity challenges in Afar region which is facing the invasive plant species. Previous studies on *Prosopis juliflora* primarily focused on various aspects including its expansion, ecological impact, environmental consequences, and potential utilization. Although some studies delved into the biological characteristics fostering its invasive nature and effects on ecological services, there is limited attention to assessing the specific impact of *Prosopis juliflora* invasion on the food security of pastoralists and agro-pastoralists in the region. This paper attempted to address this gap by conducting a focused assessment to understand the impact of *Prosopis juliflora* invasion on food insecurity severity, comparing invaded and non-invaded areas using FIES data and applying the Rasch model.

5.1. Methodology

Study Sites

The study was conducted in the Afar Regional State (ANRS), specifically in *Awash Fentale* and *Amibara Woredas*, located at approximately 40°08'-40°12'E and 09°16'-09°21'N, situated 160 km and 250 km from Addis Ababa, respectively (Figure 5.1). The Afar National Regional State is situated within the Great Rift Valley of East Africa, covering 6.67 million hectares, accounting for about 10% of Ethiopia's total land area and approximately 29% of pastoral lowlands (H Shiferaw et al., 2019). The region experiences arid and semi-arid conditions, with a mean annual temperature of 31 °C and erratic rainfall ranging between 200 and 600 mm annually. The population of the

region is around 1.99 million (CSA, 2021). *Amibara* and *Awash Fentale Woredas* have total populations of 110,427 and 55,708, respectively, with rural populations of 86,133 (14,355 households) and 43,452 (7,242 households), respectively. The average household size is seven (CSA, 2021). The livelihood system in the region predominantly relies on pastoralism (over 90%) and agro-pastoralism (less than 10%), with some engagement in small-scale irrigation activities along the rivers.

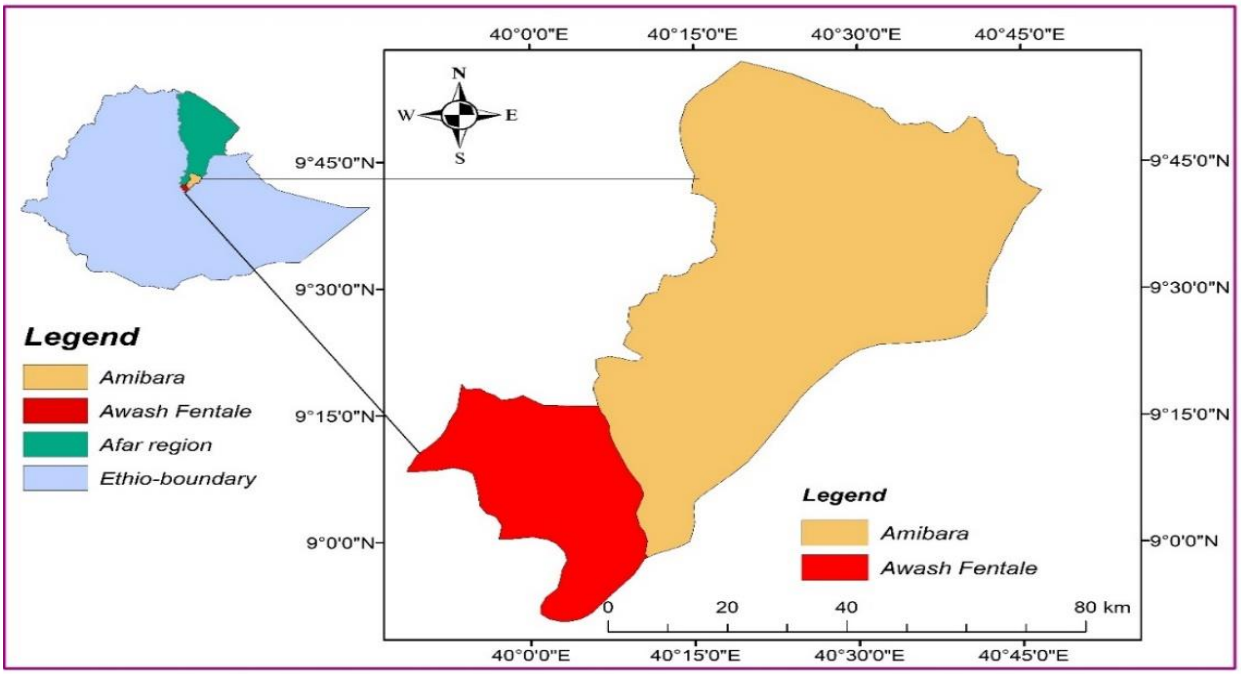

Figure 5. 1 Map of study sites, Afar region, Ethiopia

5.2. Sampling Methods

This study employed a multi-stage sampling method to select the study region, districts (woredas) and *kebeles*[7]. Firstly, Afar region was purposively chosen as it is the first region where *P. juliflora* invasion started, and amongst the woredas in the region, *Amibara* and *Awash Fentale woredas* were selected due to their distinct status in Prosopis juliflora invasion. *Amibara woreda* is one of the first *woredas* invaded by Prosopis juliflora in Afar, while *Awash Fentale* is relatively unaffected. Subsequently, specific Prosopis juliflora invaded and non-invaded *kebeles* were purposively selected within these *woredas*. Accordingly, *Bedul Ali*, *Halaydege*, *Serkamo* and

[7] *Kebele* is the lowest administrative division in Ethiopia.

Worer kebeles were chosen from invaded areas whereas *Doho, Dudub, Kebena* and *Sabure kebeles* were selected from *Awash Fentale woreda*. A random sample of pastoralist and agro-pastoral households was then selected based on probability proportionate to the relative size of households in the chosen *kebeles*. In cases of refusal to participate in the interview, households were replaced sequentially. Data collection utilized a pre-tested survey questionnaire administered by experienced local language speakers using the Kobo toolbox system on mobile/tablet devices. Additionally, a desk review was conducted, incorporating information from various sources to develop a comprehensive survey questionnaire.

5.3. Sample Size

The sample size for this study is determined by employing Yamane (1973) formula that enabled to calculate the sample size from each *woredas* of the rural population. The sample size calculation has considered a 5% acceptable error (e=0.05) and a 95% confidence level. The formula is given as:

$$n = \frac{\mathrm{N}}{(1+\mathrm{N}\,(e^2)} \qquad (1)$$

(Yamane, 1973)

Where: n = desired sample size
N = total number of population (i.e. HHs)
e = the level of precision or the quality of being careful and accurate which is equal to 0.05.

Hence, the data were collected from a total sample of 438 households from the two woredas (224 and 214 households from Amibara and Awash Fentale woredas, respectively).

5.4 Data collection methods and sources

The study used both primary and secondary sources. The primary sources are mainly the pastoralists and agro-pastoralists in the study area. Primary data collection tools, including well-designed survey questionnaire (i.e. the Food Insecurity Experience Scale (FIES)) was used for this study. This field-level data was gathered during the lean season (January and February 2022). The researcher employed a combination of quantitative and qualitative surveys at the household/individual level, utilizing mainly key informant interviews and focused group

discussions for the qualitative part. And the primary data source is complemented with secondary data sources including various published materials.

The FIES tool has consisted of eight questions that helped to measure the food security status of households in both P. juliflora invaded and non-invaded sites. FIES utilizes dichotomous responses ("yes"/"no") to compute valid indicators of food insecurity prevalence and severity. Respondents' answers are aggregated to generate raw scores ranging from 0 to 8, with food insecurity classified into three categories: 1) Food Secure (FS) with raw scores ranging from 0 – 3; 2) Moderate Food Insecurity (MFI) with raw scores of 4 – 6; and 3) Severe Food Insecurity (SFI) with raw scores of 7 – 8. FIES provides an experience-based metric for assessing the severity of food insecurity conditions of the households (Ballard et al., 2014; Carlo Cafiero et al., 2016; Saint Ville et al., 2019).

In general, the underlying premise of the FIES is that the severity of food insecurity within a household or individual can be treated as a latent trait encompassing behavior, experiences, and perceptions. Latent traits, though not directly observable, can be deduced from observable evidence using measurement models based on Item Response Theory (IRT). This statistical approach is more versatile in gauging food insecurity compared to traditional methods relying on indirect assessments through determinants (like food availability) or consequences (such as anthropometric failures and signs of malnutrition) (Ballard et al., 2014; Carlo Cafiero et al., 2016; Nord, 2014).

The FIES module comprises items directly questioning individuals about compromises in the quality and quantity of their food due to limited financial or resource means. Each FIES question pertains to a distinct situation, associated with a specific severity level (Ballard et al., 2014; Nord, 2014). FIES goes beyond other measures by capturing psychosocial effects in certain community groups (e.g., women and children), reflecting anxiety or uncertainty regarding the ability to procure sufficient food (Wambogo et al., 2018). Thus, FIES was utilized in this study to determine the prevalence of food insecurity in areas invaded and non-invaded by Prosopis juliflora.

5.4.1 Data Analysis Methods: Rasch Model and its Applications

The status and severity of food insecurity of households among the two sites (invaded and non-invaded) was examined using the Rasch modelling approach. The Rasch Model, also known as the

one-parameter logistic (1PL) model is used to gauge the severity of food insecurity based on responses to experience-based FIES questions in individual households (Ballard et al., 2014; Boone, 2016; Nord, 2014; Rosenbaum & Rubin, 1983). This model, named after the Danish mathematician Georg Rasch, assumes that households are more likely to affirm less-severe items than more-severe ones and that items are more likely to be affirmed by households experiencing greater food insecurity (Deitchler et al., 2010). Key assumptions of the Rasch Model include equal item discrimination, indicating each item is equally associated with the measured construct; and conditional item independence, suggesting that items are correlated only due to their association with the latent trait and they are conditionally independent and unidimensional (Nord, 2014; Wambogo et al., 2018).

In the Rasch model, item difficulty and respondent ability are the underlying variables measured, where respondent ability represents the severity of food insecurity, and difficulty implies the severity inferred by an affirmative response (Opsomer et al., 2002). The model assumes an unobservable, one-dimensional, and continuous trait—referred to as ability—that all respondents possess to varying degrees. The model conceptually establishes a continuous scale for item difficulty and respondent ability. In food insecurity studies, each respondent answers dichotomous FIES questions based on their latent ability where higher ability increases the probability of a positive response. The Rasch model allows simultaneous estimation of individual ability and item difficulty parameters. It assumes that the trait being measured is unobservable but can be assessed by questions whose likelihood of an affirmative response is directly related to the strength or severity of that trait (Opsomer et al., 2002). The Rasch model assumes that if the wording of an item remains constant, its estimated severity should remain consistent over time. Thus, households experiencing a certain level of food insecurity in one year are expected to respond to each item similarly in subsequent years (Owino et al., 2014). Measurement of food insecurity is challenging due to its multifaceted and continuous nature influenced by numerous variables (Owino et al., 2014).

The simple Rasch model employs a logistic function to model the probability of a correct response based on the difference between person and item parameters (Elijah, 2010; Obayelu, 2010). It formalizes the concept of severity ordering of items, allowing the estimation of item and household severity and assessing response consistency with this concept (Nord, 2014). Food insecurity, a

latent trait, lacks a standardized language for description. It is a latent trait, i.e., not directly observable. People do not say, "On a scale of 1 to 10, my food insecurity is at level 3". But people do speak readily about specific experiences such as running out of money for food, and the specific behaviors and conditions that result it such as being forced to cut back on quality or quantity of food. The Rasch model utilizes well-designed survey questions to elicit information about specific experiences, behaviors, and conditions related to food insecurity (Nord, 2014).

The one-parameter Rasch model (Rasch, 1960) predicts the probability of selecting the correct response of a test item depending on a latent trait θn. For multiple-choice items and short-answer items with a category score 1 for correct responses and 0 for incorrect responses, and this is modelled as equation (2) below:

$$Pi\ (\theta) = \frac{\text{Exp}\ (\theta n - \delta i)}{1 + \ \text{Exp}\ (\theta n - \delta i)} \qquad (2)\ \text{(Schulz \& Fraillon, 2011)}$$

Where, Pi (θ) = the probability of person n to score 1 on item *i*,

θ_n = the estimated latent trait of person *n*, and

δ_i = the estimated location of item *i* on this dimension. And for each item, item responses are modelled as a function of the latent trait θ_n.

In Rasch model, the probability that a respondent report a given experience is a logistic function of the distance between the respondent's and the item's positions on the severity scale. In this case, it is given by the equation (3):

$$\text{Prob}\ (xh, = 1|\theta h) = \frac{e^{\theta h - \beta i}}{1 + e^{\theta h - \beta i}} \qquad (3)\ \text{(Nord et al., 2016)}$$

Where, xh, = the response given by respondent *h* to item *i*, coded as 1 for "yes" and 0 for "no" (more severe experiences are reported by fewer respondents),

β_i = the relative severity associated with each of the experiences, and

θ_h = how many of the items responded affirmatively.

Furthermore, the Rasch model that the log odds of a household (V) responding to an item (i) correctly are a function of ability (θV) and the item's difficulty (β_i). We can state this model as difficult items are hard to get right even for people with high ability. The odds of getting an item

right decrease with item difficulty and thus the minus sign before β_i. And, this is depicted on the equation (4) and (5) as:

$$\text{Logit}\ (Pi, \text{V}) = \log\frac{\Pr\ (\text{Pi,V})}{1 - \Pr\ (\text{Pi,V})} = \theta\text{V} - \beta i \quad (4)$$ (A. Owino, L. Kiboijana Atuhaire, et al., 2014)

Where, V = 1, 2, . . . , number of households/respondents,

i = 1, 2, . . . , number of items, and

θV = normally distributed random variable with zero mean and variance τ.

$$\text{Prob}\ (x\text{v}, = \frac{1}{\theta\text{v}}, \beta i) = \frac{exp(\theta\text{V} - \beta\text{i}\ )}{1+exp(\theta\text{V} - \beta\text{i}\ )} \quad (5)$$ (A. Owino, L. Kiboijana Atuhaire, et al., 2014)

Where, V = 1, 2. . . n are the households [n (*Amibara)* = 224, n (*Awash Fentale)* = 214],

i = 1, 2, . . . , m (m = 8 items/questions) are the items,

$X\text{V}i$ = household (V) gives correct response to item (i),

θV = the ability of household (V) to give correct response to item (i), and

β_i = the difficulty level of item (i).

In addition, the Rasch model's data fit is assessed using infit and outfit statistics for each item. Infit statistics measure the information-weighted mean square residuals between observed and expected responses, while outfit statistics, more sensitive to outliers, serve a similar purpose (Nord, 2014; Nord et al., 2016). Values close to 1 indicate satisfactory fit, while values exceeding 1.5 or falling below 0.5 are considered misfit. Infit values between 0.8 and 1.2 are excellent, 0.5 to 1.5 are acceptable, and values above 1.5 warrant investigation, particularly for potential translation issues in subsequent years (Cafiero et al., 2016; Rasch, 1960). Positive Rasch model values classify households as food secure, while negative values classify them as food insecure (Owino et al., 2014). Hence, the food insecurity and severity level of households in prosopis-invaded and non-invaded sites was analyzed using this model.

5.5. Results and Discussions

5.5.1. Descriptive Statistics

The difference in households' food insecurity can be explained by a range of socioeconomic characteristics of households, such as income, education, employment status, and household size and others. Generally, households with lower incomes, lower levels of education, and fewer employment opportunities are more likely to experience food insecurity and lower levels of

welfare (Loopstra & Tarasuk, 2013). On the other hand, households with higher incomes, higher levels of education, and better employment opportunities may have better access to a wider range of food options and better status of food security.

As indicated in chapter four, the inferential analysis entails that there is a difference between the invaded and non-invaded areas on some socio-economic variables namely: age, distance from the market, access to veterinary services, and marital status. Besides, the analysis of the food security status of households of both *Prosopis juliflora* invaded and the non-invaded area using the FIES revealed that 50% and 43% of the sample households were severely food insecure (SFI) in invaded and non-invaded areas respectively (Figure 5.2). Similarly, 47% and 30% of the households are moderately food insecure in invaded and non-invaded sites. In addition, the analysis revealed that only 3% of the households are food secure in invaded area whereas about 28% of the households are food secure in non-invaded areas. The high severity of food insecurity in the invaded area might be due to the impact of the Prosopis invasion and its related negative effect on the livelihood system especially on the productivity of crop and livestock in the *woreda*.

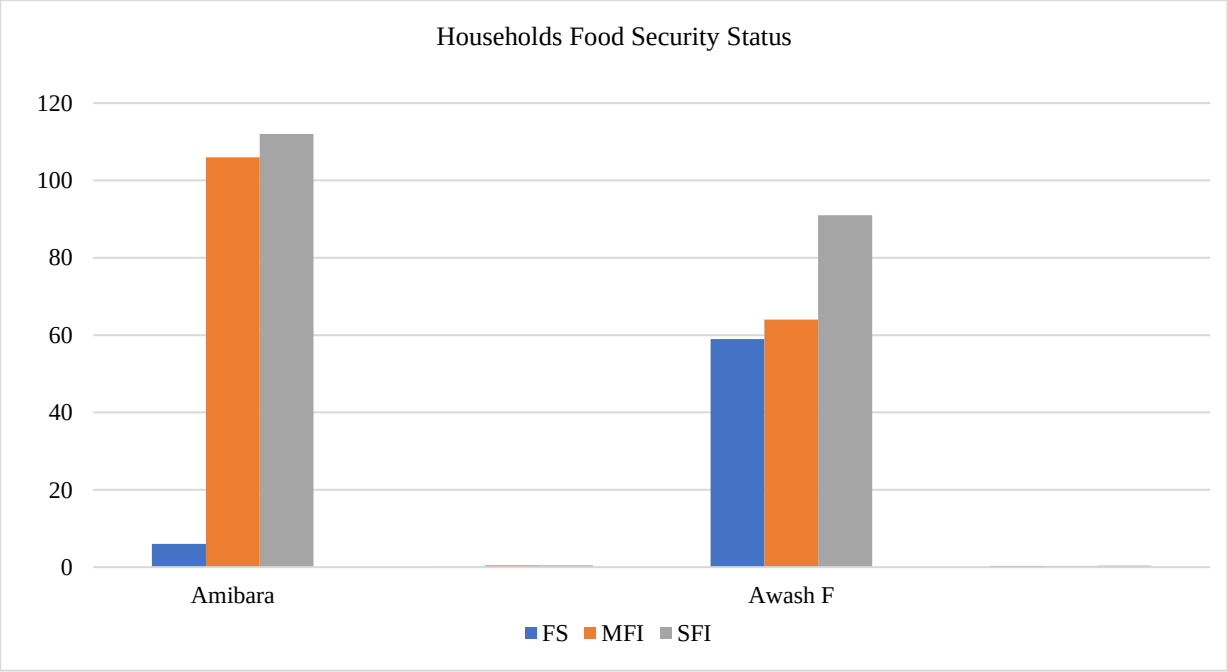

Figure 5.2: Households Food Security Status by districts

The FIES method contained eight questions (Table 1) and the reference period for all questions spans the 12 months preceding the interview day. Binary coding was applied to responses, where

"yes" corresponds to 1 and "no" to 0 for yes/no responses. The analysis reveals that the average food security assessment for *Amibara* district is 5.168 with a margin of error of ±0.8, while for Awash district, the average is 6.576 with a larger margin of error of ±3.575, both measured at a five-percentage level of significance (Table 5.2). Comparatively, households in Awash district exhibit a higher level of food security than those in *Amibara* district (Figure 5.2). The standard errors indicate a notable difference in precision between the two districts. The confidence interval for *Amibara* district spans from negative to positive values, suggesting that, on average, food insecurity of households in *Amibara* district tends to be higher than in households in Awash district.

Table 5. 1: Eight FIES questions - Study variables

Short reference	Question in word
WORRIED	**1. The last 12 MONTHS was there a time when** … You were worried you would not have enough food to eat because of a lack of money or other resources?
HEALTHY	**2.** You were unable to eat healthy and nutritious food because of a lack of money or other resources?
FEWFOODS	**3.** You ate only a few kinds of foods because of a lack of money or other resources?
SKIPPED	**4.** You had to skip a meal because there was not enough money or other resources to get food?
ATELESS	**5.** You ate less than you thought you should because of a lack of money or other resources
RANOUT	**6.** Your household ran out of food because of a lack of money or other resources.
HUNGRY	**7.** You were hungry but did not eat because there was not enough money or other resources for food?
WHLDAY	**8.** You went without eating for a whole day because of a lack of money or other resources.

Table 5. 2: Descriptive statistics for household food security for *Amibara* and *Awash Fentale* districts

Household score on food security scale		
Descriptive statistics	***Amibara***	***Awash Fentale***
Mean	5.168	6.576
Standard error	0.199	0.097
Median	6	6
Mode	7.783	7.990
Standard deviation	2.913	1.453
Sample Variance	8.488	2.111
Kurtosis	-0.9845	-0.668
Skewness	-0.666	-0.543
Range	8	6
Minimum	0	2
Maximum	8	8
Largest (10)	8	8
Smallest (10)	0	2
Confidence interval (95%)	0.8	3.575

Source: Own survey, 2023

5.5.2. Food insecurity status: Results from Rasch Model estimates

The item parameters derived from the collective response patterns of the participants is shown on Table 3 below. These parameters reflect the relative severity (difficulty) of each item within the context of the application of FIES, along with their corresponding standard errors. A lower item parameter value indicates a less severe experience associated with the respective question, whereas a higher item parameter value suggests a more intense or severe experience. The analysis of the Rasch model focused on eight items deemed influential in determining food security within the *Amibara* and *Awash Fentale* districts. Coefficients were computed for difficulty level parameters, as illustrated in Tables 5.3. Accordingly, the item with the highest severity, indicating the fewest "yes" responses or less likely to be reported by respondents is *WholeDay*, and hence, the severity level in *Amibara* is notably higher compared to *Awash Fentale*. This indicates that the level of

food insecurity of households in prosopis invaded area is significantly higher (10%) than in non-invaded area - *Awash Fentale*.

Table 5. 3 Estimated theta coefficients of the Rasch model for *Amibara* and Awash districts

	Theta (difficulty parameter level) estimates			
	Estimate for *Amibara* (Severity)	S.E.	Estimate for *Awash Fentale* (Severity)	S.E.
Fewfood	-3.378248149	0.635559455	-4.651675435	1.030089 *
Skipped	-2.314321897	0.463543542	-1.96271086	0.509972 ***
AteLess	-0.817549307 ***	0.307803092	0.09521124	0.314011 ***
RunOut	0.908564453 ***	0.24288924	1.319154347	0.280417 ***
Hungry	2.515990295 ***	0.294113978	2.296908943	0.302322 ***
WholeDay	3.085565269 ***	0.353244969	2.903112565	0.342983 ***

Sign. Codes: '***' 0.001 '**' 0.01 '*' 0.05

Source: Own survey, 2023

Infit/outfit statistics

The Infit/Outfit good range values between 0.7 – 1.3 are considered acceptable. When an item fits the model perfectly, the Infit/Outfit value equals one. Infit value above 1.0 indicates that the item discriminates less sharply than the average of all items in the scale while Outfit value above 1.0 indicates a weaker than average association of the items with the underlying conditions (Owino et.al., 2014). Values between 0.5 and 1.5 and are therefore good for productive measurement. Values above 1.5 suggested inconsistent performance, while those below 0.5 indicated insufficient variation, in accordance with the works of Rasch (1960) & Wright & Masters (1982). Notably, outfit statistics are particularly responsive to extreme scores. Accordingly, we assessed how well responses to items correspond to the Rasch model assumptions by calculating "infit" and "outfit" through the infit and outfit statistics (Table 5.4). The results showed that five of the items (FEWFOOD, SKIPPED, ATELESS, HUNGRY AND WHOLEDAY) in *Amibara* and six of the items (HEALTHY, FEWFOOD, SKIPPED, ATELESS, HUNGRY AND WHOLEDAY) in

Awash Fentale are performed well and within usual fit criteria (0.5- 1.5). After repeated check about the performance of items to measure the food insecurity, it was found that two items i.e WORRIED and HEALTHY didn't perform well in the given population of *Amibara* as a result these two items are dropped from both districts from further analysis as the number of respondents who answers yes (N_Yes) are not few (Table 4) and not good to ignore this and retain the items in the scale to estimate the food insecurity prevalence of the study sites (Cafiero et al., 2018).

Table 5. 4: Infit/outfit test result for eight FIES items

	Amibara						***Awash Fentale***					
Items	**Severity**	**S.E.**	**Infit**	**S.E Infit**	**Outfit**	**N_Yes**	**Severity**	**S. E**	**Infit**	**S.E infit**	**Outfit**	**N_Yes**
Worried	-0.931	0.509	1.581	0.382	18.197	121.00	-3.500	0.475	1.491	0.258	47.622	100.00
Healthy	-10.111	41.726	0.000	41.723	0.000	126.00	-3.338	0.460	0.571	0.246	0.128	99.00
Fewfood	-1.176	0.556	0.952	0.427	2.715	122.00	-2.392	0.416	0.824	0.232	0.270	92.00
Skipped	-0.242	0.406	0.928	0.295	7.352	117.00	-0.871	0.399	0.538	0.295	0.214	80.00
AteLess	1.047	0.284	0.674	0.190	0.967	103.00	1.036	0.301	1.048	0.183	1.552	60.00
RunOut	2.671	0.226	0.439	0.126	0.433	63.00	2.216	0.272	0.654	0.136	0.605	39.00
Hungry	4.159	0.266	0.913	0.162	1.220	22.00	3.150	0.291	1.009	0.150	0.955	22.00
WholeDay	4.583	0.299	0.565	0.195	0.302	15.00	3.698	0.322	1.039	0.180	0.845	14.00

Source: Own calculation from survey, 2023

Reliability

Rasch reliability is a measure of the consistency and stability of responses to items in a test or assessment. It assesses how well observed data align with the model's expectations. The Rasch model assumes that the probability of a person endorsing an item (e.g., answering a question correctly) depends on the person's ability and the difficulty of the item. The Rasch reliability index indicates the extent to which the observed responses align with the expected responses predicted by the model. After dropping of the two unfit items, the reliability of the Rasch model for the six items is tested and found within the acceptable limit i.e. 0.75 (Table 5.5 & 5.6).

Table 5. 5: Rasch reliability and residuals correlation (*Amibara*)

Rasch reliability					
0.75					
Residual correlation					
	SKIPPED	ATELESS	RUNOUT	HUNGRY	WHOLDAY
FEWFOOD	-0.08	0.09	-0.02	-0.27	-0.36
SKIPPED		0.00	-0.13	-0.32	-0.44
ATELESS			0.31	-0.31	-0.01
RUNOUT				-0.04	0.27
HUNGRY					0.65

Source: Own calculation, 2023

Table 5. 6: Rasch reliability and residuals correlation (*Awash Fentale*)

Rasch reliability					
0.74					
Residual correlation					
	SKIPPED	ATELESS	RUNOUT	HUNGRY	WHOLDAY
FEWFOOD	-0.04	0.07	0.03	0.02	0.01
SKIPPED		-0.01	0.05	0.07	0.05
ATELESS			0.40	-0.34	-0.15
RUNOUT				-0.04	-0.18
HUNGRY					0.13

Source: Own calculation, 2023

Residual correlation

A high residual correlation between a pair of items is considered significant when it exceeds an absolute value of 0.4 (Cafiero et al., 2018). In the context of Rasch modeling, the term "residuals" refers to the differences between observed and expected responses. An essential assumption in Rasch analysis is local independence, indicating that once a person's ability is considered, responses to different items should be independent. The existence of residual correlations among items, even after accounting for individual abilities, may signal a violation of this assumption. When addressing such correlations in Rasch modeling, researchers typically explore potential sources of local dependence, such as item content overlap, response dependencies, or other

contextual factors. Modifying the model or excluding problematic items may be necessary to enhance overall model fit. Based on our findings, the residual correlation of all items responses from *Awash Fentale* respondents are within the acceptable range however the values are somehow significant for only items (SKIPPED and HUNGRY) with WHOLDAY) in *Amibara woreda* which may be due to interpretation of those items otherwise the result has no impact on the level of food insecurity of households.

ICC Plot

The Item Characteristic Curves (ICCs) depict the probability of affirmative responses to items plotted against the ability levels to address food insecurity within a household. The ICC plot is a useful tool for understanding how well our items measure the underlying trait (ability to handle food insecurity) and how discriminating each item is across different ability levels. Items positioned on the far right of the plots indicate higher difficulty levels in managing food insecurity, whereas those on the far left suggest lower difficulty levels in dealing with food insecurity situations (Cafiero et al., 2018; Owino et al., 2014) in the districts of *Amibara* and *Awash Fentale*. The x-axis would represent ability levels to handle food insecurity, and the y-axis would represent the probability of items being answered affirmatively.

For example, in *Amibara* district, item 2 (FEWFOODS) is lower levels of difficulty than item 3 (SKIPPED) and both items 2 and 3 are at lower level of difficulty than item 1 (WORRIED) while items 4,5,6,7,8 corresponded to in similar order of higher levels of difficulty in both districts (Figure 3). This imply that households could easily respond to items 2 and 3 than item 1 in regard to food insecurity measurement in *Amibara* while households could easily respond to item 1,2,3 …8 in *Awash Fentale*. Therefore, households in *Amibara* (highly prosopis invaded sites) are much worried in answering affirmatively against the ability levels to handle the food insecurity situation in their household than *Awash Fentale woreda*.

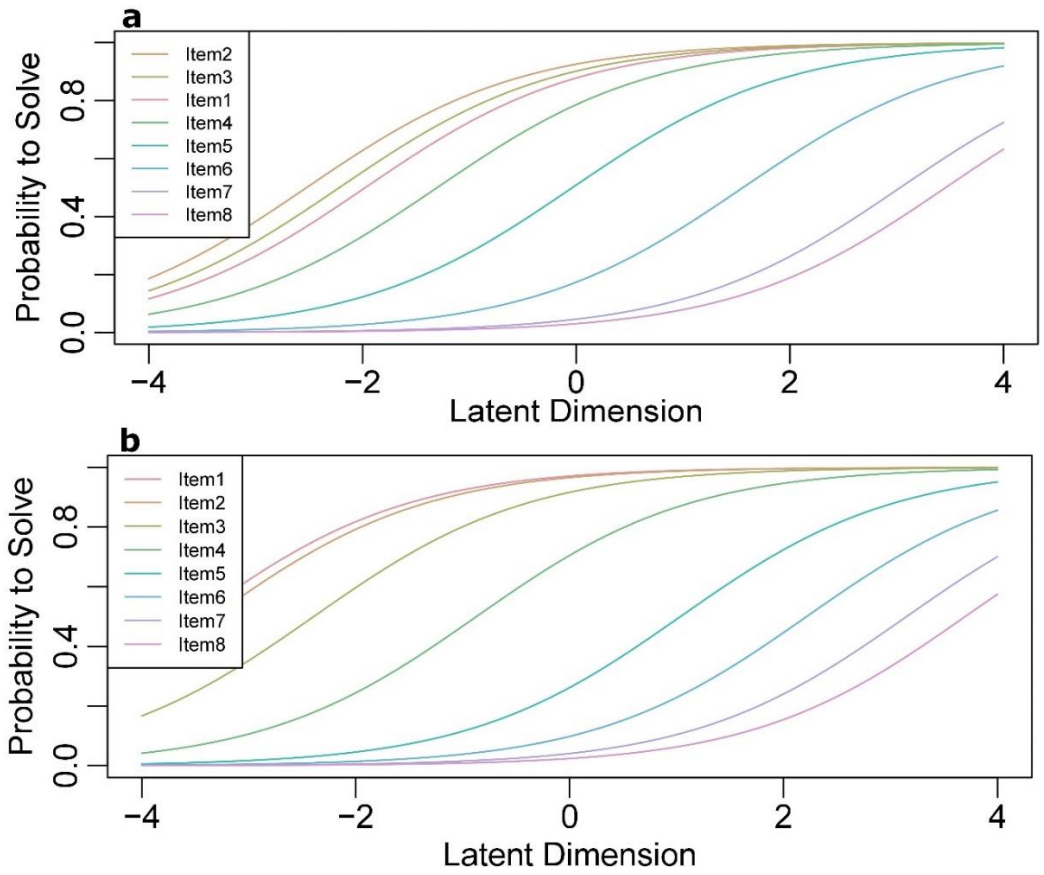

Figure 5. 3: Items characteristic curves for Rasch model check for the districts of *Amibara* (a) and *Awash Fentale* (b)

Equating

Equating becomes a necessary step whenever there is a need to compare measurements between two distinct applications of the Food Insecurity Experience Scale (FIES) or when evaluating results from different locations or countries (Cafiero et al., 2018). This is crucial because the relative positioning of items in terms of severity is contingent upon the specific data collected in each context.

Comparability can be achieved by calibrating the scales on a common metric, in a process called equating. Equating ensures that scores obtained from different forms of the FIES are comparable and can be interpreted on the same underlying scale of food insecurity. It allows for meaningful comparisons and analyses across different versions of the scale, facilitating more robust research and assessment practices (Figure 5.4). The correlation among the common items is 85.2% and

86.1% and in *Awash Fentale* and *Amibara* districts, respectively (Table 5.7 and 5.8). The result showed that SKIPPED is the most discrepant, or different in severity between the two scales.

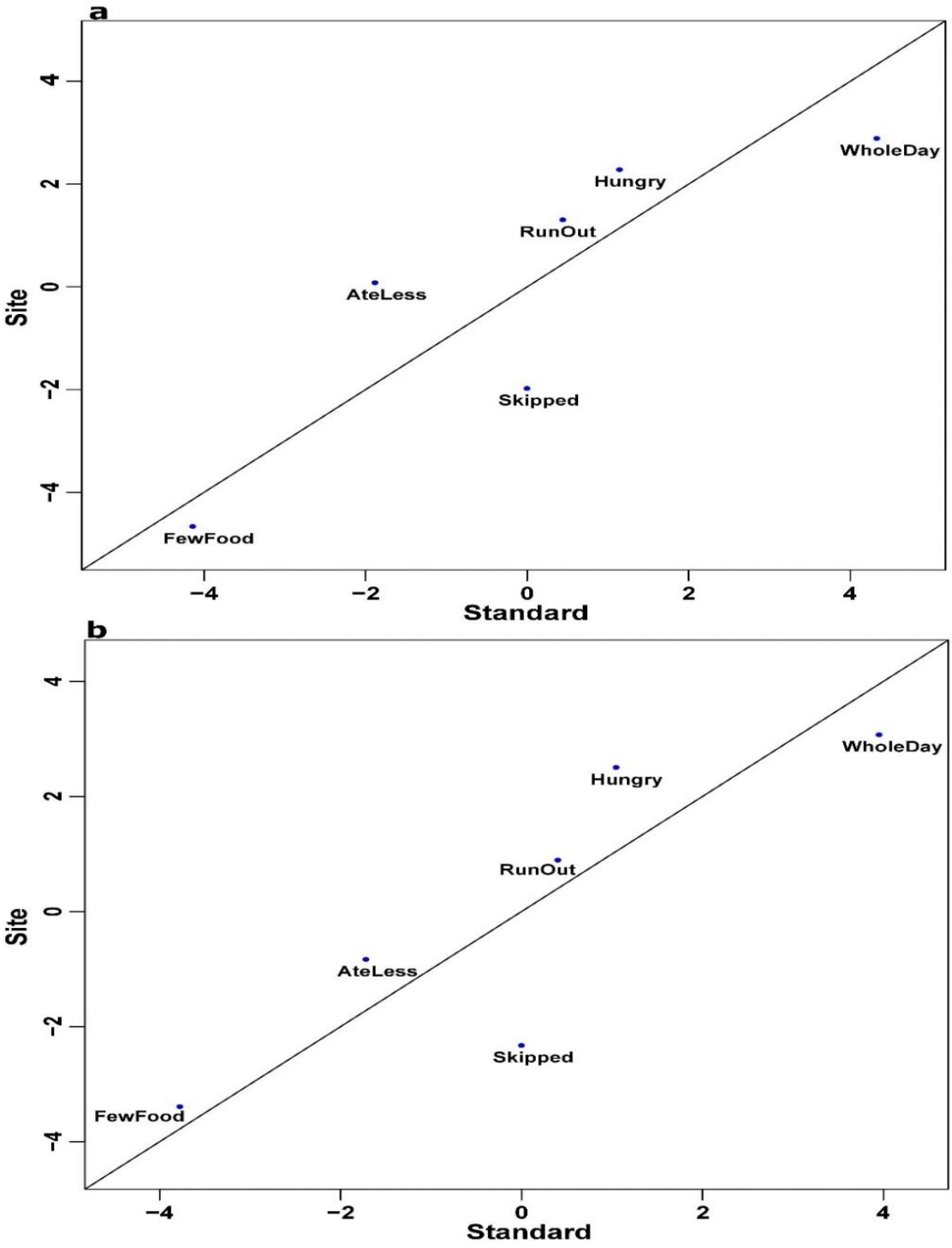

Figure 5. 4: Equating plots a) *Awash Fentale* and b) *Amibara Woredas*

Table 5. 7: Absolute difference in severity of items (*Awash Fentale*)

Fewfood	0.19
Skipped	0.70
AteLess	0.69
RunOut	0.30
Hungry	0.40
WholeDay	0.51
Correlation between common items: ***85.2%***	

Source: Own Survey, 2023

Table 5. 8:Absolute difference in severity of items (*Amibara* district)

Fewfood	0.15
Skipped	0.90
AteLess	0.34
RunOut	0.19
Hungry	0.56
WholeDay	0.34
Correlation between common items: ***86.1%***	

Source: Own Survey, 2023

5.5.3. The prevalence of food insecurity

The findings on the prevalence rates of food insecurity (% of households) revealed a substantial disparity in food security levels between the two districts. At 90% confidence level, the prevalence of food insecurity is significantly high in *Amibara* (Prosopis invaded) *woreda*. The detailed breakdown indicates that in *Amibara*, 94% of households experience moderate food insecurity, and 32% face severe food insecurity. In contrast, in *Awash Fentale*, the corresponding figures are 72% for moderate food insecurity and 21% for severe food insecurity (Table 5.9).

Table 5. 9: Prevalence of food insecurity by *woreda*

a) *Amibara Woreda*

Moderate or severe	MoE	Severe	MoE
94.23	4.02	32.20	8.02

b) *Awash Fentale Woreda*

Moderate or severe	MoE	Severe	MoE
72.44	9.63	20.81	6.81

Source: Own calculation from Survey, 2023

Thus, the invasion of Prosopis juliflora can have detrimental effects on food security in this affected region. The shrub competes with native vegetation for water and nutrients, reducing the productivity of grazing lands. Additionally, Prosopis juliflora alters ecosystems, leading to habitat loss and biodiversity decline, raising sustainability issues and further exacerbate food insecurity for local communities dependent on natural resources for their livelihoods. As indicated in chapter four, households in *P. julifloa* invaded areas *(Amibara)* more likely have a smaller number of livestock, less access to veterinary services and market function which contributes for increase of food insecurity in *Amibara* compare with *Awash Fentale* (less invaded) area. Besides, as indicated in table 2.5, there is an increase of shrubland (dominated by prosopis) in *Amibara* compared with *Awash Fentale* which indicated a high shift of LULC with an increase trend of *P.juliflora* in Amibara which can affect the crop and livestock productions and ultimately affecting the food security status of the pastoral and agro pastoral communities of *Amibara*. Therefore, the higher prevalence of food insecurity in *Amibara* is might be due to interconnected factors exacerbated by impact of increase of *P.juliflora* invasion in the Woreda.

5.6 Conclusions

The invasion of Prosopis juliflora presents challenges that intersect with sustainable development and food security goals. The spread of this invasive species undermines efforts to achieve environmental sustainability, especially in arid and semi-arid areas of Afar region where the availability and efficient utilization of natural resources is very crucial for the livelihood of the pastoral communities. The significant prevalence of food insecurity in areas invaded by Prosopis Juliflora (*Amibara* district) compared to the non-invaded area (*Awash Fentale*) implies the severity of threat posed by the invasion, highlighting the urgent need for targeted interventions to address the invasion and food insecurity in these communities.

The robustness of the Rasch model with various tests, including infit, outfit, residual correlations, reliability, and item characteristic curves, clearly exhibited the food insecurity status in the area. Notably, the item characteristic curves highlighted the significance of item ordering in gauging household food security. Specifically, it revealed that households in the *Amibara* district (areas invaded by Prosopis Juliflora) expressed higher concerns (WORRIED) about having enough food due to loss of their livestock, less access to vet services and related financial constraints compared to households in the *Awash Fentale* district. This suggests that empowering households in *Amibara* with alternative income sources could contribute to mitigating their concerns and enhancing food security. Thus, there need to consider not only the overall level of food security but also the nuanced factors contributing to households' worries and perceived difficulties in ensuring an adequate food supply.

CHAPTER 6: SYNTHESIS OF MAJOR FINDINGS, CONCLUSION, AND IMPLICATIONS

6.1. Introduction

This study was conducted with the main objective of investigating the synergies and trade-offs as well as interconnected impact of *P. juliflora* invasion, the dynamic of land use land cover changes and climate variabilities on food security of pastoral and agro-pastoral communities in the middle Awash of the Afar Region and with its specific objectives assessing the dynamic of land use land cover (LULC), determining the phenomena of climate variabilities, extremes and its implication and the impact of *P.juliflora* invasion on the food security of pastoralist/agropastoralists of the study areas. The study followed pragmatic research philosophy which provides for the adoption of mixed methods (quantitative and qualitative) as the data collection method. Both quantitative and qualitative surveys were conducted at household/individual level through well-developed survey questionnaires, key informant interviews and focused group discussions. Multistage sampling technique was deployed to reach for a total of 438 randomly selected samples of households in the *Amibara* and *Awash-Fentale* districts. Various secondary data including meteorological records of temperature and rainfall (1988 – 2018) were also used for this study.

Several descriptive, inferential statistics and econometric models were employed to analyze the quantitative data, while the qualitative data were analyzed thematically. Specifically, for climate variability and trend analysis, Mann-Kendall test and Sen's slope estimator were used to determine the spatiotemporal trend, while Coefficient of Variation (CV) and Standardized Anomaly Index (SAI) were applied to analyze climate variability. Land use land cover change (LULCC) analysis was made using techniques of satellite imagery, Kappa statistic (for accuracy assessment) and Image Differencing algorithm (for change detection). In addition, Propensity Score Matching (PSM) with average treatment effect were used to analyze the effect of *Prosopis juliflora* invasion on pastoralists' food security. And Rasch Model was employed for measuring the severity of household food insecurity in the *Amibara* and *Awash Fentale* districts. Here also, various tests including infit, outfit, residual correlations, reliability, and item characteristic curves, were conducted to check the appropriateness of utilizing the Rasch model and the data fit with the

model. As such, this chapter presents the summary of the major findings, conclusions drawn, and implications from the study results as follows.

6.2 Major findings of the study

This section briefly summarized the major findings of the study in addressing the specific objectives which included assessing the dynamic of land use land cover change (LULCC), examining the local climate variabilities and climate extremes and its implications on food security of pastoral communities living in *P.juliflora* invaded and non-invaded areas, and the impacts of *P. juliflora* invasion on food (in)security of the households.

Dynamic of LULC changes in *Amibara* and *Awash-Fentale* districts (Chapter two)

The results presented in chapter two indicated that both districts exhibited six main LULC classes: agriculture, bare land, built-up, mixed forest, shrub land, and water bodies. In *Amibara* (the highly *P.juliflora* invaded area), LULC changes from 1985 to 2021 revealed significant shifts, maintaining its primary bare land characteristic, concentrated agriculture, and expanding Prosopis-dominated shrub land (3.7%) due to livestock-mediated seed dispersal. Conversely, in Awash-Fentale bare land dominance decreased from 92.8% to 71.3%, while agriculture, built-up areas, and shrub land expanded. In addition, net gains were observed in shrub land (6.8%), agriculture (5.8%), mixed forest (6.6%), water bodies (1.4%), and built-up areas (0.9%), with bare land experiencing a loss of 21.5%.

In both districts witnessed notable increases in agricultural land, shrubland and built-up areas. This convergence suggests a shared trend of urbanization and agricultural expansion, likely driven by population growth and economic development. Specifically, the growth of shrub land in both districts indicating a common response to environmental dynamics such as Prosopis invasion. This suggests a shared challenge in managing invasive species and preserving native ecosystems. The observed changes in LULC have significant implications for sustainable development in both districts, highlighting the need for balanced strategies that consider economic growth alongside ecological conservation and land management practices.

On the other hand, the study releveled that while the Amibara district consistently displayed dominance of bare land throughout the study period, the Awash-Fentale district experienced a

substantial decrease in bare land. This difference suggests varying land use dynamics and environmental conditions between the two districts, and *this has happened may be due to an increase of agriculture land and sugar farm in Awash Fentale as the result of kesem Kebena dam construction and observed opportunities of irrigation access for crop production.* The mixed forest showed a decline vs. fluctuations, while the Amibara district showed a substantial decline in mixed forest cover, the Awash-Fentale district experienced fluctuations in mixed forest cover over the study period. This disparity suggests differing levels of vulnerability to human activities and environmental pressures between the two districts. The response to land management practices differed between the districts, with the Amibara district highlighting the vulnerability of forested areas and the Awash-Fentale district indicating potential restoration efforts. This difference suggests varying levels of effectiveness in land management strategies and restoration initiatives.

Looking at the convergence of this finding with others it is observed that there was similar trends of urbanization and agricultural expansion have been observed in various regions globally, such as studies in rapidly developing countries like India (Mohan et al., 2011) and China (Chen et al., 2022).These studies highlighted the common drivers of land use change, including population growth and economic development, which lead to increased pressure on natural resources and ecosystems. In addition, the challenges posed by invasive species, such as Prosopis, are not unique to the study areas but are widespread across different ecosystems worldwide. Studies in Ethiopia and Kenya (Linders et al., 2020) and (Rai & Singh, 2020) demonstrated the negative impacts of invasive species on native biodiversity and ecosystem functioning, emphasizing the need for effective management strategies.

While some regions may exhibit similarities in land use patterns, there is significant variability in land use dynamics across different geographic and ecological contexts. For instance, studies in some temperate regions (Kuemmerle et al., 2013) showed contrasting patterns of land use change compared to arid or semi-arid regions like the Afar region. Factors such as climate, topography, and socio-economic conditions contribute to this divergence in land use trajectories. Furthermore, the effectiveness of land management strategies can vary widely depending on local conditions and governance structures. Studies in regions with different land tenure systems, such as those in sub-Saharan Africa (Bizoza & Opio-Omoding, 2021; Deininger & Jin, 2006) revealed contrasting outcomes of land management interventions. Understanding these differences is essential for

tailoring approaches that address the specific challenges and opportunities of each context. By considering these convergence and divergence points with related studies conducted elsewhere, it becomes evident that while there are commonalities in the drivers and implications of land use change, there are also important contextual differences that must be taken into account when formulating sustainable land management strategies.

This finding presents significant contributions to scientific knowledge and methodologies, offering a comprehensive analysis of Land Use and Land Cover (LULC) changes in the Amibara and Awash-Fentale districts from 1985 to 2021. Through remote sensing and GIS techniques, the chapter establishes a systematic approach for detecting and quantifying these changes, providing valuable insights into landscape dynamics over time. By identifying six dominant LULC classes and investigating the impact of *P. Juliflora* invasion on LULC changes, particularly in Amibara, the study sheds light on the ecological consequences of invasive species on native ecosystems. Notable shifts in LULC patterns, including increases in agricultural land, shrub land, and built-up areas, signify shared processes of urbanization and agricultural expansion driven by population growth and economic development. These findings underscore the importance of balanced strategies integrating economic growth with ecological conservation and land management practices, thereby contributing to sustainable development discourse, and providing valuable insights for land management practitioners and policymakers.

Spatiotemporal climate variability and extremes (Chapter three)

The results presented in chapter three revealed that the mean seasonal rainfall varies from 111.34 to 518.74mm. Although the maximum and minimum rainfall occurred in the summer and winter seasons, respectively, there has been a decrease in seasonal and annual rainfall at the rate of 2.51mm per season 4.12mm per year, respectively. It is found that the study sites have been experiencing highly seasonal rainfall variability. The drought analysis result confirms that a total of nine agricultural droughts ranging from moderate to extreme years were observed. Overall, the seasonal and annual rainfall of the *Amibara* and *Awash Fentale* districts showed a decreasing trend with the highest temporal variations of rainfall and ever rising temperatures and frequent drought events which means that the climate situation of the area could adversely affect pastoral and agro-pastoral households' food security. However, analysis of data from secondary sources reveals that analyzing precipitation just based on the meteorological records of the study area would be

misleading. That explains why flooding, rather than drought, is becoming the main source of catastrophe to smallholder livelihoods in Afar region. Therefore, the study relied not only on meteorological records of temperature and rainfall, but also literature in the topic to make caveats on the literal picture that comes from quantitative data and that is the fresh contribution of this study to the existing debate on climate change and variability.

Similar findings of decreasing rainfall trends have been reported in other studies examining climate variability and its impacts on food security in various regions globally (Affoh et al., 2022; Holleman et al., 2020; Kotir, 2011) has documented declining precipitation patterns, which pose significant challenges to agricultural and pastoral livelihoods. The observation of increased frequency of drought events aligns with findings from other studies in USA and Southern Asia (Gbegbelegbe et al., 2014; Lassa et al., 2016) have similarly highlighted the heightened vulnerability of rural communities to recurrent droughts, emphasizing the need for adaptive strategies and resilience-building measures.

On the other hand, while the study highlights the adverse impacts of drought on food security in the Amibara and Awash Fentale districts, it also noted a divergence in the main source of catastrophe to smallholder livelihoods. Unlike the emphasis on drought in this study, findings from secondary sources suggest that flooding, rather than drought, is becoming the primary concern. This disparity underscores the importance of considering local nuances and multiple climate-related hazards in assessing food security risks and designing appropriate mitigation and adaptation strategies. Furthermore, the study underscores the limitation of solely relying on meteorological records for analyzing precipitation trends. This finding diverges from approaches that exclusively use quantitative data and emphasizes the importance of integrating multiple sources of information, including literature and local knowledge, to provide a more comprehensive understanding of climate variability and its impacts. Similar calls for interdisciplinary approaches to climate research have been made in studies examining climate change adaptation (Luetz & Nunn, 2020) and disaster risk planning (Sliuzas et al., 2021) in other regions.

This finding presents significant contributions to scientific knowledge and methodologies regarding climate variability and its implications for food security in the Amibara and Awash Fentale districts. Through an interdisciplinary approach integrating meteorological records with existing literature, and local knowledge, the study offers a nuanced understanding of climate

dynamics and their potential impacts. By conducting a detailed quantitative analysis of climate variables such as temperature and rainfall, the research provides valuable insights into spatiotemporal climate variability, informing adaptation strategies for pastoralists and agro-pastoralists. Moreover, the identification and analysis of climate extremes, particularly drought events, underscore the vulnerability of local households to climatic hazards, challenging conventional assumptions about climate impacts by highlighting the role of flooding, rather than drought, as the main source of catastrophe to smallholder livelihoods in the study area. This insight underscores the complexity of climate risks and the need for context-specific adaptation strategies that account for local environmental conditions and socio-economic dynamics. Overall, the finding advances scientific knowledge on climate variability and its implications for food security, while also providing methodological insights into interdisciplinary research approaches and the importance of integrating quantitative data with qualitative insights from existing literature.

The impacts of Prosopis juliflora (Swartz DC.) invasion on food security of pastoral and agro-pastoral communities (Chapter four)

Chapter four discussed the impacts of *P.juliflora* (Swartz DC.) on food security of pastoral and agro-pastoral communities by taking two districts (as treatment and control group) in the study area. As such, econometric results indicated that households in *P. juliflora* invaded areas were more likely to have lower number of livestock assets, less access to veterinary and government support services. They are also less likely to have better access to marketplaces to sell their livestock/agricultural produces compared to those in non-invaded areas. However, descriptive stats showed that they are more likely to be older and married households compared to those in non-invaded areas. Moreover, results from Average Treatment Effect estimation indicated that households in invaded areas (on average) have 1,167 Birr lower annual consumption expenditure compared to those in non-invaded areas. These are some of the key findings that substantiate the fact on the ground that households in *P.juliflora* invaded areas are less resilient and much vulnerable for various food security and related shocks and stresses.

The study delves into the socio-economic impacts of *P.juliflora* invasion on food security in pastoral and agro-pastoral communities. Through econometric analysis techniques, the study assesses how invasion affects household characteristics and quantitatively evaluates food security indicators, such as annual consumption expenditure. By identifying vulnerable household groups

within invaded areas and demonstrating the adverse effects of invasion on livelihoods, the research provides valuable insights for policymakers. These findings underscore the importance of holistic management strategies that consider both ecological and socio-economic dimensions of invasive species impacts, informing targeted interventions aimed at enhancing community resilience and mitigating the negative consequences of invasion.

The status of food security in the *P.juliflora* invaded and non-invaded areas (Chapter five)

The findings presented in chapter five presented revealed that 50% and 43% of the sample households were severely food insecure (SFI) in invaded and non-invaded areas respectively. Similarly, 47% and 30% of the households are moderately food insecure in invaded and non-invaded sites respectively. In addition, the analysis revealed that only 3% of the households are food secure in invaded area whereas about 28% of the households are food secure in non-invaded areas. Furthermore, at 90% confidence level, the prevalence of food insecurity is significantly high in *Amibara* (Prosopis invaded) *woreda* where 94% of households experience moderate food insecurity, and 32% face severe food insecurity. In contrast, in *Awash Fentale*, the corresponding figures are 72% for moderate food insecurity and 21% for severe food insecurity. This high severity of food insecurity in the invaded area might be due to the impact of the Prosopis invasion and its related negative effect on the livelihood system especially on the productivity of crop and livestock in the district.

Similar findings from contemporary research in other regions affected by *P.juliflora* invasion verify the negative impacts on household livelihoods, particularly in pastoral and agro-pastoral communities of the Region (Bekele Dadie, 2018; Haji & Mohammed, 2013; Mehari, 2015a; Zeray et al., 2017b). However, this study uniquely showed that households in Prosopis-invaded areas tend to have lower livestock assets, limited access to support services, and reduced market access, contributing to heightened vulnerability to food security shocks. This study also revealed that the high prevalence of food insecurity observed in Prosopis-invaded areas highlighting the detrimental impacts on agricultural productivity and livelihood resilience.

While the overall prevalence of food insecurity is high in Prosopis-invaded areas, there was variability in the severity of food insecurity among invaded and non-invaded areas. The higher

severity of food insecurity observed in Amibara (Prosopis invaded) woreda compared to Awash Fentale suggests that the impacts of Prosopis invasion on food security may vary depending on local ecological and socio-economic factors. This underscores the importance of considering site-specific conditions in assessing the impacts of invasive species on food security. Furthermore, factors contributing to vulnerability to food insecurity in Prosopis-invaded areas may vary depending on contextual factors such as land use systems, access to resources, and adaptive capacity. Comparative studies in different regions affected by invasive species (Ilukor et al., 2016b; Mussa et al., 2018) and the study highlighted the importance of understanding local socio-economic, ecological dynamics in determining vulnerability to food insecurity in prosopis invaded and non- invaded areas.

This finding provides significant insights into the relationship between *P.juliflora* invasion and food insecurity in the Afar region. By quantifying food insecurity levels using established metrics like the Food Insecurity Experience Scale (FIES), the research demonstrates the severity of food insecurity in invaded areas. Comparative analysis revealed higher prevalence rates of food insecurity in Prosopis-invaded areas, emphasizing the need for targeted interventions to support the vulnerable households in the area. Additionally, the study identified geographic variations in food insecurity, particularly in highly invaded areas like *Amibara*. These findings correlate Prosopis invasion with heightened food insecurity, contributing to our understanding of the socio-economic impacts of invasive species. Synthesizing existing research, the chapter enriches scientific knowledge on the topic and offers methodological insights into food security assessment using the Rasch model and R-Software. Figure 6.1 shows the key findings under each of interconnected impacts of dynamic of LULCC, climate variabilities and extremes and *P. juliflora* invasion in the study areas.

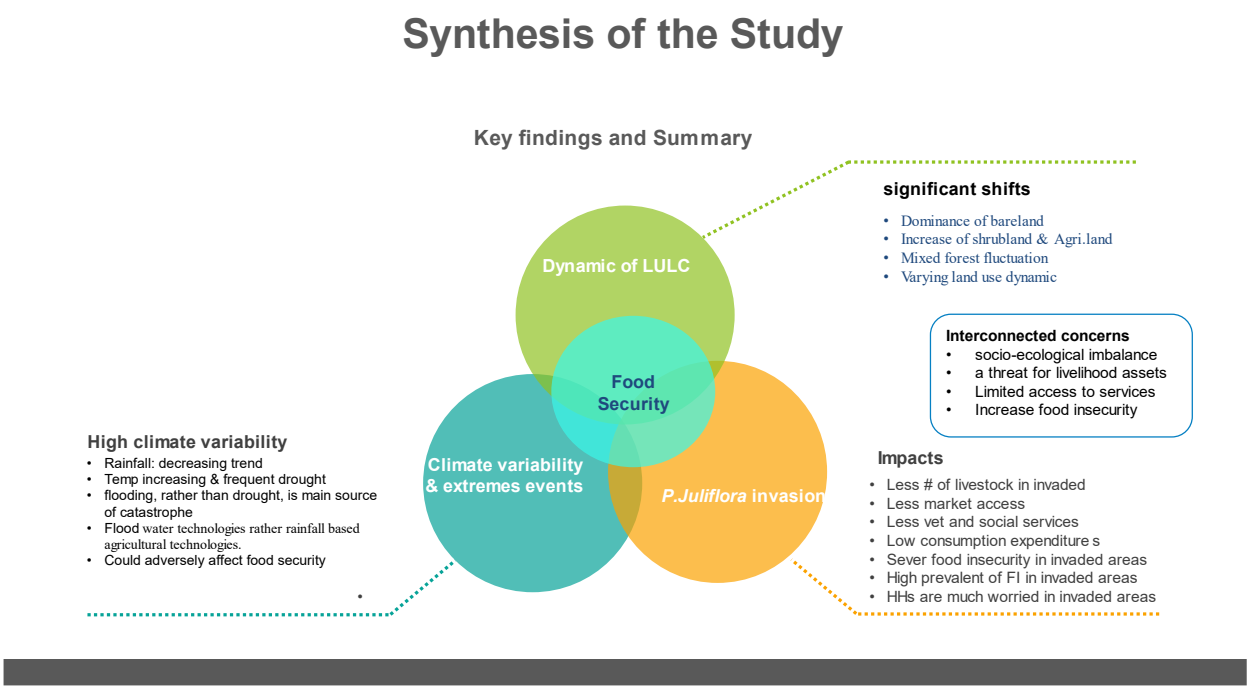

Figure 6. 1 Key findings of the interconnected impacts of dynamic of LULCC, climate variabilities and extremes and *P. juliflora* invasion in the study areas.

6.3. The synergy and trade-offs between *P. juliflora* invasion, land use land cover changes, climate extremes variability and food security

Invasive plants affect the capacity of ecosystems key functions, compositions and structures (Lázaro-Lobo et al., 2023). The synergies of these three dynamic and intern connected issues are- Prosopis species, particularly P. juliflora, present significant ecological and economic synergies, especially in arid and semi-arid regions. These species improve soil fertility through biological nitrogen fixation, a process where atmospheric nitrogen is converted into a usable form for plants. This not only enhances the nutrient profile of degraded soils but also promotes the growth of other vegetation, thereby contributing to soil restoration efforts. Additionally, Prosopis species are effective in carbon sequestration, capturing atmospheric carbon dioxide and storing it in biomass and soil, which is crucial in mitigating climate change impacts. Research has shown that Prosopis juliflora can sequester significant amounts of carbon, making it a valuable component of climate action strategies (Goel et al., 2007; Pasiecznik et al., 2001).

Beyond environmental benefits, Prosopis also offers substantial economic resources, particularly in urban and resource-scarce areas of the region. The species provides essential fuelwood, a primary energy source for many of the pre urban and rural communities, and fodder for livestock, which is especially critical during dry seasons. Studies have documented the role of Prosopis in supporting rural livelihoods, with its wood and pods serving as vital economic resources (Pasiecznik et al., 2001). Moreover, when integrated into agroforestry systems, Prosopis contributes to improved soil health, diversifies income through the sale of wood and pods, and provides shade, which benefits both crops and livestock (Tewari et al., 2000).

The adaptability of Prosopis to harsh environmental conditions, including arid and semi-arid climates, underscores its potential in climate change adaptation. Its resilience allows it to thrive where other species might fail, stabilizing ecosystems and providing a buffer against climate extremes. This adaptability is particularly valuable in regions prone to drought and desertification, where Prosopis can play a crucial role in maintaining ecological balance and supporting community resilience (Shiferaw et al., 2004).

The trade-offs of the expansion of Prosopis species, while offering certain ecological and economic benefits, presents significant trade-offs that can negatively impact biodiversity, ecosystem health, agricultural productivity, and food security (Bekele, Haji, Legesse, & Schaffner, 2018; Tadesse et al.). Prosopis is highly invasive, often outcompeting native vegetation and reducing biodiversity. Its deep root systems can deplete groundwater resources, adversely affecting other plants and agricultural activities dependent on these water sources (Shiferaw et al., 2019). Moreover, the spread of Prosopis can convert arable land into thorny thickets, reducing land available for food crops and impacting food security. Managing Prosopis invasions is costly, requiring significant resources and labor, which can strain local communities and governments (Pasiecznik et al., 2001).

The species also poses risks to human and livestock health, as its thorns can cause injuries, and the consumption of its pods by livestock can lead to health issues, further impacting agricultural productivity (Goel et al., 2007). Additionally, land use and land cover changes, such as urbanization and deforestation, can either inhibit or promote the spread of Prosopis, with urban areas generally controlling its spread more effectively than rural areas. Implementing sustainable

land management practices that integrate controlled use of Prosopis may help balance its benefits with the associated drawbacks, promoting both food security and ecosystem health (Tewari et al., 2000).

6.4. Implications

This section, based on the results and discussion from chapter 2 - 5, brings recommendations in order to mitigate the adverse effect of *Prosopis juliflora* invasion and improve the resilience and food security status of the pastoralist and agro-pastoralist community in Afar region of Ethiopia. The suggestion made here includes a systematic and relevant interventions, policy measures and notes for further studies. Specifically, the following aspects are recommended.

- **Tailored policy measures:** Policies concerning the management of climate variability and ensuring food security should be tailored to the unique ecological landscape and traditional livelihood practices of the Afar region. Given the region's reliance on floodwater for precipitation, agronomic technologies focusing on flood water management should be prioritized over rainfall-based agricultural approaches. The ongoing policy drive for irrigation-based wheat production aligns well with the findings of this research and should be encouraged. The researchers recommend the need to have strong institution at regional level to oversee the management and utilization of *prosopis* in away the communities to benefit from the invasion opportunities.

- **Integrated efforts for invasive species management**: Addressing the invasive Prosopis juliflora requires concerted efforts from all stakeholders. Management through utilization of this invasive plant is crucial for promoting climate-resilient livelihoods options and enhancing food security. Measures such as uprooting seedlings, cutting, burning, and utilizing modern technologies/machinery for seed and tree crushing should be explored. Additionally, processing the seeds for livestock feed could provide alternative income sources and support livestock production in affected areas.

- **Livelihood Diversification:** As Prosopis invasion poses significant challenges to pastoralists' livelihoods, including reduced grazing land and water scarcity, diversifying livelihood strategies is crucial. While complete eradication of *P.juliflora* may not be

feasible, pastoralists could benefit from utilizing it and from agricultural extension services to integrate irrigation-based crop production with livestock rearing. Non-farm income-generating activities should also be encouraged to mitigate the impact of Prosopis invasion on livestock assets. The prospect of harnessing climate change friendly livelihoods for an ideal level of food security requires the concerted and coordinated efforts of all stakeholders towards the proper utilization of this invasive plant.

- **Technological Solutions and Collaborative Research:** Given the global spread of Prosopis juliflora, collaborative research efforts are necessary to develop innovative solutions to mitigate its adverse impacts on community food security. Collaborating with other regions facing similar challenges, such as Asia, Latin America, and Southern Africa, can facilitate knowledge exchange and resource sharing to address the invasion effectively.

6.5. Overall Conclusions

The study examined the impacts of *P.juliflora* invasion on various aspects of the Afar region's ecosystem and community livelihoods. Firstly, through a rigorous analysis of land use and land cover changes (LULCC) using remote sensing and GIS techniques, significant shifts were identified, primarily driven by urbanization and agricultural expansion in the Amibara and Awash-Fentale districts. The expansion of Prosopis-driven shrub land along with bare land and agricultural land in the study areas of *Amibara* and Awash-Fentale underlines the multifaceted implications of land-use and land-cover changes. It informs not only the invasiveness of the plant, but also the pastoralists' gradual shift to agricultural activities as adaptation strategies. These shifts necessitate the development of strategic intervention and sustainable land management strategies, among others. These findings provided valuable insights into invasive species management and ecosystem conservation efforts, advocating for balanced strategies that integrate economic growth with ecological conservation.

Furthermore, the study delved into the intricate relationship between *P.juliflora* invasion and climate variability, shedding light on the heightened vulnerability of pastoral communities to climate extremes like droughts and flooding. Through a meticulous integration of meteorological records with existing literature, the research challenged conventional assumptions and emphasized the importance of interdisciplinary approaches in understanding and addressing climate risks

effectively. These insights not only enriched scientific knowledge, but also informed adaptation strategies aimed at bolstering community resilience in the face of environmental challenges.

Moreover, the study conducted a comprehensive assessment of the invasion's direct impacts on household food security, revealing stark consequences such as diminished food consumption and loss of vital livestock assets among affected communities. Given livestock rearing, a major means of sustenance for the pastoral community, the restriction of livestock movement in Prosopis-invaded areas also tend to limit their ability to trade and access better grazing land, and this affects the income of pastoral communities. The invasion not only disrupted access to essential services and marketplaces but also posed a significant threat to the overall well-being of the ecosystem and community livelihoods. Recognizing the adaptive responses of communities, particularly the gradual transition from pastoralism to agriculture, the research advocated for holistic land management strategies that accommodate these evolving dynamics while addressing the invasive species issue.

Employing methodologies such as the Food Insecurity Experience Scale (FIES) and the Rasch model, the study identified vulnerable household groups and highlighted the need to empower them with alternative income sources to alleviate food security concerns. The households in invaded areas expressed higher concerns (WORRIED) about having enough food due to financial constraints compared to households in the non-invaded area. This suggests that empowering households in invaded area with alternative income sources could contribute to mitigating their concerns and enhancing food security. It is of great importance to consider not only the overall level of food security but also the nuanced factors contributing to households' worries and perceived difficulties in ensuring an adequate food supply. These findings underscored the urgency of targeted interventions and policy responses to mitigate the adverse impacts of *P.juliflora* invasion on food security while fostering resilience-building efforts in affected areas. Ultimately, the study's comprehensive approach provided invaluable insights for policymakers, practitioners, and stakeholders alike, facilitating informed decision-making and promoting sustainable development practices tailored to the unique challenges posed by invasive species in arid and semi-arid areas.

In general, each chapter of the study contributes unique insights that collectively deepen our understanding of the complex interactions between land use changes, climate variability, invasive

species invasion, and food security in the studied regions. Chapter two employs remote sensing and GIS techniques to comprehensively analyze LULC changes over time, revealing significant shifts driven by urbanization and agricultural expansion. These findings emphasize the importance of balanced land management strategies for sustainable development. Chapter three expands on this by exploring climate variability's implications for food security, challenging conventional assumptions and highlighting the need for context-specific adaptation strategies. Chapter four delves into the socio-economic impacts of *P. juliflora* invasion, showcasing the importance of holistic management approaches that consider ecological and socio-economic dimensions. Finally, Chapter five quantifies food insecurity levels and identifies geographic variations, linking Prosopis invasion with heightened food insecurity and providing valuable insights for targeted interventions. Together, these chapters advance scientific knowledge and methodologies, offering comprehensive insights into the comprehensive and interconnected LULCC, climate extremes and food security challenges facing the studied areas which urges the need to suggest holistic strategies for sustainable development and ecosystem management in a way to reduce further expansion of *P.juliflora* through utilization by engaging different stakeholders, private sectors and communities to invest resources towards benefiting the vulnerable communities of the areas.

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8. Appendices

Appendix I: List of variables

List of variables	Variable description	remarks
Treatment variables Invasion	Invasion by prosopis (1= invaded, 0= otherwise)	
Outcome variables	Annual household per capita consumption expenditure (in '000 Birr), food and non-food expenditures	
	Annual household income from crop production (in '000 Birr)	
	Annual household income from livestock production (in '000 Birr)	
	Annual household income from charcoal and fuel wood selling (in '000 Birr)	
	Annual household per capita health expenditure (in '000 Birr)	
	annual average income from off-farm activities	
	Annual education expenditure	
	Annual livestock expenditure for livestock feed purchase	
Covariates	Livestock holding size (tropical livestock unit TLU))	
	Fixed asset aggregated value of main household properties (in '000 Birr)	
	Family size, Number of individuals living under the same roof	
	Sex of household head (1 = male; 0 = female)	
	Age of a household head (year)	
	Education of HH head (1= illiterate 0= otherwise)	
	Average education of a household members (years of schooling)	
	Access to irrigation (1 if has access, 0 otherwise)	
	Any household income source out of livestock and crop production (1 = yes; 0 = no)	
	Access to any aid program (PSNP or JEOP) from governments and/or non-governments (1 = yes; 0 = no)	
	Social participation of a household member in informal and/or formal institutions (1 = yes; 0 = no)	
	Credit Access to formal and/or informal credit (1 = yes; 0 = no)	
	Distance to the nearest market center (kilometers) 19.53 14.67 0.02 52	
	Number of contacts a household head with natural resources management expert	
	Effect of drought (1 if income from livestock and crop decrease due to drought, 0 otherwise)	
	Distance to the nearest water point (kilometres)	
	Distance from main road (km)	

Appendix II: FIES questions

Now I would like to ask you some questions about food. During the last 12 MONTHS, was there a time when… (label) (Q1)… you were worried you would not have enough food to eat because of a lack of money or other resources. (WORRIED)
(Q2)… you were unable to eat healthy and nutritious food because of a lack of money or
Other resources? (HEALTHY)
(Q3) … you ate only a few kinds of foods because of a lack of money or other resources? (FEWFOODS)
(Q4)… you had to skip a meal because there was not enough money or other resources
to get food?(SKIPPED)
(Q5)… you ate less than you thought you should because of a lack of money or other resources. (ATELESS)
(Q6) … your household ran out of food because of a lack of money or other resources. (RANOUT)
(Q7)… you were hungry but did not eat because there was not enough money or other
resources for food? (HUNGRY)
(Q8)… you went without eating for a whole day because of a lack of money or other resources.
(WHLDAY)

Appendix III: In fit and outfit statistics

Infit and outfit statistics

The infit and outfit statistics assess the "performance" of the items included in the scale; that is, the strength and consistency of the association of each item with the underlying latent trait. These can be obtained by comparing the way in which the observed patterns of responses compare to the ones that would be expected under the truth of the measurement model.

One of the Rasch model assumptions is that all items discriminate equally, which means that, ideally, all infit statistics would be 1.0. Infit values in the range of 0.7-1.3 are generally considered to meet the model assumption of equal discrimination to an acceptable degree. Infit statistics in the range 1.3 to 1.5 identify items that can still be used for measurement, but attention to possible improvement of such item may be worthwhile. Values larger than 1.5 indicate items that should not be used for scoring, as they may induce considerable biases in the measure.

On the opposite side, items with infit statistics lower than 0.8 can still be used for measurement, although such low values of residuals will imply that the particular item will be somewhat undervalued in its contribution to the overall measure. Similar standards may be applied to item outfit statistics, but in practice, outfit statistics are very sensitive to a few highly unexpected observations. As few as two or three highly unexpected responses (i.e. denials of the least severe items by households that affirm the most severe ones) among several thousand households can elevate the outfit for that item to 10 or 20. Carefully interpreted, outfit statistics may help identify items that present cognitive problems or have idiosyncratic meanings for small subpopulations.

Source: FAO, 2014

Item infit and outfit can be calculated as follows:

$$INFITi = SUM\ [(Xi,h - Pi,h)^2] / SUM[Pi,h - Pi,h^2]$$

where:
SUMs can be taken for the item across all non-extreme cases
Xi,h is the observed response of household h to item i (1 if response is yes, 0 if response is no);
Pi,h is the probability of an affirmative response by household h to item i under Rasch assumptions, given the item calibration and the estimated level of severity of food insecurity in the household.

The expected value of each item's infit statistic is 1.0 if the data conform to Rasch model assumptions. Values above 1.0 indicate that the item discriminates less sharply than the average of all items in the scale.

Item ***outfit*** *is calculated as the average across households of the squared error divided by the expected squared error:*

$$OUTFITi = SUM\ [(Xi,h - Pi,h)^2 / (Pi,h - Pi,h^2)] / N$$

Where:
SUM is taken for the item across all non-extreme cases
Xi,h is the observed response of household h to item i (1 if response is yes, 0 if response is no);
Pi,h is the probability of an affirmative response by household h to item i under Rasch assumptions, given the item calibration and the estimated level of severity of food insecurity in the household;
N is the number of households.

The expected value of each item's outfit statistic is 1.0 if the data conform to Rasch model assumptions. Values above 1.0 indicate a higher than expected proportion of "erratic" responses—affirmative responses to a severe item by households that affirmed few other items or denials of a low-severity item by households that affirmed many other items.

Values of infit and outfit below 1.0 indicate items that are more strongly and consistently related to food insecurity than the average item. As a rule, in fits in the range of 0.8 to 1.2 are considered to be very good. Infit in the range 0.7 to 1.3 are usable, and do not distort measurement substantially, but should be improved for general use (Linacre and Wright, 1994). Infit below 0.7 indicates an item that is strongly associated with the underlying condition measured by all of the items (food insecurity).

Source: Nord M., 2014

Appendix IV: Survey questionnaire

COVER SHEET | HOUSEHOLD SURVEY

Name of Enumerator		ID	
Date:			
Name of *Woreda*:			
Name of Kebele:			
Name of Village			
Name of Respondent			
GPS Coordinates:			

List of *Kebeles* by *Woreda* (*the study will be conducted in three Kebeles per Woreda*)

Woreda	**Kebele**	***Woreda***	**Kebele**
Amibara	Gelsa	*Awash Fentale*	Boloyta
	Haledebi'e		Doho
	Komagediyaro		Dudub
	Bonta		Kebena
	Kurkura		Sabure
	Angelelie		
	Kela'eti - Bure		
	Sidihafage		
	Badihamo		
	Hasoba		
	Worer		
	Serkamo		
	Halaysumele		
	E'eblie		
	Andedo		
	Halaydege		
	Bedul Ali		
	Arba		

Acknowledgements: Some of the enclosed Survey questions are adapted from tools developed for different food security studies by Government of Ethiopia, FAO and other related research programs

Informed Consent Statement

****

Hello. My name is _____ and I`m researcher/PhD student. I`m conducting a survey in your community and would very much appreciate your participation. I would like to ask you questions about *Prosopis* and food security related issues. This information will help me to understand the impact of P.J on food security and based on the findings to propose recommendation that can help you and your communities.

Whatever information you provide will not be shared with other surveyed individuals and your identity will be kept confidential. Participation in this survey is strictly voluntary, and you can choose not to answer any individual question or all of the questions. If you choose not to participate, no services will be withheld from you. However, we hope that you will actively participate in this survey since your views are important.

At this time, do you want to ask me anything about the survey? May I begin the interview now?

IF RESPONDENT DOES NOT AGREE TO BE INTERVIEWED → **END INTERVIEW**

IF RESPONDENT AGREES TO BE INTERVIEWED → **INITIAL BELOW & ADMINISTER THE QUESTIONNAIRE**

Surveyor Initials: _____

SECTION 1: DEMOGRAPHY: HOUSEHOLD BACKGROUND INFORMATION

1.1. Name Full name of respondent_____ Family size: _____	1.3. Sex 1. Male 2. Female	1.4. How old are you ---------	1.5. What is your marital status? 1. Married 2. Not married 3. Divorced 4. Widowed 5. Other(specify):___ If married, number of wives/husbands ____	1.6. How do you identify yourself? [Select one] 1. Pastoralist 2. Agro-Pastoralist 3. Others(specify) _____	1.7. What is your current main / primary income sources? 1. Livestock production 2. Crop production 3. charcoal production 3.handcraft 4. Shopkeeper / petty trade 5. Remittance 6. cash/food aid 7. Others (specify) _____
1.8. What is your current secondary income sources? 1. Livestock production 2. Crop production 3. charcoal production 3.Handcraft 4. Shopkeeper / petty trade 5.Remittance 6. cash/food aid 7. Others (specify)	1.9 Approximately how much total household income is earned in one month? (in Birr)	1.10. What is your educational level? 1. Has no formal education. 2. 1st cycle (grade 1-4) 3. 2nd cycle (5-8) 4. High school (9-12) 5. Technical / vocational certificate or diploma	1.11 How much is an annual education expenditure	1.12. What is your health condition in the last 12 months? 1. Good health → skip to 1.17 2. Ill for < 3 months 3. Ill for more > 3 months	1.13. If ill in 1.12, what is your main sickness? 1. Malaria 2. Diarrhea 3. Headache 4. Asthma 5. Other (specify)_____ _

1.14. Where do you go for health care? Mark three that apply 1. Did not get health care 2. Central hospital/ 3. Health center / clinic 4. Health post 8. Pharmacy 11. Traditional / spiritual healer 12. Other	1.15. If response to 1.14 is '1' – what are the main reasons for not getting health care? 1. No money for treatment costs 2. No money for travel 3. Poor quality of service 4. Religious reasons 5. Did no need formal health care 6. Did not believe in health care services 7. Shortage of health professionals 8. No reasons 9. Not aware about any health facility	1.16. If response to 1.14 is not "1" How much is your annual health expenses for your household? ---------- birr	1.17 Do any member of the Household have disability or related to age? 1.Yes 2. No If yes, please choose the type of disability. 1. Eye 2. Ear 3. Leg 4. Hands 5. Mental 6. Other		

SECTION 2: ACCESS TO SOCIAL SERVICE FACILITIES			
2.1	**How far is the nearest functioning market? How long does it take to get there?**	Distance (kilometers): _____ Minutes: _____	
2.2	**Is there an accessible road leading to the market?**	Yes, paved Yes, partly paved road Yes, gravel road Yes, dirt road (difficult for car) No road	1 2 3 4 5
2.3	**How far is the nearest health post or health Center**	Distance _____km, or _____ minutes	
2.4	**How is the access to veterinary services?**	Excellent Good Adequate Poor Very poor No vet. Service facility	1 2 3 4 5 6
2.5	**How far is the nearest primary School**	Distance _____km, or _____ minutes	
2.6	**How far is the nearest high school**	Distance _____km, or _____ minutes	
2.7	**How is the availability of water for Human?**	Regularly available seasonally Seldom available Never available	1 2 3 4
2.8	**How is the availability of water for Livestock?**	Regularly available seasonally Seldom available Never available	1 2 3 4
2.9	**How much does it cost you to get water <u>per week</u> during dry season?**	Amount (in local currency):	
2.10	**Are you a member of any credit / micro-finance society?**	Yes No	1 0
2.11	**Did you borrow many from any credit sources/microfinance institution?** **If yes,** **What were the reasons for borrowing?**	Buy food Pay for health care Pay for education Buy or rent land Buy agricultural input Pay for social event	1 2 3 4 5 6

SECTION 3: FOOD INSECURITY EXPERIENCE SCALE (FIES) HOUSEHOLD REFERENCED QUESTIONS

	Now I would like to ask you some questions about your food consumption in the last 12 months. During the last 12 MONTHS, was there a time when:			
1	Q1. You or others in your household **worried about not having enough food** to eat because of a lack of money or other resources?	0 No 1 Yes		
2	Q2. Still thinking about the last 12 MONTHS, was there a time when you or others in your household **were unable to eat healthy and nutritious food** because of a lack of money or other resources?	0 No 1 Yes		
3	Q3. Was there a time when you or others in your household **ate only a few kinds of foods** because of a lack of money or other resources?	0 No 1 Yes		
4	Q4. Was there a time when you or others in your household had to skip a meal because there was not enough money or other resources to get food?	0 No 1 Yes		
5	Q5. Still thinking about the last 12 MONTHS, was there a time when you or others in your household **ate less than you thought you should** because of a lack of money or other resources?	0 No 1 Yes		
6	Q6. Your household **ran out of food** because of a lack of money or other resources?	0 No 1 Yes		
7	Q7. Was there a time when you or others in your household were **hungry** but **did not eat** because there was not enough money or other resources for food?	0 No 1 Yes		
8	Q8. Was there a time when you or others in your household **went without eating for a whole day** because of a lack of money or other resources?	0 No 1 Yes		

3.2 Major causes of food insecurity in the study areas

3.2	**What do you think the main causes of food insecurity in the study areas?**	Drought Population growth Prosopis invasion and related rangeland degradation Livestock diseases Poor agriculture/livestock sector development Conflict Unstable market	1 2 3 4 5 6 7 8

SECTION 4: MAJOR DISASTERS, IMPACTS, ADAPTATION AND COPING STRATEGIES

4.1 What types of disasters have your household been affected in the last 20 years?	**4.2 What types of losses did your household experience due to those disasters?**	**4.3 Have you been able to recover from the losses suffered from those disasters?**	**4.4 Adaptation and Coping strategies** **A. What type of adaptation measures/coping strategies did your household take to cope with those disasters?**
1. Droughts 2. Floods 3. Crop diseases 4. Livestock diseases 5. Human diseases 6. Bush encroachment 7. Land Degradation 8. Heat waves / high temp 9. Conflicts 10. Economic / price shock 11. Earthquake 12.Road Accident 13. No disaster 14. Other (specify)	1. Physical damages on houses and property 2. Crop damage 3. Livestock damage 4. Death of household member 5. Illness / health problems 6. Loss of access to social services, including school 7. Loss of income 8. Loss of savings 9. Livestock were stolen 10. Lost access to grazing land 11. Lost access to water source 12. displaced 13. Other losses / damages	1. Yes 2. No	1. Collection and sale of firewood and charcoal 2. Sale more livestock than usual (destocking) 3. Seek alternative or additional jobs 4. Borrowing of food or cash 5. Borrow livestock. 6. Shift livestock herd type from grazers to browsers 7. Collection of wild food 8. Sale of non-productive assets (jewelry, clothing, etc.) 9. Rely on less preferred and less expensive food 10. Limit portion size at meals 11. Sending children to better of household for survival 12. Restrict consumption by adults in order for small children to eat 13. Reduced expenditure on health and education 14. Reduce number of meals eaten in a day. 15. Rely on food/cash aid 16. Basket-making, Mat-making 17. Use Prosopis as income source (charcoal, firewood and selling its pod for feed) Other (specify)

SECTION 5. PROSOPIS RELATED QUESTIONS

5.1	When do you start knowing about *P. juliflora* in your area?	since 15 years	1
		Between 15 and 30 years	2
		More than 30 years	3
5.2	In your perception, how is the impact of *P. juliflora* on your household?	Useful for the household	1
		Harmful	2 skip to 5.4
		Both useful and harmful	3
		No effect	4
5.3	If useful, for what purpose are you using prosopis	Livestock feed	1
		Charcoal	2
		firewood	3
		Local Medicine	4
		Furniture	5
		Construction	6
		Honey production	7
		Used for soil physicochemical improvement	8
		Local climate cooling effect	9
		Other (specify)----------	
5.4	What are the main negative impacts of *Prosopis* in your area and for your household	Degrade rangeland/grassland	1
		Impact on human health due to its poisonous thorn	2
		Impact on Livestock health due to its poisonous thorn	3
		Impact on livestock health due to its high protein and antinutritive factor	4
		Indigestible seed and affect /twisting of animal jaw	5
		Shade for predators	6
		Restrict livestock movement	7

5.5	Are you willing to contribute to control *Prosopis* invasion	Yes No	1 2 skip to Section 6
5.6	In what way do you want to contribute annually for control or clearing of *Prosopis*?	Contribute in direct cash payment Labor contribution Both cash and labor	1 2 skip to 5.8 3
5.7	If you were to contribute for your community to clear *Prosopis*, how much are you willing to pay annually for *Prosopis* clearing?	>500 birr 100-500birr <100 birr	1 2 3
5.8	How many days do you or your family contribute labor for *prosopis* clearing?	8hrs per week 16 hours per week 4 hours per week < 4 hours per week	1 2 3 4

SECTION 6: CROP PRODUCTION

6.1	**Does your household own farmland?**	Yes No	1 2 if no skip to section 7
6.2	**Did your household conduct crop farming activities?**	Yes No	1 2
6.3	**Are you using irrigation?**	Yes No	1 2

Crop Codes

	3. Teff	5. Groundnut			
1. Maize	4. Millet	6. Sesame			
2. Sorghum		7. Roots & tubers			
		8. Fruits			

	6.4	6.5	6.6	6.7	6.8	6.9	6.10	6.11	6.12
Crop	Which crop(s) did your household cultivate last year?	Cultivated area (hectares)		Harvested quantity (Qt)	Amount sold to market (Qt)	Sold value (in ETB)	Amount of produced and used for consumption (Qt	Amount of stored (Qt) e.g. in grain reserves	Average annual income from crop production
		Rain fed	Irrigated						
1									
2									
3									

		(a)	(b)	(c)		d	e	f
Animals #	**Type of livestock**	**Number of animals owned**	**How has the number of livestock owned by your household changed during the past 20 years?** 1. Decreased 2. Remained the same → skip to 7.13 3. Increased →skip to 7.13	**What are the reasons for the decrease in the last 20 years?** (If response to (b) is 1) 1. Conflict 2. Raiding 3. Died in drought 4. Disease 5. Poisoned 6. Sold for food 7. Sold (not for food) 8. Ate at home 9. Lent out to somebody 10. Stolen 11. Lost 12. Eaten by wild animal(s) 13. Charity 14. Contribution 15. Dowry Payment 16. Offering 17. Compensation payment 18. died due to Prosopis related grazing pasture shortage and its health impacts 19. Other		**Average annual income from livestock production**	**Average annual health expenditure for livestock treatment**	**Annual expenditure for feed purchase**
				Reason 1	**Reason 2**			
7.1	**Cattle: Cow**							
7.2	**Cattle: Oxen**							
7.3	**Heifer**							
7.4	**Calves**							
7.5	**Camels**							
7.6	**Goats**							

7.7	**Sheep**							
7.8	**Donkeys**							
7.9	**Mules**							
7.10	**Horses**							
7.11	**Poultry**							
7.12	**Bee Keeping**							
	Total							

7.13	**How is access to grazing pasture for animals?**	Regularly available seasonally Seldom available Never available	1 2 3 4
7.14	**What is the primary causes for livestock death(s)?**	Disease Drought Other natural disaster (specify) Poison (chemical) Poison (natural, such as plant disease) Malnutrition Prosopis thorn and its chemical in the pods	1 2 3 4 5 6 7
7.15	**How many animals have died, by type?** (Specify from 7.1-7.11)	Number of deaths, by type:	

SECTION 8: HUMANITARIAN ASSISTANCE

	A	B	C	D	E
	In the past 12 months, which types of assistance did your household receive from government or aid agencies?	**Did you receive this assistance in the past 12 months?** 1. Yes 2. No→ Skip to Next section 9	**How many times did you receive this assistance in the past 12 months?**	**How much did you receive?** **(Units** 1. Kilograms 2. Numbers 3. Currency)	
8.1	Food aid				
8.2	Food for Work				
8.3	Cash for Work				
8.4	Free cash				
8.5	Pulses, Grains				
8.6	Seeds & tools				
8.7	Credit from NGO				
8.8	Livestock/restocking				

SECTION 9: MONTHLY CONSUMPTION EXPENDITURES

For the following, please include all purchases made in **last 30 days** for consumption in your household, regardless of who made them. Exclude any items purchased for business purposes.		Quantity purchased during **last 30 days** Units 1=Kilogram 2=Liter 3=Number	Estimated expenditure during the **last 30 days** (in local currency)	Remarks	
9.1	Maize grain				
9.2	Wheat grain				
9.3	Teff				
9.4	Sorghum grain				
9.5	Wheat flour				
9.6	Pasta				
9.7	Rice				
9.10	Wheat bread				
9.11	Peas				
9.12	Beans				
9.13	Macaroni				
9.14	Lentils				
9.15	Spices				
9.16	Fruits				
9.17	Fish / Meats / Poultry				
9.18	Eggs				
9.19	Cooking oil				
9.20	Butter / fat				
9.21	Milk / Cheese / Yogurt				
9.22	Salt				
9.23	Sugar / Honey				
9.24	Coffee				
9.25	Any other Food Item (specify)				
9.26	Alcohol				
9.27	Tobacco				
9.28	Chat				
9.29	Fuel (wood, charcoal, kerosene, etc.)				
9.30	Telephone / Cell Phone / Email				
9.31	Meals / Snacks / Beverages				
9.32	Water				
9.33	Soap / Toiletries / HH items				
9.34	Transport				
9.35	Rent				