Addis Ababa University
College of Development Studies
Centre for Environment and Development

Analysis of changes in land use and land cover transition, climate extremes, and vegetation productivity: Drivers and agricultural risks in the Awash River Basin, Ethiopia

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Addis Ababa, Ethiopia

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Declaration

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

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This dissertation has been submitted for examination with my approval as the student's supervisor.

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Dissertation Approval

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This is to certify that the dissertation prepared by Addisu Damtew Atnafe, entitled "**Analysis of changes in land use and land cover transition, climate extremes, and vegetation productivity: Drivers and agricultural risks in the Awash River Basin, Ethiopia"** is presented in fulfillment of the requirements for the Degree of Doctor of Philosophy in Development Studies (Environment and Development Studies) and meets the accepted standards concerning originality and quality.

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Tesfaye Zeleke (PhD, Associate Professor) ____________ ____________

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List of Original Papers

This Dissertation is organized based on the following three peer reviewed research articles.

Paper 1. Damtew, A., Teferi, E. and Ongoma, V., 2022. Farmers’ perceptions and spatial statistical modeling of most systematic LULC transitions: Drivers and livelihood implications in Awash Basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, *25*, p.100661. **https://doi.org/10.1016/j.rsase.2021.100661** (Elsevier)

Paper 2. Damtew, A., Teferi, E., Ongoma, V., Mumo, R. and Esayas, B., 2022. Spatiotemporal Changes in Mean and Extreme Climate: Farmers’ Perception and Its Agricultural Implications in Awash River Basin, Ethiopia. *Climate*, *10*(6), p.89. **https://doi.org/10.3390/cli10060089** (MDPI).

Paper 3. Damtew, A., Teferi, E., Ongoma, and Esayas, B., 2022. Disentangling climate from human-induced Net Primary Productivity and its agricultural implication in Awash Basin, Ethiopia. *Science of the Total Environment*, to be submitted (Elsevier)

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Abbreviations

AEZ	Agro-Ecological Zone
ASTER GDEM	Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model
CDD	Consecutive Dry Days
CRGE	Climate-Resilient Green Economy
CSA	Central Statistical Agency
CSDI	Cold Spell Duration Indicator
CWD	Consecutive Wet Days
DA	Development Agents
DTR	Diurnal Temperature Range
EGII	Ethiopian Geospatial Information Institute
ENACTS	Enhancing National Climate Services
ETCCDMI	Expert Team on Climate Change Detection and Monitoring Indices
ETM+	Enhanced Thematic Mapper Plus
ET-SCI	Expert Team on Sector-Specific Climate Indices
FGD	Focus Group Discussion
FPAR	Fraction of Absorbed Photo synthetically Active Radiation
GCP	Ground Control Points
GIS	Geographic Information System
GLASS	Global Land and Terrestrial Satellite
GPP	Gross Primary Productivity
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter-Tropical Convergence Zone
KII	Key Informant Interview
LAI	Leaf and Index
LST	Land Surface Temperature
LUCC	Land-Use Change and Land Cover Change
LUE	Light Use Efficiency Model
LULC	Land Use Land Cover
MAEZ	Major Agro-Ecology Zone
MNDWI	Modified Normalized Difference Water Index
MuSyQ-NPP	Multisource Data Synergized Quantitative-Net Primary Productivity

NDBAI	Normalized Difference Built-up-Area Indices
NDVI	Normalized Difference Vegetation Index
NMA	National Meteorological Agency
NPP	Net Primary Productivity
NWD	Number of Wet Days
OLI	Operational Land Imager
RESTREND	Residual Trend
ROC	Relative Operating Characteristic
RUE	Rain Use Efficiency
SDII	Simple Daily Intensity Index
SWC	Soil and Water Conservation
TM	Thematic Mapper
USGS	United States Geological Survey
UTM	Universal Transversal Mercator
WSDI	Warm Spell Duration Indicator

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Dedication

Dr. Alemayehu Adugna, whose funny thoughts and concerns are always in my heart. Ofishe Bodena (Addee), who is still struggling to keep my brothers in school and proud of us.
Addee nuf jiraadhu!

CHAPTER ONE

1. General Introduction

1.1. Background of the Study

The rate and magnitude of human alterations on the earth's land surface during the last three centuries are unprecedented (Haney and Cohen, 2015). Rapid population growth and environmental factors change land use and land cover (Teferi *et al*., 2013; Shegena *et al*., 2014). Changes in the atmosphere's gas composition, land use land cover, and ecosystem degradation due to human activities, have increased and become more intensive to supply more agricultural products and energy to the growing human population (Nedd *et al*., 2021; Potapov *et al*., 2022). Land use land cover change (LULCC) responds to multiple interacting factors triggered by natural variables, anthropogenic changes, and their complex relationships. In most circumstances, LULCC is associated with socioeconomic changes mediated by institutional factors or a combination of accessibility, biophysical and demographic factors (Bekele *et al*., 2019; Berihun *et al*., 2019). Therefore, analysis of LULC dynamics is critical for understanding the interaction between human activities and global environmental changes (Hu *et al*., 2021; Roy and Inamdar, 2019).

Climate change manifested by rising temperatures, increasingly erratic rainfall, and more frequent and severe floods and droughts, is probably the most complex and challenging environmental problem today (Ayugi *et al*., 2022; Mohammed *et al*., 2018). Equally, climate change is increasing and surpassing land use land cover change as having the most significant impact on environmental change dynamics (Aerenson *et al*., 2018; Araro *et al*., 2020). Above all, climate change negatively affects agricultural productivity in many regions. These include the reduction of average yields in the longer term as well as potentially increasing yield variability (Cogato *et al*., 2019; Shoaib *et al*., 2021), changes in the geography of production through the greater frequency and intensity of extreme weather events such as droughts and floods (Afuecheta and Omar, 2021; Chhogyel *et al*., 2020).

Net primary productivity (NPP) can reflect the productive capacity and sustainability of ecosystems and has become a focal point of global change research (Xue *et al*., 2022; Yang *et al*., 2020). Furthermore, as an important component of the terrestrial ecosystem and healthy ecological indicator, NPP, the amount of energy that remains after autotrophs have met their energy requirements through respiration, has been changing in response to climate and anthropogenic land use land cover change (Tian *et al*., 2021; Zarei *et al*., 2021). Net primary productivity-based studies have also documented NPP as an ecological indicator to separate the effects of climate from human-induced changes on vegetation (Bi *et al*., 2020; Tian *et al*., 2021). Others also indicated NPP to assess land degradation (Kang *et al*., 2020; Tesfaye *et al*., 2019).

Due to its high exposure and low economic status, Ethiopia is one of the world's most vulnerable countries to climate change (Bezu, 2020; Chala *et al*., 2020). The agriculture sector has been subjected to unpredictable climatic conditions, such as erratic and intense rain with distorted seasonality, increased temperature resulting in longer drought seasons, recurrent drought, failing harvest seasons, new crop pests, and livestock diseases (Damtew *et al*., 2022; Mekonnen *et al*., 2021). Similarly, climate change and extreme events are causing significant damage to life, property, natural resources, and the economy, making essential economic systems highly vulnerable (Mekuyie and Mulu, 2021; Solomon *et al*., 2021). In particular, the risk level was raised by rapid population development, rainfed agriculture dominance, high poverty levels, environmental degradation in the form of land use land cover change, land degradation, climate change and extreme events, and biodiversity loss (Bewket *et al*., 2015; Hailemariam *et al*., 2016; Megersa *et al*., 2014; Mesfin *et al*., 2018; Muleta *et al*., 2021).

The Awash River basin is one of Ethiopia's intensively utilized river basins due to its strategic location, access roads, and available good land and water resources. From a development aspect, it has a leading position in the development practice of the country, particularly in irrigation. Naturally, the large areas of the basin are covered by arid and semi-arid climates. The economy of the Awash Basin has been highly exposed to hydrological variability dominated by prolonged drought (Mekonnen, 2021; Maru *et al*., 2022), seasonal flooding (Tadese et al., 2019), and land use land cover dynamics (Alem, 2022; Damtew *et al*., 2022a).

Overall, environmental management in the basin requires improved knowledge of changes in trends in LULC change, LULC transition, determinants, and its implication on livelihoods. The acquired knowledge can help further understand the nature of change, ascertain potential improvements, forecast likely trends, and suggest effective policy recommendations and responses (Betru *et al*., 2019; Hishe *et al*., 2021). Similarly, assessing agro ecology-based trends of mean and extreme climate is necessary for farmers whose livelihood depends on agriculture and decision-makers who develop adaptation strategies for climate change and extreme threats. Furthermore, due to the combined effect of climatic variables changes and human-induced land use land cover change, ecosystem services have been altered across various parts of the world (Park *et al*., 2021; Yu *et al*., 2022). The ability of vegetation to provide ecosystem services is widely shown by net primary production (NPP) (He *et al.*, 2022; Yu et al., 2018). Assessing Net Primary Production in a region has many implications (Park *et al*., 2021; Xue *et al*., 2022). It shows healthy vegetation status by measuring the carbon sequestration ability of a plant community (Park *et al*., 2021). When correlated with climatic variables, it measures the degree of land degradation and rehabilitation in a certain area or generally indicates that climate change can impact ecosystem productivity (Eisfelder *et al*., 2014; Xue *et al*., 2022). Variation in NPP can be monitored; still, it is difficult to separate the driving factors and their contribution to changes to the ecosystem (Redlich *et al*., 2022; Wu *et al*., 2021). Therefore, analysis of trends of NPP, measuring the separate impact of climate change and anthropogenic activities on NPP, is essential to develop policies that enhance ecosystem sustainability (Bi *et al*., 2020; Tian *et al*., 2021). Due to limited research that link land use land cover transition, climate change to vegetation productivity (NPP) and their possible risks on agriculture in the country in general and Awash Basin in particular, the study aimed to fill this gap.

1.2. Literature Review

1.2.1. Land use land cover change: concept and definition

Land use is how people utilize land, whereas land cover is the physical characteristics of the earth's surface (Briassoulis, 2020). Land cover depends on environmental variables and anthropogenic influences leading to specific land use (Hu *et al.*, 2021). LULCC is any quantitative changes in the areal extent of given land use or land cover (Munthali, Botai, *et al.*, 2019). It is a biophysical or chemical change attributable to management, which may embrace conversion of grazing to cropping, change in fertilizer use, drainage enhancements, and conversion to non-agricultural uses (Lei and Zhu, 2018; Singh *et al.*,2021). Land use land cover transition is one of the manifestations of land-use land cover change, and it refers to the changes in land use morphology of a particular region over a certain period driven by the socioeconomic change development stage (Long *et al.*, 2020). Land use and land cover change are shaped by human needs, natural features, and processes (Berihun *et al.*,2019). Because change is essential to life, neither of these forces remains stationary. The material expressions are land use and cover modifications that occur over time and at various spatial scales (Betru *et al.*, 2019).

1.2.2. Drivers of land use land cover change

The LULCC of a region is an outcome of complex natural and socioeconomic factors and their utilization by man in time and space. In this regard, human-caused LULCC activities play a crucial role in earth system dynamics through significant modifications to bio-geophysical and biogeochemical properties at different spatial scales (Arowolo and Deng, 2018; Cao *et al.,* 2019). Different researchers have put the reasons for LULCC into two broad categories: proximate and underlying causes (Lambin *et al.,* 2001; Meyfroidt *et al.,* 2013). Proximate (direct) causes constitute human activities or immediate actions originating from intended land use and directly affecting land cover. On the other hand, the underlying (indirect) factors are fundamental forces that underpin the more proximate causes of land cover change (Betru *et al.,* 2019; Xu *et al.,* 2020). Similarly, land use changes are strongly affected by international flows of goods and services, wealth, and people and are increasingly driven by factors in detached markets, often associated with the growing urban consumer class in emerging markets (Lambin and Meyfroidt, 2011; Meyfroidt *et al.,*2013).

Land use and land cover changes have exclusive spatiotemporal attributes that seriously threaten the ecology (Chaudhuri *et al.,*2018; Markos *et al.,*2018). More particularly, changes in LULC affect the environmental services through shifting biodiversity (Jewitt *et al.,*2015), forest fragmentation (Tadese, *et al.,*2020), water resources (Dibaba *et al.,*2020; Lei and Zhu, 2018), increased natural disasters such as frequent droughts and floods (Berihun *et al.,*2019) and have a significant effect on climate (Davies-Barnard *et al.,*2015) and affect many communities whose livelihood depends on subsistence farming (Kamwi *et al.,*2015).

Globally, LULCC appeared on a research agenda several decades ago as it is associated with considerable negative impacts on ecosystems observed at local, regional, and global scales (Ellis *et al.,*2013). The growing and diverse user community require globally consistent yet locally relevant LULC data for developing and implementing land use policies, monitoring sustainable development, conservation, and restoration initiatives, and Earth systems modeling applications (Azari *et al.,*2022; Yirsaw *et al.,*2017). Therefore, characterizing LULC dynamics is very important to understand the interface between human activities and global environmental variations and to select and execute land use patterns to meet welfare and human needs (Koko *et al.,*2020; Munthali, Davis, *et al.,*2019).

Currently, the Ethiopian highlands are faced with poor pastures and degraded land. The expansion of agricultural cropland into communal and private grasslands further exacerbates the situation by reducing available pastureland and increasing land use pressure. Poorly planned and unregulated urbanization, the rapid encroachment of urban areas into agricultural, pastoral, forest, wetland, and protected areas are posing a significant threat to the land use system (Rai et al., 2017; Kassahun and Tiwari, 2012). These challenges for strategic urban land use within the country are further exacerbated by the unplanned, rapid, and uncoordinated use of land resources. Industries and urban centers are also expanding into prime lands and urban wetlands (Assefa et al.,2021).

LULCC research conducted in different parts of Ethiopia shows that cultivated land has expanded because of deforestation (Berihun *et al.,*2019; Demissie, 2022). The land cover dynamics are more severe in the highlands because of higher population density and ongoing agricultural activities for millennia than lowlands (Minta *et al.,*2018). Most studies revealed that LULCC is associated with socioeconomic changes mediated by institutional factors (Bekele *et al.,*2019; Kassawmar *et al.,*2018) or biophysical and demographic factors (Damtew, 2022; Deribew, 2019). Most of these studies show that population pressure is a significant factor in land use and land cover changes (Genet, 2020). Higher-level institutions often develop land use policies, while their implementation is mostly the responsibility of lower-level entities. The efficiency of land use policies is hampered by the absence of engagement from institutions at lower levels, as well as by a lack of capability and an absence of clear institutional mandates (Ariti et al.,2019). Invariably, higher-level institutions play a larger role in creating land use regulations, while lower-level institutions play a larger part in implementing such policies.

1.2.3. Agricultural threats of climate change and extreme events

Agriculture is exposed to different risks because it is frequently carried out in the open air and always requires management. Agricultural activities are prone to risks and uncertainties of various natural, biophysical, abiotic, climatic, environmental, biotic (pests, diseases), and economic (Das and Goswami, 2021; Shah *et al.,*2021). Risk in agriculture can be seen as the probability of hazards and shocks negatively impacting the agricultural system. These risks are inherent, ubiquitous, and varied in the farming sector, posing potentially serious consequences for all stakeholders (Ortega-gaucin *et al.,*2021; Pontrandolfi *et al.,*2016). Many risks have a climatic component, most of which will be affected by climate change in intensity or frequency (Alsafadi *et al.,*2020; Dawadi *et al.,*2020).

The sixth IPCC Assessment Report (AR6) confirms its previous continuous reports' main findings on the evolution of climate and its main physical effects, including surface and ocean temperature and precipitation change, sea level rise, and ocean acidification (IPCC, 2021). Climate change brought several risks ranging from physical impacts on ecosystems (Malhi *et al.,*2020), agricultural production and productivity (Oo *et al.,*2020), food chains (Jin *et al.,*2020), and incomes (Ahmad and Afzal, 2020), with economic and social effects on livelihoods (Hossain *et al.*,2020). Climate change generates considerable uncertainty about future water availability in many regions. It will affect rainfall, surface and sub-surface runoff, and snow melt, affecting hydrological systems, water quality, and water temperature. Climate change is likely to affect the intensity and frequency of extreme events. Powell et al. (2016) stated that extreme climate events are projected to increase worldwide. Climate change is already affecting climate extremes indices across the globe (Tegegne, *et al.*,2021). The most vulnerable people, whose livelihoods depend on the agricultural sector, are expected to experience climate change's earliest and worst effects (Mun *et al.*,2020; Shi *et al.*,2020). Therefore, the study of climate change and extreme events on food security are central to the sustainable development of agriculture globally (Anderson *et al.*,2020).

Some impacts can be easily projected, such as the direct impact of a heat wave on a specific plant at a particular moment of its growth (Chung *et al.*,2014; Vogel *et al.*,2019). Others are more complex to predict, like the effect of a certain climatic change on a whole ecosystem, because each element will react differently and interact with the other. Several studies have shown how climate change-related extreme events, like droughts and floods, affect agriculture and food security. Changes in extreme events such as extreme temperature (heat waves), drought, heavy precipitation, and tropical cyclones and their attribution to human influence have been noted (Trenberth *et al.*,2015). Continued rainfall frequency and intensity changes, heat waves, and other extreme events affect agricultural production (Coulibaly *et al.*,2020). In many parts of the world, the observed impacts of historical climate trends on crop production are clear (Shi *et al.*,2020), with negative effects being more prevalent than positive effects (Chhogyel and Kumar, 2018). There is an indication that climate change has already negatively affected wheat and maize yields in many regions and globally (Lobell *et al.*,2011).

Agricultural climate risk is increasingly recognized as a significant problem for industrialized farm producers and other stakeholders, smallholder farmers, and vulnerable populations (Dendir and Simane, 2019; Tessema and Simane, 2019). In Ethiopia, due to differences in the spatial and temporal scale of the country's topography, study findings related to climate trends and variability showed different results (Habte *et al.*,2021; Nasir *et al.*,2022). In particular, the risk level was raised by rapid population development, rain-fed agriculture dominance, environmental degradation, frequent droughts, and high poverty levels. Similarly, climate change and extreme events are causing significant damage to Ethiopia's life, property, natural resources, and economy, making essential economic systems highly vulnerable (Asfaw *et al*.,2021; Chala *et al*.,2020).

Ethiopia's climate trend analysis also indicated a significant temperature increase and rainfall reduction in many areas of the country (Cattani *et al.,* 2018). The immediate impact includes effects caused by modifying physical characteristics such as temperature levels and rainfall distribution in specific agricultural production systems. The vast amount of literature addresses the negative effects of climate change and variability on agricultural production systems (Solomon *et al.*,2021; Tesfahunegn and Gebru, 2021, 2022). Indirect effects affect production through changes in other species, such as pollinators, pests, disease vectors, and invasive species. Throughout the production season, crops are sensitive to different weather events. Inter and intra-annual temperature and precipitation variability affect crop yields during any season. Extreme weather events also pose a considerable risk for food production; droughts and floods can reduce agricultural productivity in affected areas (Dai, 2011). Droughts destroy farmlands and pastures, contribute to land degradation, and cause crops and livestock to perish. Climate extreme events like droughts and floods also impact food security and the livelihoods of smallholder farmers in the country (Harvey *et al.*,2014). The agriculture sector has been subjected to variable and unpredictable climatic conditions, such as erratic and intense rain with distorted seasonality, increased temperature resulting in longer drought seasons, recurrent drought, failing harvest seasons, new crop pests, and livestock diseases (Ali *et al.*,2020; Ayal *et al.,* 2018).

1.2.4. Net primary productivity as a healthy ecological indicator

Net primary productivity (NPP) of vegetation refers to the difference between the amount of organic matter produced by green plants through photosynthesis and the amount of organic matter consumed by autotrophic respiration per unit of time and area (Yue *et al.*,2022). Net primary production measures the net increase in carbon in plant biomass due to photosynthesis (Letchov, 2018). Vegetation NPP reflects the carbon sequestration ability of a plant community in its natural environment and vegetation response to changes in climate and land use land cover dynamics not only represents the growth status and health degree of vegetation in the ecosystem (Kong *et al.*,2021; Xiao *et al.*,2019) but also is an important indicator to measure the exchange of CO2 between the atmosphere and the surface and a major factor to regulate the process of the ecosystem (Peng *et al.*,2017). Net primary productivity has become a focus of global change study as a crucial indicator that incorporates the impacts of climate change and human actions on terrestrial vegetation. It can reflect ecosystems' productive capacity and sustainability (Chen *et al.*,2017).

The feedback of vegetation carbon dynamics to climate change is a hot issue in global change research (Wang *et al.*,2017; T. Yu *et al.*,2018). As a component of the terrestrial ecosystem, climate significantly affects vegetation (Yu *et al.*,2022). The vegetation's growth process is not only related to the coupling effects of climate change but also is subject to geographical and environmental factors (Wang *et al.*,2022). When climate change exceeds the threshold of vegetation's adaptability to the environment, it will significantly change the function and intensity of terrestrial ecosystems (He *et al.*,2022). Some studies based on NPP have documented the effects of precipitation and temperature changes on vegetation dynamics (Anić *et al.*,2018).

The amount of NPP on land is often constrained by four main abiotic factors: light, water, temperature, and mineral nutrients. Global environmental changes like those in the climate, atmospheric CO_2, nitrogen deposition, introduction of exotic species, etc. will have a big impact on global NPP (Woo and Do, 2021). Due to human activity, many of these abiotic elements are changing quickly, with extremely ambiguous implications for local and global NPP. Across the terrestrial biomes of the planet, a diverse array of NPP has been seen, with the highest values occurring in tropical forests and wetlands, intermediate values occurring in temperate forests and grasslands, and the lowest in extremely cold deserts (Xiao *et al.*,2021). Water shortage is perhaps the most pervasive single factor limiting global NPP, but two or more of these abiotic variables frequently work concurrently or sequentially to limit NPP (Yu *et al.*,2022). In temperate and high-latitude regions, subfreezing conditions that shorten the growing season are closely connected to how temperature affects NPP (Wang *et al.*,2016). When average precipitation is sufficient to support highly productive communities, as it is in semiarid and sub-humid environments, NPP appears to respond to inter-annual variation in rainfall very strongly (Wang *et al.*,2016). Forests show a recurrent pattern where NPP peaks after a few decades of stand development, followed by a reduction with aging in older stands, following natural or human disturbances (Xiao *et al.*,2019).

Land use land cover change can make the ecological system vulnerable, increase greenhouse gas (GHG) emissions and decrease carbon storage, especially in developing countries with high land use land cover dynamics (Touma *et al.*,2021). Therefore, in the context of global change, climate and LULC changes have an important and discernible influence on the NPP of natural and artificial ecological systems (Luo *et al.*,2018). The ability of plants to provide ecosystem services is shown by net primary production (NPP), which can also reflect changes in response to climatic change and human activity. Understanding the relative effects of climate change and human activities on land degradation requires determining the drivers of NPP change. Measuring the impact of climate change and anthropogenic activities on terrestrial ecosystems is essential to develop policies that enhance ecosystem sustainability (Bi *et al.*,2020).

1.2.5. General Flow chart of the dissertation

To achieve the specific objectives and answer the basic research question, the study incorporated different datasets, methods of data analysis and software used. The overall workflow of the study is presented in Figure 1.1

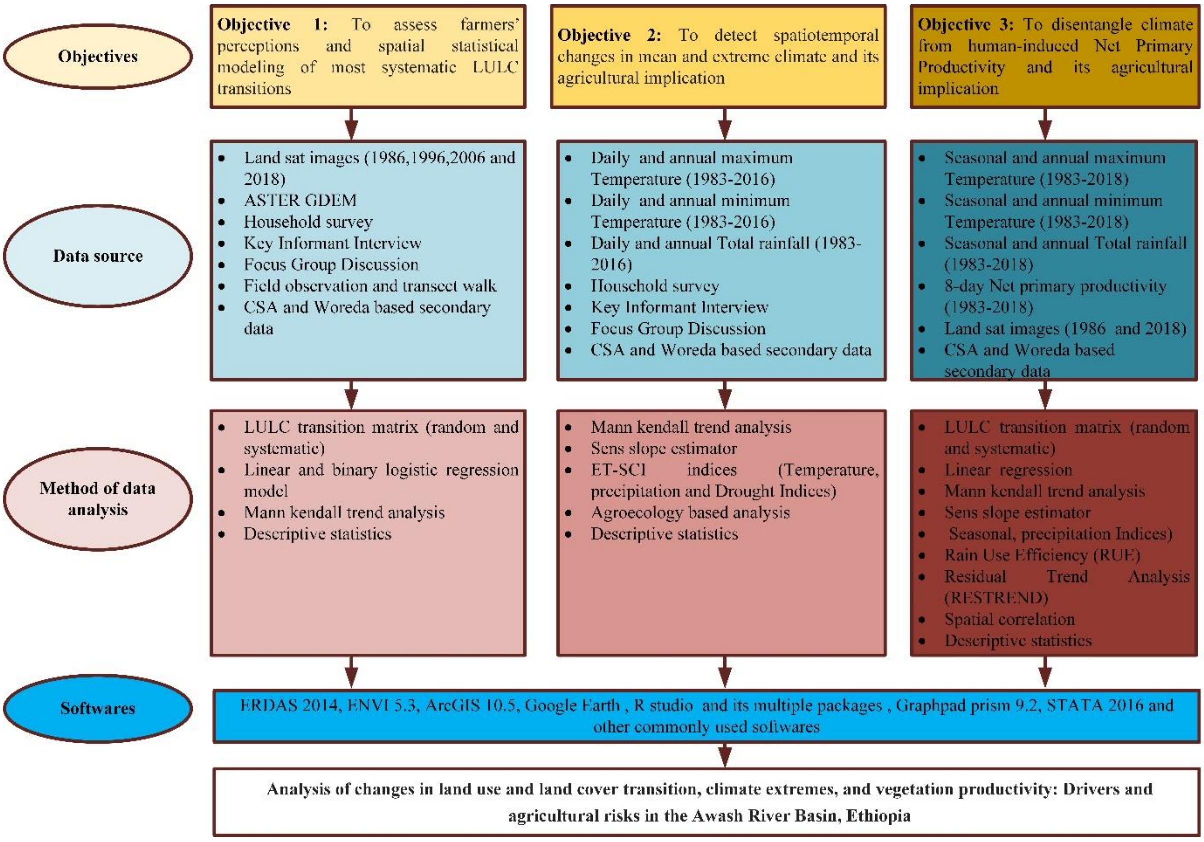

Figure 1.1. Work flowchart of the study

1.3. Problem Statement

Environmental change in the form of land degradation, climate change, biodiversity change, and LULCC are the major challenges for humans in most parts of the world. Climate change adversely affects socioeconomic sectors, including water resources, agriculture, forestry, fisheries, human settlements, ecological systems, and human health, with developing countries being the most vulnerable (Ma *et al.*,2020; Prestele *et al.*,2017). The major problems that are hindering the development in the Awash River basin are recurrent large-scale flooding and drought (Emiru *et al.*,2022; Tadese *et al.*,2020), periodic extreme weather events (Damtew et al.,2022), which adversely destroy crops and livestock (Tesfaye *et al.*,2019). High population growth, improper land use, and traditional agriculture resulted in land degradation (Alem, 2022). Therefore, it is very important to understand trends of land use and land cover change, climate extreme events and ecosystem health indicators of the basin.

The change in land use land cover significantly impacts the functioning of socioeconomic and environmental systems with important tradeoffs for sustainability, food security, biodiversity, and socioeconomic vulnerability of people and ecosystems (Luo *et al.*,2018; Yang *et al.*,2020). LULCC is also associated with large negative impacts on ecosystems observed at local, regional, and global scales (Shiferaw *et al.*,2019; Solomon *et al.*,2019). More particularly, changes in LULC affect the sustainability of environmental services by altering the hydrology, forest resources, soil, climate, biological diversity and increasing natural disasters such as droughts and floods (Msofe *et al.*,2019; Samie *et al.*,2019). These can directly or indirectly affect many people whose livelihood depends on agriculture (Pachauri *et al.*,2014). Therefore, characterizing LULC dynamics is crucial for understanding the interaction between human activities and global environmental changes and selecting and executing land use patterns to meet welfare and human needs (Guidigan *et al.*,2019).

Previous studies conducted in different parts of the country and basin used a transition matrix table to make conclusions about land use land cover dynamics based on the net change, rate change, and type of change between two different times (Chang *et al.*,2018). At their investigation core, they use ‘net change’ as the dominant signal of landscape transition. This fails to consider the reality on the ground, where there are simultaneous gains and losses in LULC change (Pontius *et al.*,2004). Therefore, there is a need to find methods and indicators that show in-depth information about the prominent signals of LULC change (Teferi *et al.*,2013; Teixeira *et al.*,2014). Furthermore, quantitative outputs from earth observation tools do not provide insightful information about the driving forces behind the patterns of these changes (Kleemann *et al.*,2017). Investigations that exclusively focus on biophysical, socioeconomic, or political aspects are commonly seen in literature (Teferi *et al.*,2013; Munthali *et al.*,2020). However, a single research approach is insufficient for analyzing LULC change. Therefore, to better understand LULC changes and their determinants, combining earth observation information with land users' information is highly recommended (Bekele *et al.*,2019; Betru *et al.*,2019).

As global temperatures and precipitation continue to change, climate extremes are projected to increase in intensity and frequency (Ayugi *et al.*,2021; Ngoma *et al.*,2021). Climate change in Awash is noticeable by its extreme climate factors like drought and flood (Mekonnen et al.,2021; Tadese et al.,2020). These extremes highly affect agricultural productivity, society's social welfare, infrastructures and markets, and farmers' livelihoods (Daba *et al.*,2020; Emiru et al.,2022). Observed changes in extremes in the country depend on the reliability and quantity of available data (Ayehu *et al.*,2018; Dinku, 2019). However, there is low to medium confidence in extreme historical temperature and heavy rainfall trends over most parts of Ethiopia because of a lack of empirical evidence. In the Awash basin and elsewhere in Ethiopia, where extreme climate events are studied, limited climate extreme indices are explored, and the emphasis is given to showing the overall trends across stations being investigated.

Similarly, most studies are confined to areas where long-term climatic data are available. However, linking the mean and climate extreme with local perception and its implication for the livelihood of the society is not prioritized. Therefore, considering the history of major climate disasters, conducting long-term mean and extreme climatic events through basins in the major agroecological setting is essential as extreme climate indicators affect various socio-economic activities (Dula, 2018; Tesfahunegn and Gebru, 2021). Furthermore, micro-scale studies about the trend of extreme weather events are critical for understanding local-scale indications of climate changes and designing context-specific adaptation interventions.

The population growth and corresponding human needs have increased human pressure on the ecological system, resulting in a slow of potential ecological and environmental issues (Ganivet, 2020; Pan *et al*.,2021). Various studies conducted in different parts of the world investigated that ecosystem services given by terrestrial vegetation are affected by climate change, extreme events, and land use land cover change (He *et al*.,2022; Lin *et al*.,2018). Taking NPP as an important indicator of a healthy ecosystem and land degradation, understanding the relationship between NPP and climate variables is important (Li *et al*.,2019; Mohammed *et al.*,2018). In the semiarid and arid ecosystems of the Awash basin, increased human activity and climate change can cause ecological and economic damage (Alem, 2022;

Emiru *et al*.,2022). However, distinguishing between climatic drivers and human impacts on ecosystems has long been a contention in arid and semi-arid regions because ecosystem dynamics and climate variability are inextricably linked and difficult to separate (Hossain *et al.*,2020; Y. Wang *et al.*,2019). These gaps call to identify and accurately assess and separate the contributions of climate change and human activities to ecological changes that can be used for ecological regulation and management.

The combined changes in land use and land cover transition, climate extreme events and vegetation productivity in the basin possibly threaten agriculture, which is the main means of livelihood in the study area. Thus, in bridging and filling the study gaps, the study aimed at analyzing land use land cover transition, climate extreme and vegetation productivity in the Awash basin, Ethiopia.

1.4. Objectives of the study

1.4.1. General objective

The general objective of the study is to analyze changes in land use and land cover transition, climate extremes, and vegetation productivity to agricultural risks in the Awash River Basin, Ethiopia

1.4.2. Specific objectives

i) To investigate the drivers of land use and land cover transitions and their livelihood implications in Awash -Awash sub-basin
ii) To investigate the spatiotemporal changes in mean and extreme climate and its agricultural implications in the Awash-Awash sub-basin
iii) To disentangle climate from human-induced Net Primary Productivity and its agricultural implication in the Awash basin

1.5. Research Questions

The study answered the following basic research questions.

i) What is the trend, extent, and spatiotemporal variability of land use and land cover transitions in the Awash-Awash sub-basin?
ii) What are the major signals of land use, land cover transition, and local perceptions about the change?
iii) What are the drivers of major land use and land cover transition in the sub-basin?
iv) Do mean and extreme temperature and precipitation events in the sub-basin vary across agro ecology?
v) How do farmers perceive the mean and extreme climate changes and their agricultural impact in the sub-basin?

vi) What is the spatio-temporal variability of Net Primary Productivity and the mean climate in the Awash Basin?

vii) Can the relative impacts of human activities and climate change on Net Primary Productivity be disentangled and used as an agricultural risk indicator?

1.6. Scope of the study

As the field of study, the environment and development stream touches on various themes linking the current environmental issues with the sustainable development of society. Taking climate change and extreme events, land use, land cover change, and net primary productivity as major threats to developmental issues in the country, the study was conducted in one of the environmentally fragile areas of the country. The study was geographically confined to the Awash-Awash sub-basin, encompassing three major watersheds (Keleta, Awash Arba-1, and Awash Arba-2) in the upper and middle parts of the Awash basin. Different methodological approaches were followed to analyze the data types based on the objectives' multi-dimensionality nature. Methodologically, quantitative data (Household survey, time series climatic, satellite imagery, net primary productivity datasets, and terrain attributes) and qualitative data (from the community, experts, and reports) were used to attain the objectives. Due to the availability of quality data, the study analyzed 34 years (1983-2016) of climatic data for analysis of extreme climate and 37 years (1983-2018) for net primary productivity analysis.

1.7. Limitation of the study

The main target of the study is to analyze land use and land cover transition, climate extremes, vegetation productivity and its agricultural implication in one of the environmentally fragile basins of Ethiopia. To achieve the study's objectives, the availability of long-term and quality data related to climate, land use land cover data and estimated NPP was a prerequisite. In the first objective, new grid datasets (ENACT) were used to compute the mean and climate extreme trends due to the limited availability of station data. Similarly, due to the lack of long-term availability of quality satellite data (high resolution) that show NPP, the researcher is forced to use the global product with a medium spatial resolution of 0.05 degrees and eight days of temporal resolution. Due to the spatial resolution of the data set, the result might not be suitable for use at individual farm levels.

1.8. Organization of the Dissertation

The dissertation is structured into five chapters. The first chapter presents the introductory part containing the background, concise review literature, statement of the problem research questions, objectives and scope and limitation of the study. Chapter two presents the dissertation's first objective, assessing the drivers of land use and land cover transitions and their livelihood implications in the Awash-Awash sub-basin. Chapter three analyzed the spatiotemporal changes in mean and extreme climate and its agricultural implications in Awash-Awash sub-basin. Chapter four deals with disentangling climate from human-induced Net Primary Productivity and its agricultural implication in the Awash basin. Finally, the fifth chapter synthesizes the main findings of the study. It specifically describes the study's contributions and forwarded context-specific recommendations.

CHAPTER TWO

2. Farmers' perceptions and spatial statistical modeling of most systematic LULC transitions: drivers and livelihood implications in Awash Basin, Ethiopia[1]

Abstract

LULC studies have produced many methodological approaches that quantify and describe LULC change patterns and drivers. This study was conducted to quantify the major LULC transition and its drivers through a spatial statistical model by surveying the local understanding of possible drivers of LULC changes driving forces in the Awash-Awash River Sub-Basin. Landsat data from 1986 to 2018 were analyzed to understand the magnitude of LULC transitions. The study revealed that the LULC in the sub-basin is under a considerable change in pattern, structure, and extent. The amount of LULC that experienced loss and gains over the period indicates that the gains throughout a sub basin's bare land, cultivated land, and water bodies are related to the loss in shrub and bushland, forest, and woodland. The study revealed that about 52 % of the area experienced different forms of LULC transition and the remaining 48% of the area was persistent. The transition from shrub and bushland to cultivated land was identified as one of the strong signals of LULC transition in the sub-basin. The spatial explicit regression model result indicated that drivers such as elevation, the cosine aspect, and distance to the major river were significantly and positively associated with the transition from shrub and bushland to cultivated land. The socio-economic survey result showed that population growth, cultivated land expansion, deforestation and overgrazing, urbanization, infrastructure expansion, and government laws and regulations were drivers of LULC change in the study area. In contrast, variables like slope, sine of aspect, distance to town center, and major road were negatively associated with this LULC transition. Therefore, it would be vital to implement cohesive and viable land use planning to contribute considerably to the country's overall economic development.

Keywords: GIS and Remote Sensing; LULC transition; drivers; local perception; spatial statistical model

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[1] Damtew, A., Teferi, E. and Ongoma, V., 2022. Farmers' perceptions and spatial statistical modeling of most systematic LULC transitions: Drivers and livelihood implications in Awash Basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, *25*, p.100661. **https://doi.org/10.1016/j.rsase.2021.100661** (Elsevier)

2.1. Introduction

Land resources provide basic human needs and other multiple ecosystem services. Human-induced environmental change in the form of climate change, biodiversity change, and LULC change are the major challenges experienced in many parts of the globe (Nobre *et al.,* 2016; Cao *et al.,* 2019; Kertész et al., 2019; Näschen *et al.,* 2019). LULC is a dynamic process that is currently a leading-edge research topic in the field of global environmental changes (Lambin and Meyfroidt, 2011; Prestele *et al.,* 2017; Ayele *et al.,* 2018; Chang *et al.,* 2018). Direct and underlying factors have been considered as the two major ways LULC of a particular area is shaped (Lambin *et al.,* 2001). More recently, LULC change is also severely affected by globalized flows of goods, knowledge, capital, and people and is increasingly driven by factors in distant markets, often correlated with the growing urban consumer class in emerging markets (Meyfroidt *et al.,* 2013).

Land use and land cover changes have unique spatiotemporal attributes that seriously threaten the ecology (Ma *et al.,* 2020). The change affects climate by altering soil surface physical characteristics and atmospheric concentrations of greenhouse gases (Arora and Boer, 2010). These can directly or indirectly affect many people whose livelihood depends on agriculture (Pachauri et al., 2014). More particularly, changes in LULC affect the sustainability of environmental services through altering biological diversity (Jewitt et al., 2015; Sarparast et al., 2020), forest fragmentation (Kogo et al., 2019), water resources (Kumar et al., 2018; Nyatuame et al., 2020) increase natural disasters such as droughts and floods (Msofe et al., 2019; Samie et al., 2019) and have a significant effect on climate (Li et al., 2018). Therefore, characterizing LULC dynamics is crucial for understanding the interaction between human activities and global environmental changes and selecting and executing land use patterns to meet welfare and human needs (Guidigan *et al*., 2019).

Land use and land cover studies have employed many methodological approaches that focus on quantifying and describing patterns and drivers of LULC Change from different perspectives (Kuemmerle *et al.,* 2013; Meyfroidt *et al.,* 2013). Researchers have analyzed the change using the transition matrix table to make conclusions about LULC dynamics based on the net change, rate change, and type of change that happens between two different times (Chang *et al.,* 2018). At their investigation core, they use ‘net change’ as the dominant signal of landscape transition. This result fails to consider the reality on the ground, where there are simultaneous gains and losses in LULC change (Pontius *et al.*, 2004). For example, there would be zero net change due to sudden gain and loss of LULC within the landscape. This trend does not always indicate total change (Ouedraogo *et al.*, 2011; Zewdie and Csaplovics, 2016). In addition, net change fails to indicate the most dominant landscape change signal. This pattern does not offer insight into the likely processes that fix the LULC processes (Pontius *et al.,* 2004). Therefore, there is a need to find methods and indicators that show in-depth information about the prominent signals of LULC change (Pontius *et al*., 2004; Alo and Pontius, 2008; Teferi *et al.,* 2013; Teixeira *et al.,* 2014). Furthermore, quantitative outputs from earth observation tools do not provide insightful information about the driving forces behind the patterns of these changes (Kleemann *et al.*, 2017). Investigations that exclusively focus on biophysical, socio-economic, or political aspects are commonly seen in literature (Teferi *et al.*, 2013; Munthali *et al.,* 2020). However, a single research approach is insufficient for analyzing LULC change. Therefore, to better understand LULC changes and their determinants, combining earth observation information with land users' information is highly recommended (Bekele *et al*., 2019; Betru *et al.,* 2019).

The transition matrix method used in most LULC change studies fails to account for persistence land, which is used to separate land change according to their different components. This method fails to explain a detailed understanding of the processes driving the change and the major signal of LULC change (Veldkamp and Lambin, 2001; Pontius *et al.*, 2004). The methodology set out for this research focuses on identifying and analyzing inter-categorical random and systematic transitions, which makes it possible to emphasize the major signals of LULC (Pontius *et al.*, 2004). Based on methods developed and recommended by Pontius *et al.* (2004) and applied in previous studies (Ouedraogo *et al.,* 2011; Carmona and Nahuelhual, 2012; Adugna *et al.*, 2017; Haque and Basak, 2017; Deribew, 2019) it is important to emphasize detecting LULC transitions, as they give most important signals of change.

Furthermore, associating LULC changes to the drivers can also help to understand the nature of change, ascertain potential improvements, forecast likely trends of change, and suggest effective policy recommendations and responses (Braimoh, 2006; Alo and Pontius, 2008). Based on its ability to associate LULC transitions with explanatory variables, simplicity to compute and reliability of the results, spatially explicit modeling of LULC was found very helpful (Ouedraogo *et al*., 2016; Deribew,2019).

Deforestation and encroachment of cultivation into marginal areas are the major drivers of LULC change. In Ethiopia, agricultural land has expanded at the expense of natural vegetation (Wubie et al., 2016; Moges, 2018; Belay and Mengistu, 2019; Bekele et al., 2019; Kabite et al., 2020). Methodologically, LULC change research conducted in different parts of the country was done through the conventional cross-tabulation method (Mussa *et al.*, 2017;

Milkias and Toru, 2018; Athick and Shankar, 2019; Berihun *et al.*, 2019). Many studies did not emphasize the degree of LULC categories persistence relative to gross gains and losses; only recent studies addressed random and systematic LULC transition (Teferi *et al.*, 2013; Abate and Angassa, 2016; Zewdie and Csaplovics, 2016; Adugna *et al.*, 2017; Bekele *et al.*, 2018; Deribew and Dalacho, 2019) are outside the Awash River Basin. Hence, understanding the major processes of LULC transitions in the basin requires the detection of strong signal transitions and their determinants, which can be used for environmental management. Since the Awash River Basin is one of the most intensively used river basins in Ethiopia, its development is hindered by the recurrence of extreme climate events (Maru et al., 2021), rapid population growth, improper land use practices (Kassawmar et al., 2018; Bekele et al., 2019), and expansion of irrigation at the expense of vegetation resources (Degefa and Saito, 2017). This complex problem calls for intensive research on LULC dynamics.

The objectives of this study are, therefore, (1) to quantify the trend, extent, and spatiotemporal variability of LULC transitions in the period from 1986 to 2018; (2) to identify major signals of LULC transition and local perception about LULC change; and (3) to identify spatial statistical explanatory drivers of LULC transition in the sub-basin.

2.2.Materials and methods

2.2.1. Study area

Awash in Awash (hereafter Awash-Awash) sub-basin is one of six major water resource-planning areas classified based on hydrological, administrative, economic, and social boundaries in Awash River Basin (Awash River Basin Authority, 2017). The sub-basin, with a surface area of 12302.9 km2, is located between latitudes of 7°54′ and 9°16′N and 38°55′ and 40°46′E. The Keleta-Werenso River, Awash-Arba 1 and 2, and Awash-Arba 2 are the subbasin's three principal rivers. The altitude ranges from 744 to 4,181 meters above sea level (Figure 2.1). The slope gradient ranges from flat terrain at the valley's bottom to extremely steep slopes on the neighboring mountain ranges. According to FAO (1998), the dominant soils of the Awash-Awash sub-basin include Eutric cambisols (17%), Eutric regosols (12%), Vertic cambisols (8.9%), Leptosols (8.2%), Pellic vertisols (6.5%), and Orthic Luvisols (6%), which account for around 56% of the sub-basin. The average annual rainfall in the region is about 773 mm, while the annual mean maximum and minimum temperatures are 28.6 and 14.1 °C, respectively (NMA, 2019). The Inter-Tropical Convergence Zone (ITCZ) greatly influences the sub-basins' climate.

Administratively, the major area of the sub-basin is found in Oromia Regional State, and small areas are found in both afar and the Amhara Regional States. The sub-basin contains large, mechanized state and private farms such as Wonji-Shoa sugar factory, Fentale-Tibila, Metahara sugar factory and Upper Awash Agro-Industry. Various crops are cultivated, from cereals to vegetables, Khat (*Chata edulis*), perennial fruit orchards and sugarcane. The Central Statistical Agency (2007) estimated that the subbasin population was 2,093,216 in 2007 and was projected to reach 2,718,638 in 2019.

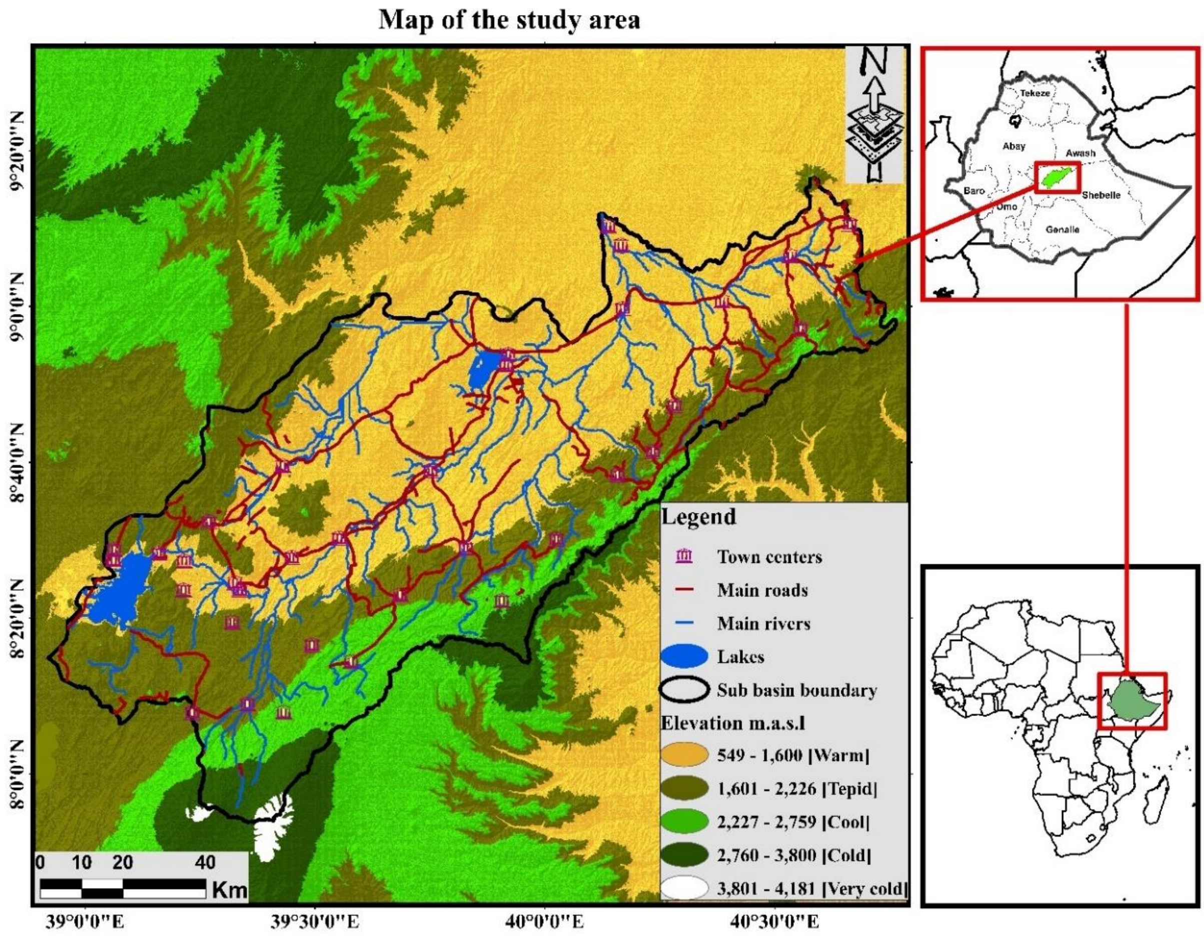

Figure 2.1. Map of the study area

2.2.2. Data and methodology

Spatial data

Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) data between the years 1986 and 1996 and 2006 and 2018 were used. The data was provided by US Geological Survey (USGS) (https://earthexplorer.usgs.gov/). The acquisition dates of satellite imagery were made between December and February. This was to reduce the impact of cloudiness and seasonal variation and enhance the classified imagery's accuracy (Table 2.1). Additionally, ASTER Global Digital Elevation Model (ASTER GDEM) version 3 (http://gdex.cr.usgs.gov/gdex/) was used to drive topographic attributes and then used to identify drivers of the most dominant signal of change in the sub-basin **(Table 2.6, and Annex A).** Proximity drivers such as proximity to a major river, major road networks and towns were calculated. Euclidean distance of locations to permanent rivers, town centers and major road networks were calculated. Major road networks and town center shape files were accessed from the Ethiopian Geospatial Information Agency (EGIA).

To minimize the effect of spatial autocorrelation, an initial random sampling of 252,745 observations (about 5 % out of 5,057,859 observations) was carried out for the model. Thus, 252,745 observations for Shrub-bushland to cultivated land transition were sampled with a proportion number of 0 and 1 observations of the dependent variable.

Table 2.1 Description of used satellite images

Satellite/ Sensor	Path/Raw	Acquisition date	Spatial resolution	Sun Elevation	Sun Azimuth
Landsat TM	167/054	1986/01/30	30*30m	44.7300	0.9851
	168/054	1986/01/21		43.9276	0.9840
Landsat TM	167/054	1996/02/11	30*30m	41.6238	0.9868
	168/054	1996/12/02		45.7073	0.9858
Enhanced TM +	167/054	2006/01/29	30*30m	49.0381	0.9849
	168/054	2006/02/05		50.0770	0.9859
OLI	167/054	2018/12/24	30*30m	49.8391	0.9839
	168/054	2018/12/15		50.6206	0.9846

Source: https://earthexplorer.usgs.gov/

2.2.3. Socio-economic data and method of analysis

Qualitative data from Key Informant Interview (KII), Focus Group Discussion (FGD), Field Observation (FO) and Household Survey (HHs) were used to assess local level perception about trends and drivers of LULC change in the sub-basin. To obtain in-depth and various information about the extent, trend, and drivers of LULC change, agro-ecology-based classification was used to select households and FGD participants in the sub-basin **(Table 2.7, Annex B).** A multistage sampling technique was applied to select the study area and sample respondents. Firstly, the Awash-Awash sub-basin was purposively selected as one of Ethiopia's environmentally fragile and vulnerable areas. Secondly, three woredas (districts) were identified and selected based on their unique agroecological zones. Thirdly, two kebeles (villages) from each district were chosen randomly. Finally, a simple random sampling technique was applied to obtain individual farmers from the available lists of each sample village. The Kothari (2004) formula was employed, and 384 HHs were proportionally selected as sample respondents. Close and open-ended questionnaires were employed to get possible drivers of LULC change in the study area.

Data collected from households was analyzed using STATA v.14, while FGD and KII were transcribed, summarized, and analyzed qualitatively. Finally, qualitative information gathered from key informant interviews, observation, and FGDs were used to triangulate, substitute, and complement Landsat quantitative information.

2.2.4. Image preprocessing and classification

The spatial and temporal resolution of the satellite imagery was modified to allow better classification and analysis of LULCs. A pre-field analysis map was prepared, and the ground-truthing was done by direct observation. Topo sheets scanned in the 1993 edition (0839 C2, 0839 B3 and 0839 B4) with a scale of 1:50,000 obtained from the Ethiopian Geospatial Information Agency (EGIA) were used for satellite image geo-references. They are re-projected into zone 37N, WGS 1984-Universal Transversal Mercator (UTM). The ground truth information was collected by GPS survey with an appropriate number of Ground Control Points (GCP) for the study area.

Before image classification, intensive image preprocessing was performed using ERDAS Imagine 2014 software. Contrast stretching was performed to increase the tonal distinction between various features in a scene, spatial filtering to enhance (or suppress) specific spatial patterns in an image, layer stacking, and mosaicking of the required bands. Arithmetic operations were performed to combine and transform the original bands into other images that highlight certain scenes' features. After creating subset images covering the sub-basin, a classification scheme was developed to derive various LULC classes of the sub-basin. For the 2018 Landsat image, about 2100 pixels were used to generate the signature of each land cover type.

Not surprisingly, the spectral signature between two or more classes can be similar **(**Lu *et al.*, 2010; Afrasinei *et al.*, 2018**)**. Different indices were computed to minimize confusion between the different LULC types. The land was separated from water bodies using Modified Normalized Difference Water Index (MNDWI) (Tian *et al.*, 2014; Rawat and Kumar, 2015). Normalized Difference Built-up-Area Indices (NDBAI) were computed to distinguish the bareland from built-up areas. However, NDBAI exaggerated the area of built-up areas, and sandy soils found in the lower part of the sub-basin were considered bareland.

Furthermore, because of the nature of the building material roof (earlier house roofs were built from straw and grass, and they look considerably like cultivated land. On the other hand, most recent houses were built from tin) and hence do not have similar reflectance of earlier Landsat image. In addition, with the presence of small-sized scattered settlements surrounded by cultivated land and the use of 30m spatial resolution of landsat image, spectral signature confusion was observed between built-up areas and cultivated land. Due to these facts, most built-up areas in the sub-basin were classified as cultivated land. Normalized Difference Vegetation Index (NDVI) was used to detect and separate vegetation distribution in the basin. As per the procedure followed by Kassawmar et al. (2016), repeated reclassification was applied following the selection of proper training signatures. Therefore, to reach the desired result, signature editions were performed via merging, deleting, and renaming the class categories (Figure 2.2). Finally, under the Maximum Likelihood Classification algorithm in ArcGIS 10.5, supervised classification and visual interpretation techniques were applied for all images (Haque and Basak,2017; Alam *et al.*, 2019). Setting training sites and using spectral information found in individual pixels to generate the LULC classes requires prior knowledge of the area. Based on our prior knowledge about the area, we defined and classified the study region LULC categories into major classes. The operational definition of each LULC category is given in (Table 2. 2).

Table 2.2 Operational definition and description of different LULC in Awash-Awash Sub River Basin

Category	Description
Bareland	Land surface devoid of vegetation mainly contains rocks and sands exposed to the surface found over the steep and gentle slope of mountains and valleys, non-agricultural bare soils.
Forestland	Montane evergreen forest, areas covered by trees forming closed or near closed canopies and plantation forest
Grassland	Landscapes in which grasses are the dominant vegetation types or areas dominated by natural grass and small shrubs, including areas used for traditional grazing and a bareland covered in seasonal grass.
Cultivated land	Arable and fallow land grows annual or perennial crops through rain-fed and small-scale or commercial irrigation. These LULC types also include all settlement types found in the sub-basin.
Shrub and bushlands	Lands covered by small trees, bushes, and shrubs and, in some cases, mixed with grasses; less dense than forest or woodland
Waterbody	Area covered by surface water.
Woodland	Acacia dominated land cover, and sometimes bushes, shrubs and tree species are mixed with it. This type of LULC is found in the middle and lower parts of the sub-basin.

2.2.5. LULC accuracy assessment

Individual pixels were used as validation units. Training sites (pixels) were identified from field observations, discussion with elders, image interpretation, and high-resolution images from Google Earth to generate the reflectance signature of each land cover type. For this study, reference points for geographically inaccessible areas such as dense forests and unnavigable water bodies and high-resolution Google Earth images were taken as reference points. As the sub-basin area is wide, the thumb rule of Congalton (2001) was selected for each LULC class of at least 75 samples (pixels). A stratified random sampling method was used to collect sample reference points from individual strata. This method is important because it increases sample size in groups that occupy a limited area to minimize standard errors in class-specific accuracy estimates (Olofsson et al., 2014). The number of samples was selected for each mapping class by assigning equal sample sizes to all strata. This procedure is important for estimating the user's accuracy and overestimating the producer's overall accuracy (Olofsson et al., 2012). Reference data for the 2018 accuracy assessment map were acquired at various sub-basin locations. Generally, each classified image was assessed using the post-classification function of ERDAS imagine 2014 by identifying 600 reference pixels from 2100 collected reference pixels.

The error matrix and kappa coefficient were used to assess image classification accuracy (Congalton, 2001; Rwanga and Ndambuki, 2017; Morales-Barquero *et al.*, 2019). The accuracy measures derived from the error matrices were computed as described in **(Table 2.8, Annex D).** The producer's accuracy is determined by dividing the overall number of pixels obtained from the sample reference data into the total number of pixels within a category. User accuracy is determined by dividing correctly identified sample units in the error matrix by the number of sample reference data. The accuracy was also determined by dividing the number of sample units correctly identified by the total number of sample units in the error matrix. Finally, kappa analysis (K) is the measure of agreement based on the arithmetic change between the actual agreement in the error matrix and the chance agreement indicated by the row and column totals (Congalton, 1991). The computational details are provided in the supplementary material (Eq. 15, **Annex C**).

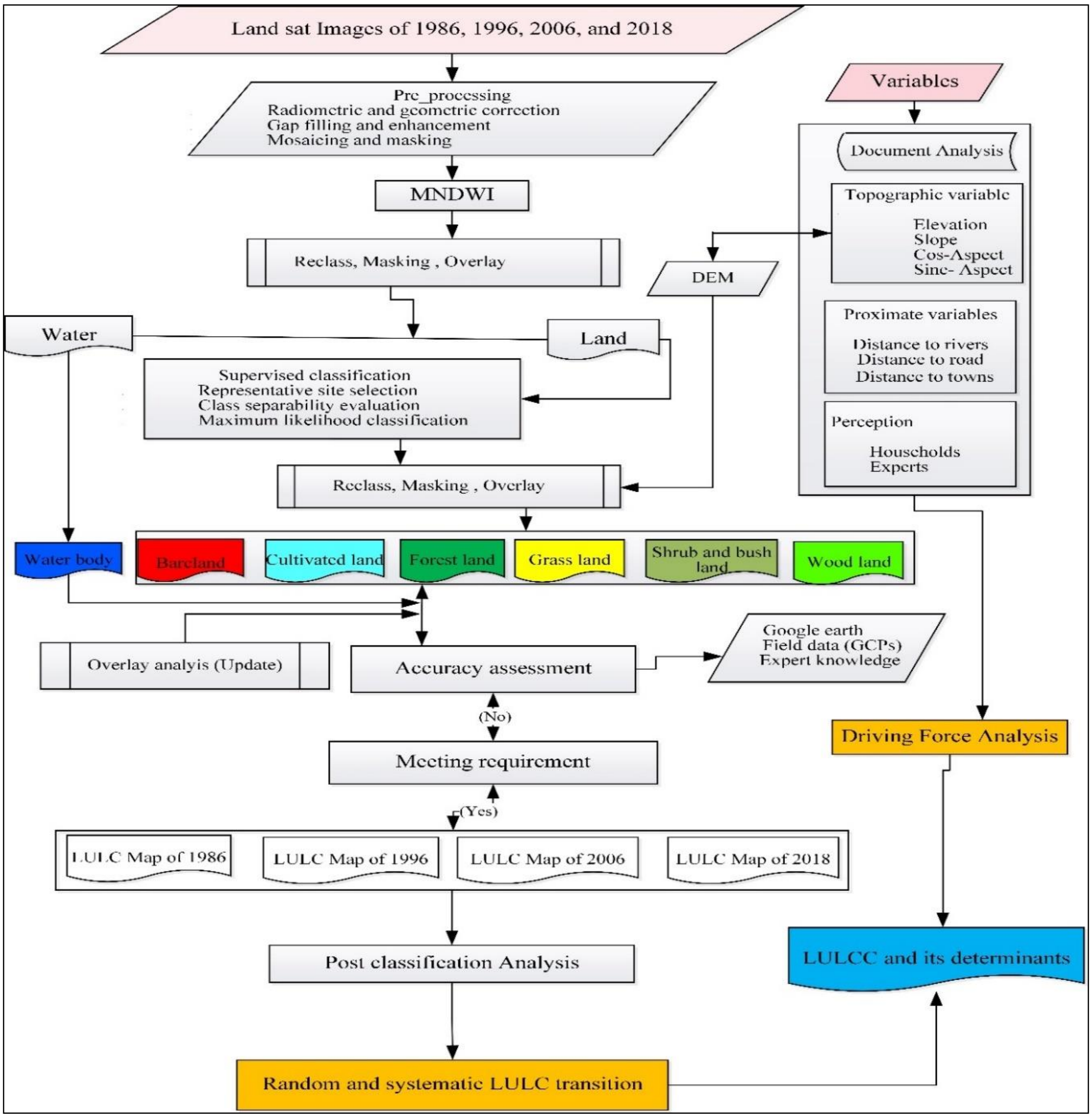

Figure 2.2. Flow chart showing the steps for identifying land use land covers.

2.3.Post classification processing

2.3.1. Land use and land cover change detection and analysis

Land use and land cover dynamics in the sub-basin were assessed by quantifying and evaluating changes in LULC classes during four periods: 1986–1996, 1996–2006, 2006–2018, and 1986-2018. The transitions among land use types can be described by a conversion matrix (Equation 1) that depicts the structural characteristics and the direction of land use changes**.** Many researchers (e.g., Shi *et al.*, 2018; Hu *et al.*, 2019) have successfully used this method.

$$\boldsymbol{X_{ab}} = \begin{vmatrix} X_{11}X_{12}X_{13} \cdots & X_{1n} \\ X_{21}X_{22}X_{23} \cdots & X_{2n} \\ \cdots\ \cdots\ \cdots & \cdots \\ X_{n1}X_{n2}X_{n3} \cdots & X_{nn} \end{vmatrix} \tag{1}$$

Where **X$_{ab}$** is converted the area from the **ath** to **bth** LULC type and reflected the number LULC, records on the diagonal (X_{ab}) indicated the persistence LULC category and were used to drive the losses and gains of the LULC category. The area transformed from class *a*” to “*b*” in the study time interval was shown by off-diagonal records (Pontius *et al.*, 2004). The proportion of the landscape category in time 1 (X_{a+}) and in category b in time 2 (X_{+b}) is given by Equation (2) and Equation (3), respectively. Gains, losses, total change, swaps, and persistence were computed for each classified image. The Gain (G_{ab}) of a given LULC was computed by deducting the persistence (X_{ab}) from the proportion of landscape category 2 (X_{+b}) (Equation 4). The Loss (L_{ab}), on the other hand, was calculated by deducting the persistence (X_{ab}) from the proportion of landscape category 1 (X_{a+}) (Equation 5).

$$X_{a+} = \sum_{a=1}^{n} X_{ab} \tag{2}$$

$$X_{+b} = \sum_{a=1}^{n} X_{ab} \tag{3}$$

$$G_{ab} = X_{+b} - X_{ab} \tag{4}$$

$$L_{ab} = X_{b+} - X_{ab} \tag{5}$$

Swap (Sb) is the ratio of a given class category that changes position by keeping the total surface area. Swap specifies that a lack of net change does not necessarily mean a lack of change in LULC in the sub-basin. It was calculated by multiplying two with the minimum value of the gains and losses (Equation 6). The net change indicates the definite change between the two periods. It was computed by deducting the total rows from the total columns. The total change for each category (X_b) was the sum of net change (D_b) and the swapping (S_b), or the sum of gain and loss (Equation 7).

$$S_b = 2 \times min(X_{b+} - X_{ab}, X_{+b} - X_{ab}) \tag{6}$$

$$X_b = (D_b + S_b) \tag{7}$$

To know the total percentage of change in each LULC category, Equation (8) was used. The annual rate of change in specific land use categories was also calculated by equation (9). These equations are well adopted by recent research (Sahle and Yeshitela, 2018; Abera et al., 2020).

$$\mathbf{P} = \left(\frac{\mathbf{A_{T2} - A_{T1}}}{\mathbf{A_{T1}}}\right) \times 100 \qquad \textbf{(8)}$$

Where P is the percent change in a land use type between initial time (T_1) and final time (T_2); AT_1 is the area of the land use at T_1 time; AT_2 is the area in Km^2 of the same type at T_2 time.

$$\boldsymbol{r} = \left(\frac{\mathbf{100}}{\boldsymbol{T_2 - T_1}}\right) \times \boldsymbol{ln}\left(\frac{\boldsymbol{A_2}}{\boldsymbol{A_1}}\right) \qquad \textbf{(9)}$$

Where r corresponds to the annual percentage of change of a single LULC, A_1 and A_2, represent the area in Km^2 of the specific LULC. T_1 and T_2 represent the time under the LULC study.

2.3.2. Detection of vulnerability to most systematic and random transition

The gain to persistence ratio (Gp), loss to persistence ratio and net change to persistence ratio (Np) were computed to measure a LULC’s gains relative to its initial period, losses relative to its initial period and to show the degree and direction of LULC class transition respectively. Gp and Lp value greater than one mean that a given class of LULC has a higher chance of moving to another class of LULC than of persisting in its current state. Unless the value of Np is negative, the LULC class would have a greater chance of losing area to other classes of LULC than gaining from them (Adugna *et al.*, 2017). The changes relative to the sizes of the categories are thus important to interpret because the systematic and random transition is evident (Pontius *et al.*, 2004). Random LULC transition happens if LULC class gains from other classes in proportion to their availability, and systematic transition occurs if the class loses to a certain class or a large deviation from a certain class. Earlier studies satisfactorily applied four sequential procedures and detected systematic and random transitions (Pontius *et al.*, 2004; Alo and Pontius, 2008). The first step begins by calculating the expected gain (E*Gab*) for each class under a random process of gain (Equation 10).

$$\boldsymbol{EG_{ab}} = (\boldsymbol{X_{+b}} - \boldsymbol{X_{ab}})\left(\frac{\boldsymbol{X_{b+}}}{\mathbf{100} - \boldsymbol{X_{b+}}}\right), \forall \boldsymbol{a} \neq \boldsymbol{b} \qquad \textbf{(10)}$$

where: E$G_{ab}$is expected gain of each cover type, $X_{a+}$is the proportion of land cover in 1986, $X_{+b}$is the proportion of land cover in 2018, and $X_{ab}$is the proportion of persistent land-cover classes.

In the second step, random gains were computed from the differences between the observed and expected proportions. Systematic transitions between categories were identified by detecting large negative or positive deviations from zero. If the difference between the observed and expected proportion is zero or close to zero, a random transition between two LULC classes will be noted. The third step computes the expected loss, EL_{ab}, under a random loss process using the formula in Equation 11. By making the loss of each class static, the equation proportionally distributes the losses of each row to existing LULC classes of 2018.

$$\boldsymbol{EL_{ab} = (X_{b+} - X_{ab})\left(\frac{X_{+b}}{100 - X_{+b}}\right), \forall a \neq b} \qquad \textbf{(11)}$$

In the fourth step, deduction of expected from observed random process of loss was undertaken. This deduction is to easily detect the existence of random and systematic transitions between groups. Large negative and positive deviations from zero suggest systematic transitions. Alo Pontius (2008) stated that the dominant signal of LULC change is detected when class 1 must systematically gain from class 2, and at the same time, class 2 must systematically lose to class 1.

2.3.3. Modeling drivers of the most dominant signal of transition

The identification of dominant change signals and quantification of explanatory variables were computed by following the standard logistic probability distribution assumption employed in previous studies (Teferi *et al*., 2013; Deribew, 2019). The binary logit model considers the outcome variables as dichotomous, which assumes the value of 0 (changed to other LULC) or 1(changed to cultivated land). In our situation, a dependent variable was shown to be the primary signal of changes from shrub and bushland to cultivated land between 1986 and 2018. The model assumes the dependent variables are the function of independent variables. Equation 12assumes the logarithm of the odds as the logit probability. Linear logistic regression appeared as *p* is the probability, and the analogous odds would be *p/(1-p).* The notation α is the intercept, and βn is the logit coefficient. Since the coefficient does not indicate the magnitude of change in the explanatory variable, it is essential to compute the standardized coefficient. The standardized coefficient assumes a unit change (here, standard deviation) in the explanatory variable on the probability of a dependent variable, i.e., probability (y=1). The expounding variables in this study were expressed following the probability in Equation (13). Explanatory variables were standardized to zero mean (ẍ) and a unit standard deviation (SD). This method can help to evaluate explanatory variables’ relative importance (Equation 14).

$$\boldsymbol{logit(p) = log\left(\frac{P}{1-P}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n} \qquad \textbf{(12)}$$

$$\boldsymbol{p = \frac{exp\ (\alpha+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_n X_n)}{1+exp\ (\alpha+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_n X_n)}} \qquad \textbf{(13)}$$

$$\boldsymbol{X'_i = \frac{X_i - \bar{X}_i}{SD}} \qquad \textbf{(14)}$$

2.4.Result and Discussion

2.4.1. Accuracy assessment results

All the images from the different years were classified with an overall accuracy above 85% and a kappa coefficient above 0.85, which are acceptable values for supervised classification (Wulder *et al.*, 2006). Validation of image classification results of the year 2018 using ground truth GPS points gave an overall accuracy of 92.16 % and a kappa coefficient of 0.90 **(Table 2.8, Annex D).**

2.4.2. Trends in land use and land cover transitions

Seven categories of LULC classes were identified and used for change detection. The main LULC types are bareland, cultivated land, forestland, grassland, shrub and bushland, water body, and woodland (Figure 2. 3).

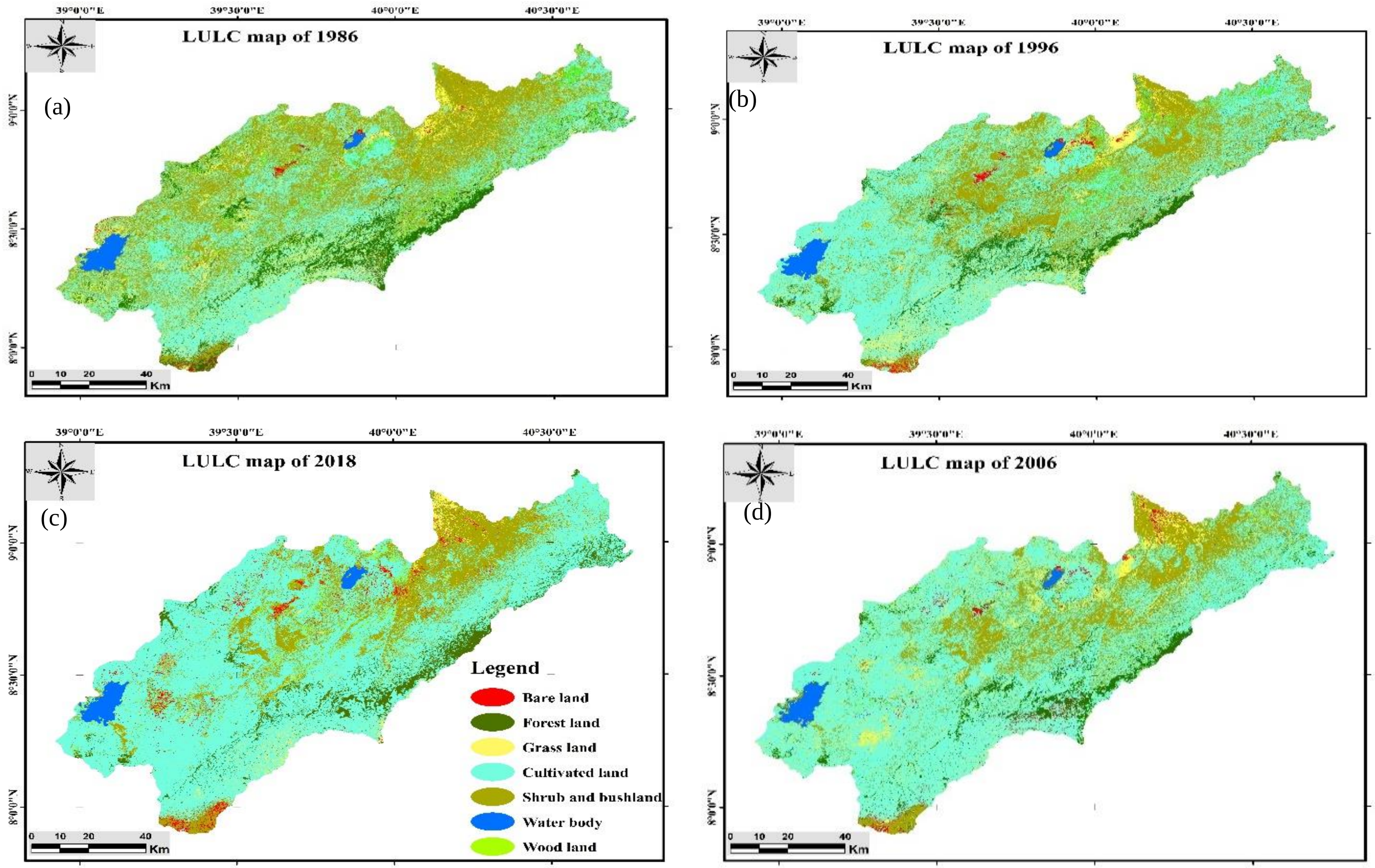

Figure 2.3. LULC map for (a) 1986, (b) 1996, (c) 2006, and (d) 2018 (the legend is similar for the maps)

The sub-basins LULC has recorded significant changes in pattern, structure, and extent (Figure 2. 3). Table 2.3 reveals the proportion of each LULC class that made a transition from one class to another for each of the study years. The change tendency of the main LULC class in the sub-basin from 1986 to 2018 is shown in Table 2.3. Between 1986 and 2018, bareland, cultivated land and waterbody increased in the area. However, grassland, woodland, shrub and bushland, and forestland declined.

During 1986 - 2018, considerable losses and gains among major LULC classes were observed (Table 2.3). Expansion in bareland, water body and cultivated land are among the changes attributed to gains, whereas the decline in shrub and bushland, woodlands, forestland, and grasslands are the major changes attributed to losses. Since 1986, cultivated land has experienced a significant transition from shrub and bushland (Table 2.3). Similarly, the gradual increase in bareland has come from shrub and bushland. Furthermore, the waterbody of the sub-basin area has gradually increased, and its major LULC transitions came from shrub and bushland. Gains in bareland, cultivated land and the water body of the sub-basin were likely because of the substantial changes in other LULC transitions.

Most importantly, it was related to the loss of shrub and bushland, woodland, and forestland (Table 2.3). The findings agree with recent studies conducted in different parts of the country, where the expansion of cultivated land in the sub-basin is mainly at the expense of shrub and bushland, woodland, and grassland losses. A study by WoldeYohannes et al. (2018) in the Abaya Chamo basin, Southern Ethiopia, from 1995 to 2010 showed a rapid change with high growth in agricultural areas at the expense of shrubland. Similarly, Meshesha *et al.* (2016) reported the expansion of agricultural land at the expense of grazing, barren and forestland in Baressa watershed in the highland part of the country from 1984 to 2015. However, the study by Adugna *et al.* (2017) in North-Eastern Wollega reported the opposite, where agricultural land was abandoned and naturally rehabilitated to the existing environment.

Furthermore, bareland expanded at the expense of shrub and bushlands and grasslands. This expansion occurred due to widespread land degradation (Belay *et al.,* 2014; Bekele *et al.*, 2019), urbanization (Athick and Shankar, 2019), quarry development and intensified. This result agrees with the findings of Gidey *et al.* (2017) over Northern Ethiopia, where bareland intensified. In addition, land clearing for cropland expansion, fuel wood gathering, and livestock grazing have been observed during fieldwork, which could lead to an increase in bare lands.

Likewise, findings in different parts of Ethiopia stated the shrinking of water bodies at the expense of agricultural land (Assen, 2011; Bekele *et al.,* 2018). However, in the study area, the water body is increasing in its area coverage. The expansion of water bodies in the sub-basin was related to the variability of Lake Beseka in response to the changes in its surface and subsurface constituents of the lake's water balance (Dinka, 2017) and the expansion of surface storage in major agro-industry farms and governments effort in expanding rainwater harvesting structures in the sub-basin. In addition, informants were asked from the surrounding lake Beseka and replied that during the past (some 40 to 50 years), the current lake used to be a pond created during times of the rainy season and diminished as the rainy season ceased. The second major LULC category, shrub, and bushland in the sub-basin, showed a decreasing trend throughout the analysis. This decline indicates other LULC categories for their gains targeted shrub and bushland.

On the other hand, woodland in the sub-basin area steadily declined from 1986 to 2006 (Table 2.3). Similarly, the total land area covered by forestland declined up to 2006; after that, both the forestland and woodland area of the basin recovered. This recovery was attributable to government and non-government support of household and community level afforestation and reforestation practices. Households living in highland parts of the sub-basin practice planting eucalyptus trees around the homestead for commercial, household energy, and construction purposes.

Table 2.3 Percentage of land use and land cover change flow matrices and vulnerability indicators

1986/1996	BL	CL	FL	GL	SBL	WB	WL	TOTAL	Loss (L_{ab})	(X_{ab})	(C_b)	(D_b)	(S_b)	(L_p)	(G_p)	(N_p)
BL	0.2	0.3	0	0.1	0.1	0	0	0.9	0.6	0.2	1.5	0.2	1.3	2.6	3.5	0.8
CL	0.2	24	0.9	3.2	11.5	0.1	0.4	40.3	16.3	24	45.6	13	32.5	0.7	1.2	0.5
FL	0.2	2.8	3.1	0.4	1.2	0	0	7.7	4.6	3.1	11.2	2.1	9.2	1.5	0.8	-0.7
GL	0.1	4.9	0.5	1.6	2	0	0.1	9.3	7.7	1.6	16.8	1.5	15.3	4.7	3.7	-0.9
SBL	0.3	19.4	0.6	2.3	13.5	0.1	0.7	37	23.4	13.5	54.9	8.1	46.9	1.7	1.1	-0.6
WB	0	0	0	0	0	1.6	0	1.7	0	1.6	0.2	0.1	0.1	0	0.1	0.1
WL	0	1.9	0.4	0.1	0.5	0	0.2	3.2	3	0.2	4.7	1.7	3	17.7	7.8	-10
Total	1.1	53.3	5.6	7.8	28.9	1.8	1.5	100	55.7	44.3	134.9	26.7	108.2			
Gain	0.8	29.3	2.5	6.1	15.4	0.2	1.3	55.7								
1996/2006																
BL	0.2	0.5	0.1	0.1	0.3	0	0	1.1	0.9	0.2	2.4	0.9	1.4	5	5.9	0.9
CL	0.4	38.4	1.3	3.6	8.9	0.2	0.6	53.4	15	38.4	75.1	58.5	16.6	0.4	0.6	0.2
FL	0	2.3	2.5	0.1	0.5	0	0.2	5.6	3.1	2.5	11.7	0.7	11	1.2	0.8	-0.4
GL	0.4	5.5	0.1	1.1	0.6	0	0	7.8	6.6	1.1	11.6	6.1	5.5	5.9	5.4	-0.6
SBL	0.3	15.2	0.4	2.1	10.6	0.2	0.1	28.9	18.4	10.6	44.4	7	37.4	1.7	1	-0.7
WB	0	0.1	0	0	0.1	1.6	0	1.8	0.2	1.6	2	1.9	0.1	0.1	0.3	0.1
WL	0	0.6	0	0.2	0.6	0	0.1	1.5	1.4	0.1	4.8	1.5	3.2	26.5	20.6	-5.9
Total	1.2	62.5	4.5	7.1	21.5	2	1.1	100	45.5	54.5	54.5	76.6	75.4			
Gain (G_{ab})	1	24.1	2	6	10.9	0.4	1	45.5								
2006/2018																
BL	0.3	0.6	0	0.1	0.3	0	0	1.2	1	0.3	2.6	0.7	2	3.8	6.3	2.5
CL	0.9	49.6	2.3	1.5	7.4	0	0.8	62.5	12.9	49.6	30.7	4.9	25.8	0.3	0.4	0.1
FL	0.1	1.5	2.4	0.1	0.4	0	0.1	4.5	2.1	2.4	5.2	1	4.2	0.9	1.3	0.4
GL	0.2	4.6	0	0.4	1.8	0	0	7.1	6.7	0.4	9	4.3	4.7	15.2	5.3	-9.9
SBL	0.4	10.1	0.4	0.6	8.9	0.4	0.7	21.6	12.7	8.9	22.7	2.8	20	1.4	1.1	-0.3
WB	0	0.3	0	0	0	1.6	0	1.9	0.3	1.6	0.8	0.1	0.7	0.2	0.3	0
WL	0	0.6	0.3	0	0.2	0	0	1.1	1.1	0	2.7	0.5	2.2	68.1	98.5	30.4

Total	1.9	67.3	5.5	2.8	18.8	2	1.6	100	36.8	63.2	73.7	14.2	59.5			
Gain (G_{ab})	1.6	17.8	3.1	2.3	10	0.4	1.6	36.8								
1986/2018																
	BL	**CL**	**FL**	**GL**	**SBL**	**WB**	**WL**	**TOTAL**	**Loss (L_{ab})**	**(X_{ab})**	**(C_b)**	**(D_b)**	**(S_b)**	**(L_p)**	**(G_p)**	**(N_p)**
BL	0.2	0.4	0	0	0.3	0.1	0	1	0.8	0.2	2.5	0.8	1.6	5.3	10.5	5.2
CL	0.4	31.9	1.1	1.1	5	0.2	0.6	40.3	8.4	31.9	43.6	26.9	16.7	0.3	1.1	0.8
FL	0.1	3.8	2.8	0.1	0.7	0	0.1	7.7	4.8	2.8	7.5	2.1	5.4	1.7	1	-0.8
GL	0.3	6.6	0.5	0.4	1.3	0	0.1	9.3	9	0.4	11.3	6.6	4.7	19.9	0.3	-19.7
SBL	0.7	22.6	0.5	1	11	0.3	0.8	37	25.9	11	33.9	18	15.9	2.3	0.7	-1.6
WB	0	0	0	0	0	1.5	0	1.6	0.1	1.5	0.6	0.5	0.1	0	0.4	0.3
WL	0	1.9	0.6	0.1	0.5	0	0.1	3.2	3.1	0.1	4.7	1.6	3.1	52.1	26	-26.1
Total	1.8	67.2	5.5	2.8	19	2	1.6	100	52	48	104.1	56.6	47.5			
Gain (G_{ab})	1.6	35.3	2.7	2.3	7.9	0.5	1.6	52								

BL: Bareland, CL: Cultivated land, FL: Forestland, GL: Grassland, SBL: Shrub and Bushland, WL: Woodland, WB: Water body, Obs: Observed, X_{ab}: Persistence, C_b: Total change, D_b: Net change, S_b: Swap, Gain-to-persistence (G_p), Loss-to-persistence (L_p), and net change-to-persistence (N_p) ratio of the land cover classes in the Awash-Awash Sub-Basin, Ethiopia

2.5. Vulnerability and identification of major signals of LULC transition

The result analysis in Table 2.3 also identified vulnerability and major signals of change observed during the entire study period (1986–2018). Compared to other LULC categories, cultivated land shares the highest area and experienced the topmost persistence, 31.9%. Similarly, this LULC class experienced the highest gain compared to other LULC categories, with a net gain of 35.3%. However, shrub and bushland experienced a significant loss of about 25.9%. Major vulnerable LULC classes in the sub-basin were identified by computing the gain-to-persistence ratio (G_p), the loss-to-persistence ratio (Lp), and Net change-to-persistence (N_p). Instantaneous losses and gains were observed in every LULC class except cultivated land and water bodies **(Table 2.10, Annex E).** Correspondingly, woodland, bareland, cultivated land experienced less persistence than gain. The net change to persistence (Np) is negative for woodland, grassland, Shrub and bushland, and forestland. This result indicated that these LULC classes are more likely to change areas to other LULC classes.

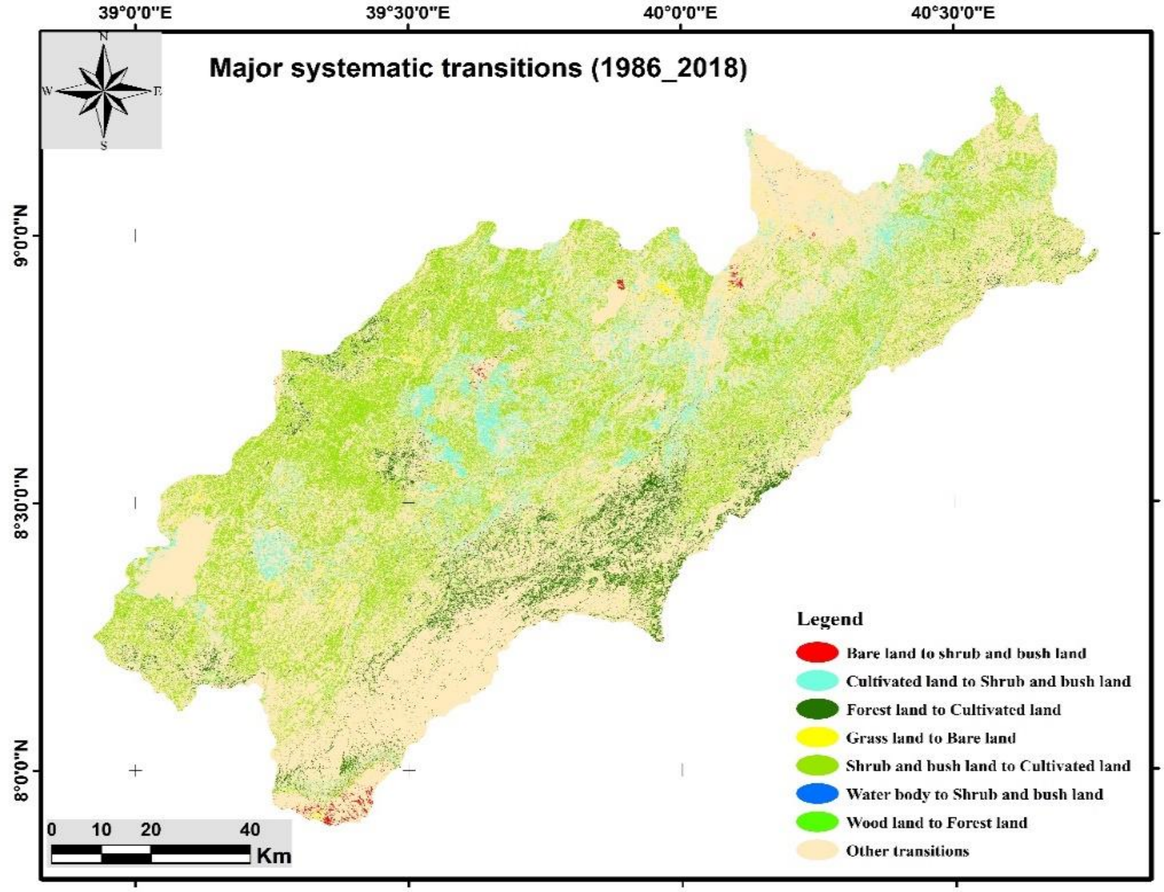

Figure 2.4. Map of spatial representation of the major systematic LULC transition between 1986 and 2018.

The results show that the study area experienced both random and systematic land cover transitions from 1986 to 2018 (Table 2.4, Figure 2. 4). The study identified the major difference between observed and expected gains under the random process of change for shrub and bushland to cultivated land, which is about 4.9%. On the other hand, shrub and bushland systematically gained 1.5% from cultivated land (Table 2. 4). This indicated that cultivated land systematically gained 22.6% of shrub and bushland (Table 2. 3). There is a systematic transition from cultivated land to shrub and bushland (2.7%) as cultivated land was systematically gaining from shrub and bushland. At the same time, shrub and bushland were systematically losing to cultivated land. Similarly, shrub and bushland systematically gained (0.7%) from the bareland, followed by grassland (0.4%) (Table 2.3). Thus, the transition of 0.3% of the area from bareland to shrub and bushland was due to systematic change processes (Table 2.3). In contrast, the difference between observed and expected gains of cultivated land from bareland expressed by negative values tells that cultivated land avoided systematical gains from bareland **(Table 2.10,** and **Annex E).**

The concurrent occurrence of systematic gains and losses in the sub-basin gives major clues about the most dominant signals of change (Ouedraogo *et al.*, 2011). Therefore, the study identified the highest difference between observed and expected gains under an unexpected change from shrub and bushland to cultivated land. On the other hand, shrub and bushland were systematically gained from cultivated land (Table 2.3). Similarly, the transition of bareland to shrub and bushland, bareland to a water body, cultivated land to grassland, forestland to cultivated land, and woodland to forestland, grassland to cultivated land was systematic (Table 2.3). The systematic conversion of shrub and bushland agrees with studies conducted in different parts of the country. The study by Teferi et al. (2013) was also consistent with our finding that a systematic transition of cultivated land came from grasslands. Furthermore, newly cultivated land tends to gain systematically from shrub and bushlands (Bekele *et al.*, 2018) and forestlands (Braimoh, 2006). Nevertheless, the gains and losses of LULC transitions in this study are not systematic Because of different factors of LULC transition.

Table 2.4 Random and systematic transition (1986-2018)

1986/2018	BL		CL		FL		GL		SBL		WB		WL	
	D_{jj}*	R_{ij}	D_{jj}	R_{ij}	D_{jj}	R_{ij}	D_{jj}	R_{ij}	D_{jj}	R_{ij}	D_{jj}	R_{ij}	D_{jj}	R_{ij}
BL	**0.0**	**0.0**	**0.1**	**0.2**	**0.0**	**-0.1**	**0.0**	**-0.3**	**0.2**	**2.5**	**0.1**	**18.1**	**0.0**	**-1.0**
	0.0	0.0	-0.2	-0.3	0.0	-0.5	0.0	-0.3	0.1	0.7	0.1	4.9	0.0	-0.9
CL	**-0.3**	**-0.5**	**0.0**	**0.0**	**-0.1**	**-0.1**	**0.1**	**0.1**	**1.5**	**0.4**	**-0.1**	**-0.3**	**-0.1**	**-0.1**
	0.1	0.6	0.0	0.0	0.3	0.4	0.7	1.8	2.3	0.9	-0.1	-0.4	0.4	1.6
FL	**0.1**	**0.0**	**0.9**	**0.3**	**0.0**	**0.0**	**0.0**	**-0.2**	**0.1**	**0.2**	**0.0**	**-0.9**	**-0.1**	**-0.6**
	0.1	0.5	0.2	0.1	0.0	0.0	0.0	0.0	-0.3	-0.3	-0.1	-1.0	0.0	-0.4
GL	**0.4**	**0.0**	**3.0**	**0.8**	**0.2**	**0.7**	**0.0**	**0.0**	**0.5**	**0.7**	**-0.1**	**-1.0**	**-0.1**	**-0.6**
	0.2	1.0	0.0	0.0	-0.1	-0.1	0.0	0.0	-0.5	-0.3	-0.2	-1.0	-0.1	-0.6
SBL	**0.7**	**0.0**	**4.9**	**0.3**	**-0.8**	**-0.6**	**-0.1**	**-0.1**	**0.0**	**0.0**	**0.0**	**-0.1**	**0.1**	**0.1**
	0.0	0.0	-5.1	-0.2	-1.8	-0.8	-0.1	-0.1	0.0	0.0	-0.6	-0.7	0.2	0.3
WB	**0.0**	**0.0**	**-0.5**	**-1.0**	**0.0**	**-1.0**	**0.0**	**-1.0**	**-0.1**	**-0.7**	**0.0**	**0.0**	**0.0**	**-1.0**
	0.0	-0.3	0.0	0.0	0.0	-1.0	0.0	-0.5	0.0	1.8	0.0	0.0	0.0	-1.0
WL	**0.0**	**0.0**	**0.8**	**0.7**	**0.5**	**5.4**	**0.0**	**-0.2**	**0.3**	**1.1**	**0.0**	**-0.9**	**0.0**	**0.0**
	0.0	-0.5	-0.3	-0.1	0.4	2.2	0.0	-0.4	-0.1	-0.1	-0.1	-1.0	0.0	0.0

*D_{ij} = the difference between the observed and the expected value, R_{ij} = the difference between the observed and the expected value, relative to the expected value. The numbers in bold are values for the gains (%), and the numbers in normal font are valued for the losses (%). The systematic transitions are highlighted.

2.6. Drivers of the locations of the most systematic transitions

2.6.1. Perception of major drivers of LULC transition

The focus group discussants argued about the range of LULC change drivers and their effects. Similarly, our key informants from government offices and community elders described many of the causes of LULC change in their area. Households were also asked to describe various biophysical, demographic, economic, infrastructural, and technological factors. The informants described seven drivers as important to land-use/cover changes in the study area (Figure 2.5). The topmost important drivers of LULC change perceived by the sampled households were population growth (94.5%), agricultural land expansion (86.5%), deforestation and overgrazing (69.8%), and urbanization (63%).

The focus group discussant and community elder key informants strongly emphasized the growth of population, agricultural land expansion, deforestation and overgrazing as the major contributor to LULC change. Furthermore, they ranked infrastructural expansion (46.9%), poverty (40.9%), government laws (28.1%), and quarry site development (20.8%) as the drivers of LULC change in their respective areas change. Discussion with key informant interview at district level shares the ideas of focus group discussant and elders.

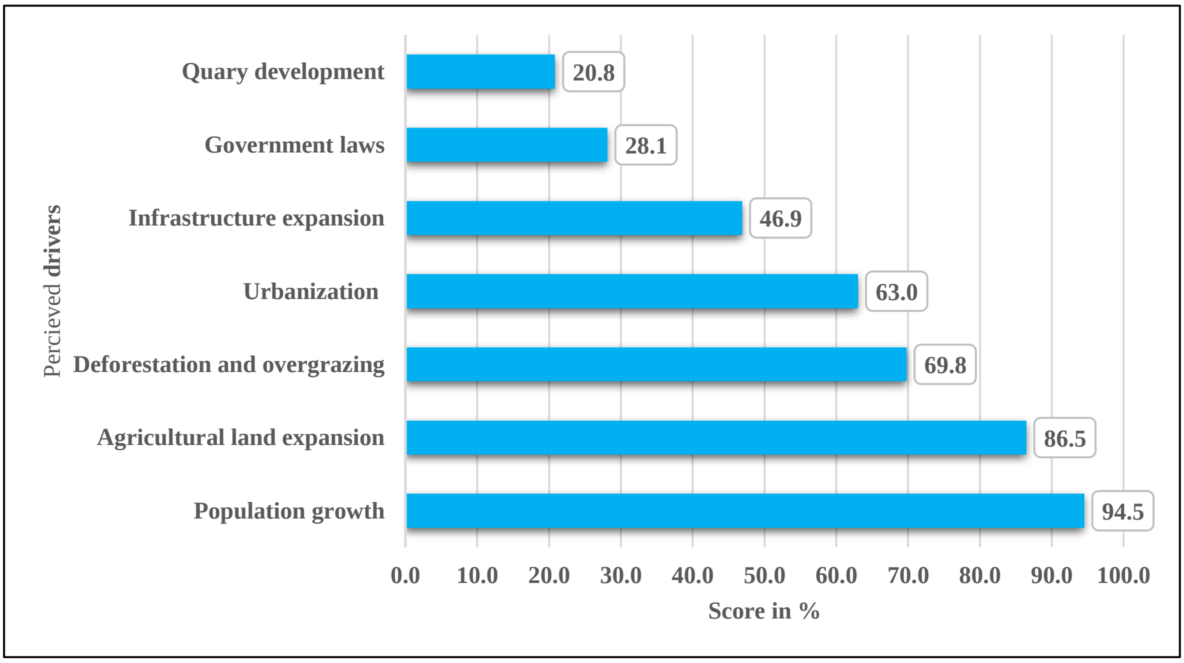

Figure 2.5. Perceived drivers of land use and land cover change

In Ethiopia, the distribution and change in LULC are usually associated with changes in demographic characteristics (Bekele *et al.*, 2019; Abera *et al.*, 2020; Ewunetu *et al.*, 2021). Most sample respondents (94.5%) stated that the increase in population size (the number of persons in the village) was the direct driver of LULC change in the sub-basin. The high population growth rate in the study area has exerted multiple effects on land resources. As per discussion with focus group discussants, an average of 5 to 7 people live under a single roof. One discussant from Gebbe village of Lode Hitosa district stated that.

> "To feed the increasing family, it is unquestionable to have enough cultivated land. So, where do farmers access that land? Many farmers are forced to convert land once used and covered by either forest or grassland."

Statistical data from Central Statistical Agency (CSA, 1994, 2007) shows that the population of the sub basin is increasing by 58.5 % over 32 years (Table 2.5). This change shows that the population was exerting multiple pressures on land resources. Our informants from different villages share a similar understanding of population growth as the most important determinant of LULC change in their area. Key informants from the districts elaborated that population growth is a fundamental reason behind LULC dynamics in their districts. According to them, each newborn needs land for cultivation, built-up area, and other needs, which entirely depend on these fixed and limited resources. The study was conducted in different corners of the country, e.g., Northern Ethiopia by Ewunetu *et al.* (2021), Northwestern Ethiopia (Dibaba *et al.,* 2020), Central Ethiopia by (Tessema *et al.*, 2020), and Western Ethiopia (Betru *et al.*, 2019) were consistent with our finding where population growth was perceived and reported to be the main determinants of LULC change.

Table 2.5 Demographic characteristics of the sub-basin

Year	**Growth Rate**	**Population data**	**Population density (Pop. number/Km^2)**
1986	2.9	1,126,031	91.52
1996	3.0	1,504,858	122.3
2006	2.6	2,034,258	165.4
2018	2.6	2,714,747	220.7

Source: 469 Kebele based CSA census of 1994 (1,418,356) and 2007 (2,093,210)

Expansion of agricultural land was also perceived as the major cause of LULC change in the study area. Smallholder farmers were forced to convert marginal lands to cultivated land due to population growth, low cropland productivity and increasing land degradation (Shawul and Chakama, 2019). In the current setting in the study area, it is normal to see the expansion of agricultural land in areas experts do not recommend. These areas include steep slopes once covered by forest, bush and shrublands, and grasslands. The traditional land preparation practice for cultivating cereal crops in the study area was also considered the cause of LULC conversion, leading to the expansion of bareland in the study area. Key informants from Lode Hitosa and Merti districts stated that some districts are prone to land degradation because of poor land management practices in the highland and rugged terrain. Our findings agree with recent studies conducted in various parts of the country (Ayele *et al.*, 2018; Ewunetu *et al.*, 2021), where agricultural lands are expanded at the expense of marginal lands.

Deforestation and overgrazing are ongoing problems in the basin that alters the ecosystem service and lead to major socio-economic and environmental consequences (Oljira *et al.*, 2019). According to the focus group discussants, the vegetation resources of their village are continually decreasing. This trend was mainly associated with expanding agricultural land to fulfill domestic energy, source of off-farm income and construction material. Furthermore, key informant interviews were conducted with three sub-basin district agricultural officers, who reported that the loss of the area's vegetation resources is an overwhelming reality. The loss of vegetation cover in their corresponding district mainly resulted from expanding agricultural land at both small farm levels and large commercial farming. Merti district agricultural expert said that much of the shrub and woodlands in the district were cleared for commercial farming mainly by upper awash agro-industry and other similar irrigation-based commercial farms. Adama district agricultural experts also stated the conversion of shrub and bushland, grassland, and woodland to agricultural land by Wonji sugar factory, to urban land by expansion of urban centers like Adama are the main causes. This is Due to the growing demands of commercial agricultural land in the area, existing land uses are being converted without due consideration of optimal land use potentials and are being undertaken in a manner that adversely impacts the functioning of vital ecosystem and healthy environments.

Similarly, experts stated that the household contribution to vegetation loss is immense as they clear the vegetation resource for their livelihoods, such as the source of income for farmers through selling firewood and charcoal, expanding their farmland to marginal lands and lack of farmland management. Communities that reside around forest areas use the forest for day-to-day livelihoods. Interviewed community elders in the area responded that there is a quite visible difference in vegetation cover over the years. One elder informant from Merti district, Watero Dino village, reacted to the degree of vegetation loss as:

> "The forest resource I never expect to lose in my age is unexpectedly deforested."

This perception amplifies the vegetation loss in the area. Furthermore, the informants stated that demand for productive land, population growth, construction material and household energy consumption (firewood and charcoal production) lead to a great loss of vegetation resources. Charcoal and firewood production from the lower parts of the sub-basin is favored by major roads that cross the sub-basin and proximity to major towns like Metehara, Wolenchiti, and Adama. Focus group discussants explained that the destruction of the vegetation resources has negatively affected households who benefited greatly from it. One woman discussant from Gedemsa Kurfa village, Adama district, elaborated that the loss of woody vegetation caused her to travel long distances to collect firewood and be exposed to different socio-economic challenges. Discussant from Tullu Jebi village, Lode Hitosa district, stated that the loss of firewood and construction materials forced many farmers to plant *eucalyptus* trees around their homestead, and now even it is considered as one source of off-farm income for most rural households. Our observation agrees with previous studies (Dessie et al., 2019; Oljira et al., 2019) conducted in different parts of the country, where eucalyptus trees are considered a source of off-farm income.

In contrast, the transect walk in the lower parts of the sub-basin showed expansion of exotic plant species called *Prosopis juliflora*. A significant land use change and conversion occurred in the recent decade. According to an informal interview with local dwellers in Gelcha village of the Fentalle district, the land area covered by *P. juliflora* has been expanding at the expense of grazing, cultivation, and woodland. The observation results supported research findings from earlier studies (Mehari, 2015; Shiferaw *et al.*, 2019), where this invasive plant species is widespread in the middle and lower part of the Awash Basin.

The sub-basin is endowed with various livestock due to diversity in the agroecological zone. Even though livestock productivity is low, most smallholder farmers in the sub-basin still practice free grazing on very limited communal land. According to participants in a focus group discussion in Sekekelo village, Adama district, it has become common to see communal lands devoid of grasses even during the rainy season. This evidence shows how much grazing land is being degraded by overgrazing. Likewise, district experts affirmed the situation and added that the production and productivity of the livestock sector in their district are very low. The low level of local breed productivity, the low adoption rate of livestock feed and forage varieties, the low level of agricultural extension works, and the perception of smallholder farmers to continually see the number of livestock as an indicator of wealth contributed to overgrazing in their district. A transect walk conducted by the first author in different sub-basin areas verified the situation. Even in the lower part of the sub-basin, the agro-pastoralist is forced to encroach on Awash National Park to feed their livestock, and they are continually in conflict with park administrators.

As part of a developing countries, Ethiopia's high rate of urbanization in Ethiopia threatens the urban and surrounding environment differently (Geleta *et al.,* 2020). Discussion with key informants and the household survey indicated that urbanization and infrastructural expansion is another important determinant that changed LULC in the sub-basin. As the sub-basin is of geologically rich areas, different parts of the sub-basin are endowed with active quarry sites. Expanding small and medium-scale industries, towns, and infrastructural development in the sub-basin accessed these sites as a raw material for constructing infrastructures (mainly roads). The expansion of asphalt roads, gravel roads, small streets, and towns are also contributing to the dynamicity of LULC in the sub-basin.

Policy and institutional amendments and changes on land resource management by different regimes in Ethiopia resulted in its role in LULC change in the sub-basin. Unregulated urban expansion, infrastructures development and human settlements have also contributed to shrinking land resources and inefficient land usage. The situation is exacerbated by the lack of a comprehensive land use policy and appropriate institutional arrangements. Furthermore, households stated that government laws towards different land use promotions contributed to LULC change in their area. Key informant interviews with district officers believed that agricultural investment promotion along river edges in the form of small, medium, and large-scale irrigation in their district is considered a determinant factor that changed LULC. Land reform conducted in 1974, the resettlement program of the 1980s, extensive campaign works in the form of food for work program, and more recently, intensive Soil and water conservation (SWC) practices in different parts of the sub-basin are also among the major perceived drivers of LULC change. All key informants mentioned that the favorability of soil, climate, slope, altitude, and permanent rivers in the study area still contribute to the transitions between land use and land covers. Different socio-economic and environmental factors are responsible for LULC transition in the study area.

2.6.2. Topographic and proximity drivers

Table 2.6 List of driving forces for systematic LULC transitions in the sub-basin

Dependent Variable	**Model Evaluation**	**Independent Variables**	**Unstandardized logit Coefficient.**	**St.Err.**	**Standardized logit coefficient**	**Standard deviation**	**Sig**
SBL to CL conversion	LR X^2 =83966.81 (P<0.000) AdjustedR^2= .962 ROC=.817	ELEV	0.268	0.001	0.999	265.6	***
		SLP	-0.073	0.001	-0.271	5.891	***
		COS-ASP	0.005	0.001	0.02	0.71	***
		SIN-ASP	-0.007	0.001	-0.027	0.708	***
		DIS-TC	-0.007	0.001	-0.027	1500.2	***
		DIS-RIV	0.038	0.001	0.142	5596.7	***
		DIS-RD	-0.016	0.001	-0.058	2967.2	***
		Constant	0.579	0.001	0.031	-	***

****** p<.01, ** p<.05, * p<.1, ELEV=Elevation, SLP=Slope, COS-ASP=Cosine of aspect, SIN-ASP=Sine of aspect, DIS-RIV=Distance to river, DIS-TC=Distance to town center, DIS-RD=Distance to major road***

A major change signal was detected in the LULC transition from shrub and bushland to cultivated land. Table 2. 6 and Figure 2. 5 shows observed major signals of LULC transitions between 1986 and 2018. After identifying the major transition signal in the basin, the binary logistic regression model was used to predict and analyze the determinants of this transition. Based on the availability of spatial data, four topographic and three proximate drivers were identified and used to feed the model. In addition to these determinants, survey-based qualitative and quantitative data were collected and used to supplement the analysis. Relative operating characteristic (ROC) was checked to test the errors incurred in the predicted model for better decision-making (Table 2.6). The evaluation of binary logistic regression model outputs shows the Likelihood Ratio or Chi-square (LR X^2 = 83966.81, adjusted R^2 = 0.962 with the degree of freedom df =1 and significance level (p) < 0.000 and number of observation (N) = 252,745. The model's goodness of fit is excellent ROC = 0.817 (81.7%) as per the rate (Archer and Lemeshow, 2006). The model predicted that 74.5% was correctly classified. The determinants of changes indicated in Table 2.6 explained variables such as (elevation, cosine of aspect, and distance to the major river) which are positively associated with the transition from shrub and bushland to cultivated land. In line with this, computed variables contribute statistically significantly to shrub and bushland to cultivated land conversion in the Awash-Awash sub-basin.

The positive sign of topographic variables (elevation and aspect) indicates the increasing probability of shrub and bushland to cultivated land conversion (Table 2.5). Hence, massive shrub and bushland conversion was observed at relatively higher altitudes. A unit standard deviation increase in elevation (266m) is associated with a (.999) standard deviation increase in the logit of shrub and bushland to cultivated land conversion. This trend can be explained by the favorable condition for agriculture's high population in higher elevations than in low elevated areas (Debesa *et al.*, 2020). Furthermore, the positive sign of the cosine of aspect (Northness) and the negative sign of the Sine aspect (Eastness) indicate the probability of conversion of shrub and bushland to cultivated land is positively correlated with Northness than Eastness. Shrub and bushland to cultivated land conversion increase with approaching the north-facing slope, suggesting the slope direction is much extended by cultivated land than other LULC in the sub-basin. The positive sign of distance to major rivers indicates the probability of shrub and bushland to cultivated land conversion increases as one moves to the rivers. A unit standard deviation increase (5.597km) is associated with a (0.142) standard deviation increase in the logit of shrub and bushland to cultivated land conversion. This result shows that the shrub and bushland conversion is positively associated with distance to the rivers. The probability of shrub bush to cultivated land conversion increases from 0.55 to 0.67 for an increase in distance from major rivers 0–35km **(Annex G,** and **Table 2.11).** Even at 1m from the river edge, the predicted probability is 0.49. This figure suggests a moderately higher probability of loss in shrub and bushland during the transition. With a gentle slope and fertile soil, irrigated agricultural land expansion in the middle and lower part of the sub-basin was favored by the nearness to rivers like Keleta, Awash Arba 1 and Awash Arba 2. A study by Zhao *et al.* (2018) in Southwestern China bears the same result, where the distance from rivers plays a key role in the irrigated land expansion.

The topographic variable's statistically significant and negative sign (slope) indicates the probability of shrub and bushland to cultivated land conversion can decrease as one moves to a steeper slope. A unit standard deviation increase (5.9 degrees) in slope will decrease the probability of shrub and bushland to cultivated land by (-0.271). According to Birhane et al.

(2019), who studied how LULC changed over topographic gradients in Northern Ethiopia, cultivated land is significantly more prevalent than other land uses on slopes between 6 and 1 degrees. Similarly, a study conducted by Ewunetu *et al.*, (2021) indicated the favorability of a gentle slope for agricultural land expansion over other land uses.

An agricultural land suitability analysis study conducted by Debesa *et al.* (2020) shows proximity to major roads, rivers and towns is the major factor in LULC changes. The statistically significant and negative signs of proximity drivers (distance to town centers and major roads) were shown in the sub-basin. A unit standard deviation increase (1.5km) in the distance to town centers will decrease the probability of (-0.027) in the conversion rate from shrub and bushland to cultivated land. The probability of shrub bush to cultivated land conversion decreases from 0.83 to 0.50 for an increase in distance from major town centers 0–30km. This result indicates the increased distance to the town center, the less probability of shrub and bushland conversion to cultivated land. The model also predicted a unit standard deviation increase (2.96km) in the road distance would decrease the probability of (-0.058) in the conversion rate from shrub and bushland to cultivated land.

Similarly, the expansion of roads in the basin favors the expansion of agricultural land. This trend implies that deforestation increases with decreasing distance from rivers and roads. Generally, the statistical model predicts topographic and proximate variables as determinants contributing to the major transition of shrub and bushland to cultivated land. This pattern further helps to protect the basin’s shrub and bushland, and it is important to consider these contributing factors.

2.7. Implications of land use and land cover transition on farmer’s livelihoods

Following direct and indirect pressures exerted on natural resources, studies have shown that there were significant land use and land cover changes in Ethiopia (Etefa *et al.,* 2018; Berihun *et al.,* 2019; Deribew and Dalacho, 2019; Shiferaw *et al.*, 2019; Tadesse *et al.,* 2020). Among other changes (Tadesse *et al.*, 2014), deforestation and forest degradations are major problems in Ethiopia and key factors challenging food security, community livelihood and sustainable development. Ethiopia is where most of its population’s livelihood depends on the well-being of nature, including vegetation resources. As the major type of LULC changes, vegetation resource loss has brought a major threat to the environment and has been a focus area of global studies (Henry *et al.*, 2018; Ullah *et al.*, 2020). Some literature indicates that a change in LULC could be positive as various conservation measures are applied and can be negative as they alter the environment in undesirable ways. There is a consensus among experts that the problem of deforestation and forest degradation in Ethiopia has different socio-economic and institutional causes. Studies conducted in Ethiopia revealed that natural vegetation resources are continually declining at the expense of agricultural land expansion, logging for construction and fuel wood, population growth and expansion of urban centers (Aynekulu *et al.*, 2012; Hailemariam *et al.*, 2016; Minta *et al.*, 2018). Few studies, however, have also discovered that the because of efforts exerted by the community and NGOs in collaboration with the government, the vegetation cover of the country has been increasing (Berihun *et al.*, 2019). The research demonstrates that the subbasin's vegetation resources are steadily diminishing (Figure 2. 6). Around 5886 km^2 (47.8%) of the earth's surface was estimated to be covered by vegetation in 1986; this decreased to 4432 km^2 (32%) in 1996 and then to 3358 km^2 (27.3%) and 3198 km^2 (26%) in 2006 and 2018, respectively.

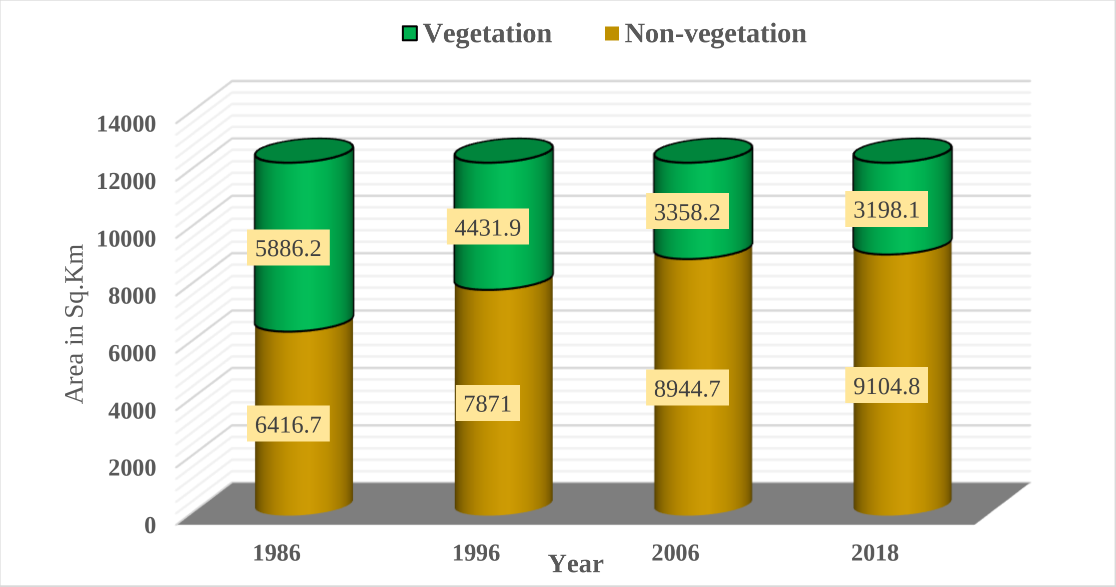

Figure 2.6. Area of vegetation and non-vegetation of the sub-basin, 1986 -2018

From 1986 to 1996, 23.4 km^2 (2.7%) of vegetation was transformed, and from 1996 to 2006, 21.4 km^2 (2.4%) and 16.4 km^2 (1.5%) of vegetation were gradually lost. The vegetation cover in the sub-basin has decreased an average by 49.6 km^2 (2.1%) per year between 1986 and 2018. Hence, the observed vegetation cover change in the sub-basin likely comes from the expansion of agricultural land (Table 2.3). The study's finding is supported by similar investigations by different scholars (Bareke, 2018; Sahle and Yeshitela, 2018; Kabite *et al.*, 2020) where the loss of natural vegetation like removal of wood and Shrubland, grassland and forestland towards agriculture. As per our discussion with the local communities, the degradation of vegetation resources in the sub-basin has several implications for their day-to-day activities. Focus group discussants in the highland parts of the sub-basin stated that due to deforestation and overgrazing, soil erosion, loss of land productivity, climate change is one of the common problems observed in their farmland. A key informant from Tullu Jebi village of Lude Hitosa district expressed the situation as:

> “No one was aware of the benefit of conserving forest until many farmers were forced to apply high priced fertilizer and labor-intensive soil conservation techniques in their farmland.”

The study conducted in the highlands of Ethiopia shows that because of the conversion of natural vegetation to cultivated land, 20 - 50% losses in soil carbon are recorded with the first meter of soil depth (Berihu et al., 2017). This change indicates that deforestation in the study areas affected farmers’ agricultural land by reducing production and productivity. Farmers in the lower part of the sub-basin complained about the expansion of the Metehara sugar factory at the expense of their vegetation resources. An informal interview with farmers from Gelcha village of Fentale district described the situation as follows:

> “Before feeding our livestock with very short distance travel, the expansion of Metehara sugar factory to our grazing and browsing land created a serious problem on our livelihoods. Like this, the recent expansion of destructive invasive plant species locally called ‘shola’ encroaching our grazing and agricultural land. This tree, in many aspects, is bullying our livelihood.”

Discussion with key informants shows that this species' change of bushland, cultivated land, and grassland had both benefits and harms. The benefits mentioned are that because of fast expansion, they are sometimes considered blessed for the shortage of firewood and charcoal production. Nevertheless, they are demolishing agricultural and grazing lands for most agro-pastoralists in the other direction. According to recent studies conducted by Hailu *et al*. (2021), the invasion of this plant species harms the water quantity in the lower part of the Awash Basin. The impact on the agro-pastoralists' way of life in the area is uncertain unless the species' expansion is closely watched.

Key informants and focus group discussants described that the variability and change in climate are consequences of LULC change in their locality. They perceived that climate change is one indicator of the loss of vegetation resources. Additionally, the duration and intensity of rain have been highly variable in the last decades. As per our key informant from the Merti district:

> "Because of variability in onset, offset and frequent occurrence of drought in the district the majority villages area under safety net program."

Recent studies in different parts of the world associated LULC change with climate change (Clerici *et al*., 2019; Sy and Quesada, 2020). According to data from National Meteorological Agency (NMA) (http://www.ethiomet.gov.et/) 1983-2016, the maximum and minimum temperature of the sub-basin is progressively increasing, and total rainfall is steadily decreasing (**Figure 2.7**, See Annex F). This trend is consistent with local perception about the variability in climate elements in the study area.

Furthermore, aiming to achieve broad-based and sustainable economic growth to reduce poverty and become a middle-income country by 2025, Ethiopia is implementing Climate-Resilient Green Economy (CRGE) development strategy. The strategy identifies four strategic pillars for CRGE implementation, and forestry is one of these pillars. The pillar has prioritized afforestation, reforestation, and forest management programs to increase carbon sequestration in forests and woodlands (FDRE, 2011). Despite their great potential in influencing carbon balance, these vegetation types (woodland, shrub, and bushland) are largely neglected in forest-related discussions, including carbon negotiations. Under a business-as-usual scenario, the CRGE development strategy planned to expand agricultural land by 3.9% per year, where 55 percent of this agricultural land expansion (550,000 hectares per year) is at the expense of vegetation. Hence, there could be visual threats to the existing vegetation resource of the country in general and the sub-basin. Therefore, it is important to prioritize the restoration and conservation of vegetation to go between the expansion of agricultural land and the loss of vegetation in the sub-basin. It could contribute significantly to their regulating and providing ecosystem services, leading to overall economic development in rural areas. Additionally, providing fertile and productive land for crop production is one of the most important roles that vegetation resources play. Hence, it is essential to implement integrated and sustainable land use planning that could significantly contribute to regulating and provisioning ecosystem services, leading to the region's overall economic development.

2.8. Conclusions

Land use and land cover change is one of the most environmental issues progressing on the earth's surface at different rates, and factors of change. The rate of change, processes, and drivers of LULC in the Awash-Awash sub-basin from 1986 to 2018 was quantified. The study revealed the change tendency of the main LULC class in the sub-basin. During the study period, bareland, cultivated land and water body showed the highest rate of change. Conversely, the grassland, woodland, shrub and bushland, and forestland declined.

The net change in gains and losses for each LULC class during 1986-1996, 1996-2006, and 2006-2018 depicts a major change in the basin. Gains in bareland, cultivated land and the water body of the sub-basin are likely because of the substantial loose in shrub and bushland, woodland, and forestland. In addition, the proportion of different LULC classes that were persistent between 1986 and 2018 was observed and found that about 48% of the area has shown persistence and the rest 52% not. Furthermore, about 47.5% of this transition occurred due to swap change, in which a concurring gain and loss existed among the LULC categories. Cultivated land experienced the topmost persistence of 31.9% and the highest gain compared to other LULC categories. However, shrub and bushland experienced a significant loss in size, with about 25.9%.

The LULC class proportion showing a net change between 1986 and 2018 indicated the highest for cultivated land (26.9%) and shrub and bushland (18.0%). The study area experienced 56.6% of the total change. The loss-to-persistence ratio (Lp) for water bodies and cultivated land is less than 1. This trend indicates all land classes except cultivated land and water body showed a higher tendency to loss than to persist. On the other hand, bareland, woodland, and cultivated land categories experienced the highest gain-to-persistence ratio (G_p) than others, indicating that these land classes experienced more persistence and less gain. The net change to persistence (Np) is negative for vegetation resources of the sub-basin. More particularly, LULC class such as woodland (-26.1), grassland (-19.7), Shrub and bushland (-1.6) and forestland (-0.8) shows negative, which indicates the LULC class has a higher probability of change to other LULC classes.

The study area experienced random and systematic land cover transitions between the years 1986 to 2018. The study identified the largest difference in the random change process between the observed and expected gains for shrub and bushland to cultivated land. Systematically, cultivated land gains the highest from shrubs and bushlands (4.9%), followed by grasslands (3%). This gain indicated that cultivated land systematically gained 22.6% shrub and bushland. The difference between observed and expected gain is relatively large, and the negative value is experienced when forestland avoids gaining systematically from shrub and bushland. Similarly, it happens when cultivated land to avoid systematically gaining from waterbodies.

Survey data show that population growth, agricultural land expansion, deforestation and overgrazing, urbanization, and infrastructure development in the sub-basin were important drivers of LULC change in the study area. The spatial statistical model result indicated that topographic and proximate drivers such as elevation, slope, sine and cosine of aspect, and distance to major roads, rivers and town center were considered major drivers of shrub and bushland for cultivated land transition. Furthermore, the informants stated that demand for productive land, population growth, construction material and household energy consumption lead to the loss of vegetation resources. Therefore, to go between the expansion of agricultural land and vegetation loss in the sub-basin, it is important to consider this prominent signal of

LULC change. Though the restorations in vegetation resources require follow-up studies investigating various drivers and impacts, priority should be given to vegetation conservation and restoration. Hence, implementing integrated and sustainable land use planning could significantly contribute to the regulating and provisioning of ecosystem services, leading to overall economic development.

CHAPTER THREE

3. Spatiotemporal changes in mean and extreme climate: Farmers’ perception and its agricultural implications in Awash River Basin, Ethiopia[2]

Abstract

The increase in intensity and frequency of climate extremes threatens socio-economic development. This study examines mean and extreme climate trends, farmers’ perception of the changes, and impacts in the Awash River Basin Daily rainfall and temperature data were used to analyze 23 extreme climate indices. Mann-Kendall test statistic was used to assess the magnitude and significance of the changes. Results show an increase in minimum (0.019 to 0.055 °C/year) and maximum temperatures (0.049 to 0.09 °C/year), while total rainfall is on a downward trend (-3.84mm/year to -10.26mm/year). Warm extreme temperature indicators: warmest day (TXx), warmest night (TNx), warm day (TX90p), warm night (TN90p), and warm spell duration indicator (WSDI) show a significant increasing trend ($p < 0.05$). Nevertheless, except for the tepid to cool humid agro-ecology zone, extreme cold temperature indicators on cool days (TN10p), cool nights (TX10p), as well as cold spell duration (CSDI) are declining. Most extreme precipitation indices: maximum 1-day precipitation amount (RX1day), count of days when precipitation≥ 10mm (R10mm), maximum 5-day precipitation amount (RX5day), count of days when precipitation≥ 20mm (R20mm), very wet days (R95p), extreme wet days (R99p), and total precipitation (PRCPTOT) show a decreasing trend. There is a relationship between most farmers’ perceptions of selected climate change and the reported climate extremes. The major impacts perceived and asserted over agro-ecologies are food price inflation, crop productivity decline, crop pests and diseases spread, livestock disease increase, and the emergence of pests and weeds. The increasing trend in extreme warm temperature, decreasing trend in the cold extreme, and declining trend in precipitation indicators affected agricultural productivity and farmers whose livelihood depends on rainfed agriculture. The agro-ecology-specific study results provide critical information to policymakers, decision-makers, and farmers about the potential impacts of climate change and extreme events, leading to the development of agro-ecology-based adaptation measures.

Keywords: Extreme climate; ClimPact2; Agriculture; Farmers’ perception; Awash River Basin

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[2] Damtew, A., Teferi, E., Ongoma, V., Mumo, R. and Esayas, B., 2022. Spatiotemporal Changes in Mean and Extreme Climate: Farmers’ Perception and Its Agricultural Implications in Awash River Basin, Ethiopia. *Climate*, *10*(6), p.89. **https://doi.org/10.3390/cli10060089** (MDPI).

3.1. Introduction

The influence of human activities has altered the climate systems resulting in the warming of the land and atmosphere (IPCC, 2021). From pre-industrial (1850-1900) to current post-industrial (2006-2015), the mean land surface temperature (LST) is amplified by 1.53°C while global mean surface temperature has risen by 0.87°C (Shukla *et al.*, 2019). Temperature and rainfall are vital to weather variables that determine the climate condition of a particular area. A small shift in the mean of these variables threatens peoples whose livelihood depends on rainfed agriculture (Maxwell *et al.*, 2019; Malhi *et al.*, 2020). As global temperatures and precipitation change, climate extremes are projected to increase in intensity and frequency. Thus, understanding the extreme precipitation and temperature events is important as drought and flood indicators affect various socio-economic activities (Maru *et al.,* 2021).

Climate extreme events have received significant attention given the associated devastating impacts (Leal *et al.*, 2018; Raymond *et al.*, 2020**)**. The extreme event has come to be framed descriptively as driving adaptation and prescriptively as useful indicators that the climate is changing. Such information would be useful for adaptation planning (Pasquier *et al.,* 2019). Recent studies (e.g., Ongoma *et al.*, 2019; Ayugi *et al*., 2021; Ojara *et al.*, 2021) have revealed patterns and trends in extreme weather events over East Africa. On the other hand, droughts and storms have become much more frequent within the last three decades (Kilavi et al., 2018). According to Funk *et al.* (2008), continued warming in the Indian Ocean contributes to spring and summer droughts. Climate change is widely believed to occur in various parts of Ethiopia (Kiros *et al.,* 2016; Alemu and Bawoke, 2020; Belay *et al.,* 2021). Observed changes in extremes in the country depend on the reliability and quantity of available data. However, there is low to medium confidence in extreme historical temperature and heavy rainfall trends over most parts of Ethiopia because of a lack of empirical evidence. Meanwhile, extreme temperatures have risen in most parts of Ethiopia, where reliable data are available (Esayas *et al.,* 2019; Etana *et al.,* 2020).

The development of internationally agreed-upon climate indices Expert Team on Climate Change Detection and Indices (ETCCDI) that represent more extreme aspects of climate has promoted research in climate change. Ongoma et al. (2019) used extreme climate indices and showed a general decreasing rainfall trend at various significance levels in Kenya and Uganda. A study conducted in Ethiopia, Kenya, and Tanzania (Gebrechorkos *et al.*, 2019) reported an increasing daily and monthly temperature trend. Like other East African countries, Ethiopia is vulnerable to climate change and variability due to its over-reliance on rain-fed agriculture to sustain the economy. Unpredictable rainfall patterns and frequent extreme events such as drought, flood, and hail have a greater negative impact on the biophysical environment, food security, and economic growth than long-term mean temperature and precipitation alteration alone (Wiebe *et al.,* 2019; Nhemachena *et al.,* 2020). Considering the country's history of major climate disasters, conducting long-term trend and variability studies on what has changed in recent decades has contributed to agricultural productivity and adaptation and mitigation of climate change (Asfaw *et al.*, 2021; Habte *et al.*, 2021).

Furthermore, when looking at different biophysical setups in Ethiopia, a few researchers that have addressed the issue of climate extreme studies using indices obtained from the Expert Team on Climate Change Detection and Monitoring Indices (ETCCDMI) have yielded contradictory results. Teshome and Zhang (2019) found that precipitation extents such as annual total precipitation (PRCPTOT), the number of heavy precipitation days (R10mm), and consecutive wet days (CWD) are decreasing. Kiros *et al.* (2016) examined trends in 12 extreme indices in the Geba River basin between 1971 and 2013. Precipitation indices such as the number of consecutive dry days (CDD), PRCPTOT, the number of days when precipitation is≥ 10mm, 20mm, and 25mm, maximum precipitation amount of 1 and 5 days (RX1day and RX5day), as well as simple daily intensity index (SDII), showed a decreasing pattern in the most of river basin stations. In contrast, most stations in the river basin show increasing trends in temperature indices, including the number of CWD and precipitation indices like very wet (R90p) and extreme wet days (R95p and R99p). Geremew et al. (2020), in their study, examined an increasing trend in the mean annual number of CWD, the number of wet days (NWD), and the mean annual CDD at some stations in Northwest Ethiopia. Generally, various studies across the country show varying outcomes, stressing the need for location-specific analysis. Recent studies conducted in various parts of the country confirmed an agro-ecology-based analysis that can benefit local climatic adaptation measures (Etana *et al.,* 2020; Mekasha *et al.*, 2014).

Recent studies in the Awash River Basin identified drought and flooding events (Maru *et al.,* 2021), land use and land cover transition (Tadese *et al.,* 2020; Damtew *et al.,* 2022), improper land-use practices (Bekele *et al.*, 2019), and deforestation (Degefa, 2019) as key development challenges. Examining their characteristics across agro-ecologies in the basin is vital given the agricultural importance of extreme climate events. A comprehensive assessment of how various climate extremes change across the basin can provide valuable information to stakeholders and decision-makers. Essentially, climate change and extreme events perception are complex processes that encompass a range of psychological constructs such as knowledge, beliefs, attitudes, and concerns about if and how the climate changes (Whitmarsh and Capstick, 2017; Dendir and Simane, 2021). Perception is influenced and shaped, among other things, by the individuals' characteristics, experience, information, and cultural and geographic context in which they live (Whitmarsh and Capstick, 2017; Ayal *et al.*, 2021; Gebrehiwot and van der Veen, 2021). Considering farmers' trend perception of climate change and extreme events is important. Failure to assess farmers' beliefs and impacts of climate change and adaptation attitudes will result in ineffective and inefficient long-term adaptive measures (Nguyen *et al.*, 2016, Aidoo *et al.*, 2021). Therefore, assessing trends in climate extremes based on data and farmer perceptions is critical to understanding its sectoral implications and developing adaptation strategies (Ayanlade *et al.*, 2017**)**. Evidence suggests that individual perceptions of climate change accompanied by climate extremes can influence beliefs, concerns, risk perceptions, mitigation, and adaptation behaviors (Mase *et al.*, 2017; Reser and Bradley, 2020). Furthermore, most studies do not emphasize different agroecological settings. Existing studies are primarily confined to the Blue Nile Basin, excluding areas where analyzed trends of such climate extremes in constrained spatial and temporal in the Awash basin (Gari *et al.*, 2018; Maru *et al.*, 2021). Moreover, these studies have been undertaken with climatic data quality issues unrelated to local perception.

Consequently, studies do not comprehensively analyze the spatial and temporal variability in temperature and precipitation extremes across agro-ecologies. Studies of extreme climates and their characteristics are critical for applying integrated climate-related policy formulation and implementation. Ethiopia has complex patterns of climate trends; micro-scale studies into the variability and trend of extreme weather events are critical for understanding local-scale indications of climate changes and designing context-specific adaptation interventions. The study's objectives are (1) to analyze agro-ecology based on mean and extreme temperature and precipitation events from 1983 to 2016 and (2) to assess farmers' perception of and adaptation response to changes in mean climate and extreme events in the Awash-Awash sub-basin.

3.2. Materials and methods

3.2.1. Study area

The Awash at Awash sub-basin (hereafter Awash-Awash) is one of six major water resource planning areas classified according to the Awash River Basin's hydrological, administrative, economic, and social boundaries. It has an area of 12302.9 km^{2,} located between latitudes 7° 54'N to 9°16' N and longitude 38° 55' E to 40° 46' E (Figure 3.1). The elevation of the sub-basin ranges between 744 to 4,181 meters above sea level. Awash-Arba 1, 2 and Kaleta-Werenso rivers are the main rivers in the sub-basin that contribute major flows to the Awash River Basin. The sub-basin climate is influenced by the north-south shift of the Inter-Tropical Convergence Zone (ITCZ) (Halcrow, 1989). According to the Ministry of Agriculture (MoA, 1989). The classification system, hot to warm arid, tepid to cool sub moist, tepid to cool moist, and hot to warm moist, dominate the agro-ecological zone (AEZ) of the sub-basin. According to the Köppen classification, Hot semi-arid climate (Bsh), Tropical rainy climate (Aw), Warm temperate rainy climate (Cfb) and Warm temperate rainy climate (Cwb) dominate the sub-basin (Beck *et al.,* 2018). The mean minimum and maximum temperatures are 14.1 and 28.6 °C, while the mean annual rainfall in the region is about 773 mm (Damtew *et al.,* 2022). Being found in one of Ethiopia’s intensively used river basins, about 67% of the sub-basin is covered by cultivated land, and 19% of the sub-basin area is covered with shrub and bushland. The sub-basin is known for its large, medium, and small-scale irrigated lands, making it one of the country's economic centers. Seasonal and perennial crops are widely cultivated, ranging from cereals to vegetables, khat (*Chata edulis*), fruits, and sugarcane. The population of the sub-basin is estimated to be 2,093,216 in 2007 and is projected to reach 2,718,638 by 2019 (Damtew *et al.,* 2022).

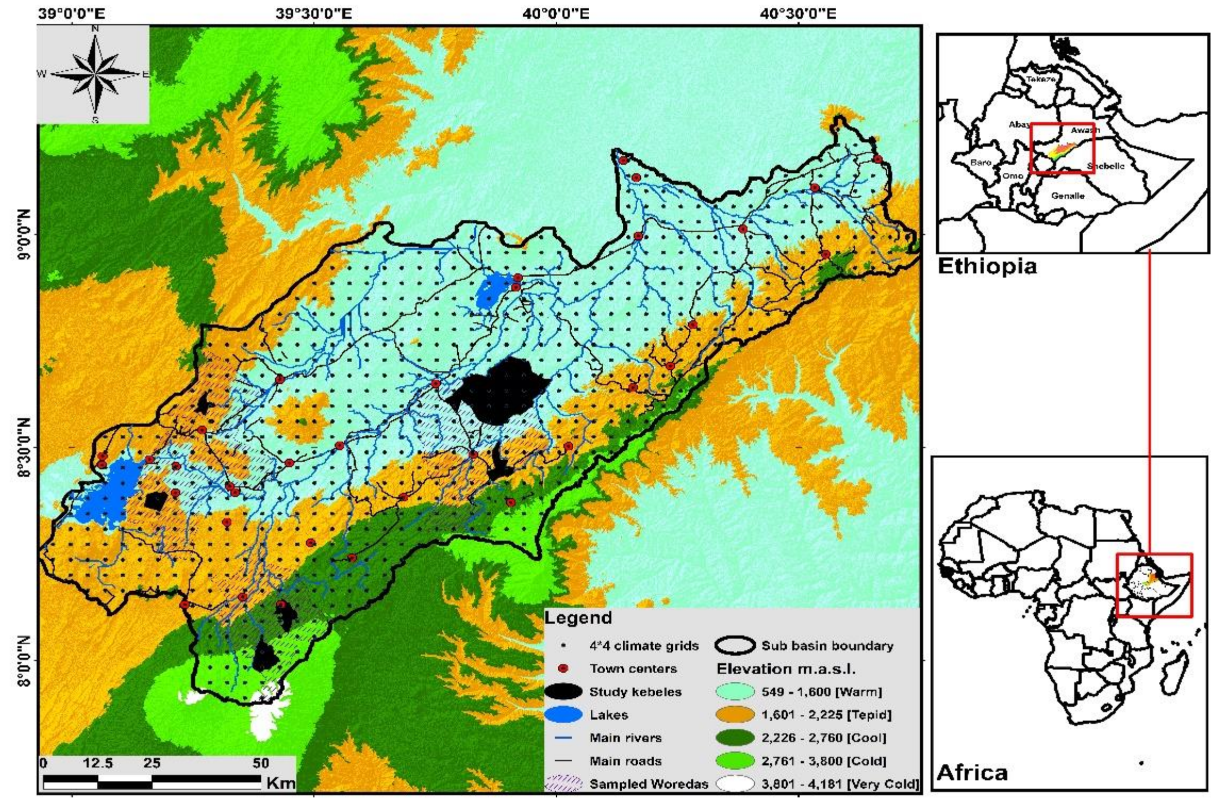

Figure 3.1. Map of the study area

3.3. Data types and sources

3.3.1. Data preparation, quality control, and analysis of extreme climate indices

Daily maximum and minimum temperature and precipitation records were sourced from the Enhancing National Climate Services (ENACTS) dataset (http://www.ethiomet.gov.et/). The dataset combines precipitation estimated from EUMET-SAT, temperature from NASA satellites, and ground observation from National Meteorological Agency (NMA) (Dinku et al., 14). An observed dataset from 1983 to 2016 with a spatial resolution of 0.0375° NMA provided x 0.0375°. The ENACTS has demonstrated strong performance when considered at station locations throughout the country (Dinku *et al.*, 14; Alemayehu and Bewke, 2017; Asfaw *et al.*, 2021; Dinku *et al.*, 2022).

Using RHtestsV4 and RHtests dlyPrcp, R software packages for temperature and rainfall, respectively, artificial shifts in climatic data series, homogeneity, and change points were examined and corrected (Wang and Feng, 2015). The R software package ClimPACTv2 was used to do a basic quality check on the supplied data. The website https://github.com/ARCCSS-extremes/climpact2 provides access to ClimPACT2's software and pertinent materials.

The study used the Expert Team on Sector-specific Climate Indices (ET-SCI), introduced in 2011, to expand the generic ETCCDI (Alexander and Herold, 2015). The ET-SCI developed several sector-specific climate indices considering agriculture, water, and health. A standard deviation of three (3) was used to detect the outliers, and some detected outliers were adjusted. The prepared time-series dataset was used to compute 12 temperature, 10 rainfall indices, and a drought index in 6 Major Agro-Ecology Zone (MAEZ) of the sub-basin (http://etccdi.pacificclimate.org/list_27_indices.shtml). These indices describe the frequency, amplitude, and persistence of extremes and have been used by many researchers (e.g., Worku *et al.*, 2019; Abdila and Nugroho, 2021, Ridder *et al.*, 2021).

3.3.2. Socio-economic data and method of analysis

One of Ethiopia's most susceptible regions in terms of the environment is the Awash-Awash subbasin. Three woredas and six villages from the sub-basin were identified and chosen using an agroecological zone classification. The agro-ecology-based classification was used to choose participants in the sub-basin to obtain in-depth and diverse information on the perception of trends in climate change and extreme events. Qualitative data from nine Key Informant Interviews (KII) (one Development Agent per village and one Agriculture Office Expert per district ‘woreda’) and six Focus Group Discussions (FGD) (one per village) were used, as well as quantitative data from a household survey. From the accessible lists of the chosen communities, individual farmers were chosen randomly. Following Kothari’s (Kothar, 2004) formula, 384 households were chosen as sample respondents (Table S1). Climate change perceptions were gathered using closed, open-ended questionnaires and temperature and rainfall indicators. The household data were analyzed using STATA v.15, whereas data from KII were transcribed, summarized, and analyzed qualitatively. Finally, qualitative data from key informant interviews and FGD were used to triangulate, substitute, and supplement quantitative climatic data.

3.3.3. Standardized Precipitation-Evapotranspiration Index

The drought frequency was calculated based on the SPEI-12 index value categorization (Maru *et al.*, 2021). Drought frequency is obtained by dividing the years of drought occurrence by the whole years under analysis and multiplying by 100% (Haile, 2020).

3.3.4. Climate trend analysis

The nonparametric tests have been widely used in climatic time series analysis due to their simplicity and suitability for data with outliers. The most used nonparametric statistical tests in trend analysis are Mann–Kendall's trend test (Mann, 1945; Kendall, 1975) and Sen's Slope tests (Sen, 1968) for slope estimation. The Mann-Kendall (MK) test is a non-parametric approach for testing the significance of monotonic trends, linear or nonlinear, in time series data. The method has been widely used to detect trends in hydrometeorological data (Ongoma *et al.,* 2019; Ayugi et al., 2022). Similarly, Sen's slope estimator has been widely used to estimate the slope of a linear trend for a time series. Therefore, the method was adopted to explore the trends in temperature and precipitation in the study area. Mann-Kendall trend test is expressed by Equation. 1.

$$\boldsymbol{S = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} sgn\left(x_j - x_i\right)} \tag{1}$$

Where S is Mann Kendall test statistics, xi and xj are the sequential data values of the time series in the years i and j (j > i), and N is the time series length. A negative S value indicates a decreasing trend, and a positive value indicates an increasing trend in the data series.

The sign function sgn is given by Equation 2.

$$\boldsymbol{sgn\left(x_j - x_i\right) = \begin{cases} +1 \; if \; \left(x_j\right) > 0 \\ 0 \;\; if \;\; \left(x_j - x_i\right) \; = 0 \\ -1 \;\; if \;\; \left(x_j - x_i\right) < 0 \end{cases}} \tag{2}$$

If the data is independent and normally distributed, the variance of the K statistic is given by Equation. 3.

$$\boldsymbol{Var\;(K) = \frac{1}{18}\left[P(P-1)(2P+5) - \sum_{i=1}^{q} d_i(\,(d_i - 1)(2d_i + 5)\right]} \tag{3}$$

Where P is the number of points, q is the number of tied groups in the data set, and d_i is the number of data points in the i^{th} tied group. A tied group is the sample data with the same value; there is zero difference between the compared values. The summation aspect of Equation. 3 can be ignored if there are no tied groups.

K and Var(K) values will be used to compute the test statistic Z by Equation 4.

$$\boldsymbol{Z} = \begin{cases} \dfrac{\boldsymbol{K-1}}{\sqrt{\boldsymbol{Var(K)}}} & \boldsymbol{if\ K} > 0 \\ \boldsymbol{0} & \boldsymbol{if\ K} = 0 \\ \dfrac{\boldsymbol{K+1}}{\sqrt{\boldsymbol{Var(K)}}} & \boldsymbol{if\ K} < 0 \end{cases} \tag{4}$$

The Z value is used to calculate the statistically significant trend. A positive or negative value of Z represents an upward or downward trend. The null hypothesis is rejected at the significance level of α if |Z| ≥ Z_(α/2), where Z_(α/2) is the critical value of the standard normal distribution with a probability exceeding α/2 and shows that the trend is significant. If |Z| < Zα/2, the null hypothesis is accepted, and the trend is insignificant. A trend will be considered statistically significant, and if it is significant at the 95% confidence level. Sen's slope estimator is applied when the trend is assumed linear, showing the quantification of changes per unit time (slope). It is given by Equation 5.

$$\boldsymbol{T_s} = \frac{\boldsymbol{x_a - x_b}}{\boldsymbol{a - b}} \tag{5}$$

Where T_s is the estimate at year xa, and xb are considered data values at the time a and b (a > s) correspondingly.

3.4. Results and discussion

3.4.1. Observed annual trend in mean temperature and rainfall.

Observed changes in annual mean temperature and rainfall show a significant decrease in annual total precipitation (TRF) and an increase in minimum (Tmin) and maximum temperature (Tmax) between 1983 and 2016 (Figure 3.2 and Table 3.1). A significant and highest decreasing trend (-3.83 mm/year) in TRF was observed in hot to warm arid, while the lowest (-10.26 mm/year) is observed in cold to very cold AEZ. The trend in hot to warm semi-arid AEZ shows an insignificant increase (2.16 mm/year) in TRF (Figure 3.2 and Table 3.1). Five of the six AEZ tend to show a positive Tmin trend, with only one hot to warm semi-arid station depicting an insignificant decreasing trend (Figure 3.2 and Table 3.1). The hot to the warm-arid region had the largest and most positive rate of change in the Tmin, at 0.055°C/year, and the lowest rate, at 0.019°C/year. The trend in Tmax is significantly increasing in all AEZs

($p < 0.05$). In relative terms, the magnitude of change was reported to be highest at 0.091°C/year for the hot to warm semi-arid and lowest at 0.054°C/year for the hot to warm arid.

Table 3.1 Annual trends of TRF, Tmin and Tmax across agro-ecologies (1983−2016).

Variables	**TRF_tau (sen's slope)**	**Tmin_tau (sen's slope)**	**Tmax_tau (sen's slope)**
Cold to very cold humid [AEZ_1]	-0.371(-10.26) *	0.308(0.019) *	0.480(0.049) *
Tepid to cool humid [AEZ_2]	-0.242(-6.75) *	0.373(0.023) *	0.447(0.062) *
Hot to warm moist [AEZ_3]	-0.237(-3.94) *	0.312(0.028) *	0.661(0.056) *
Hot to warm arid [AEZ_4]	-0.264(-3.83) *	0.515(0.055) *	0.501(0.054) *
Tepid to cool sub-moist [AEZ_5]	-0.169(-5.96) ns	0.465(0.034) *	0.619(0.061) *
Hot to warm semi-arid [AEZ_6]	0.112(2.16) ns	-0.119(-0.014) ns	0.640(0.091) *

***** = p <0.05, ns = insignificant

Generally, annual trends in TRF observed in this agro-ecology align with previous studies conducted in different parts of Ethiopia. Worku *et al.* (2019) examined a decreasing trend of total rainfall in the Alemketema and Mehalmeda stations in the Jema sub-basin of the Blue Nile. Nasir *et al.* (2021), in their study in the North-Western escarpment of Ethiopia, show a significant increase in Tmax and Tmin over the studied livelihood zone. Similar findings were reported by Shawul and Chakma (2020) over Upper Awash. The change in mean maximum and minimum temperature is of concern due to ripple effects on agriculture in general and crop productivity (Coulibaly et al., 2020). Though yield response to temperature varies among crop varieties, a significant increasing trend in mean minimum and maximum temperature can negatively affect crops through increasing evapotranspiration. This pattern affects the cellular process related to crop growth, development, and lower crop yield (Hatfield and Prueger, 2015).

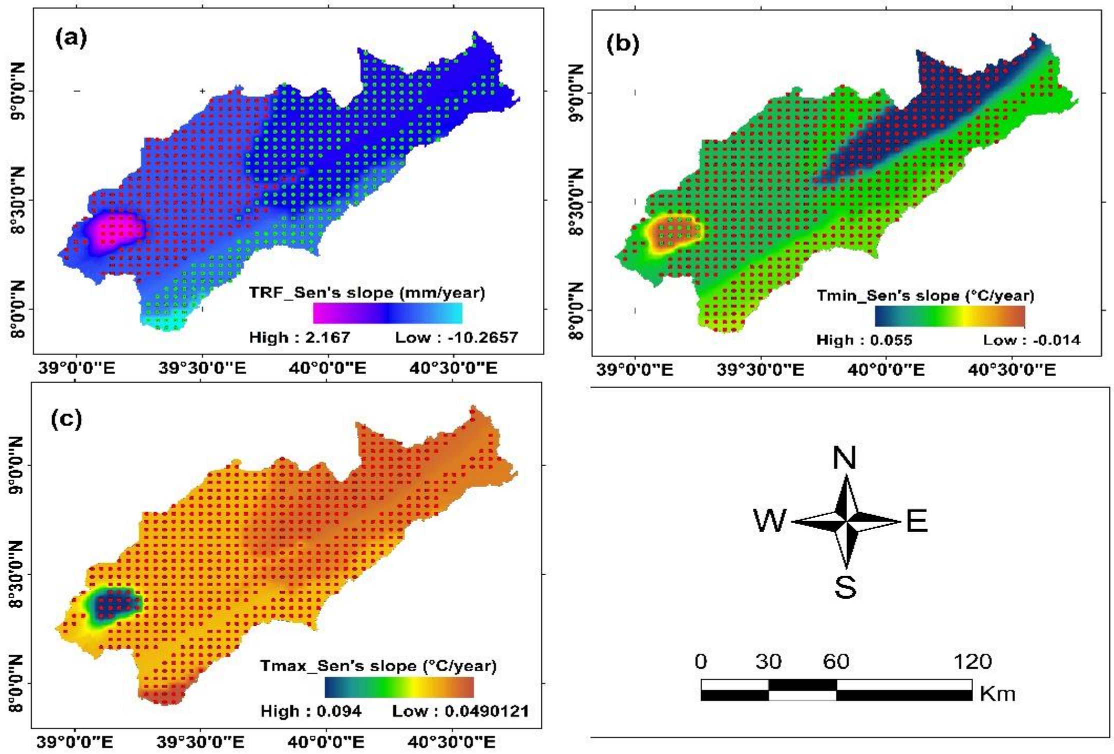

Figure 3.2. Trends of TRF (a), Tmin (b), and Tmax (c) of the study area. Red dots indicate 95% confidence level, while green dots indicate not significant at 95% confidence level.

3.4.2. Observed annual trend in extreme temperature.

Coldest night and Warmest night

Table 3.2 shows the temporal trends of temperature extremes across agro-ecologies. The Mann-Kendall test revealed a significant decrease in the coldest night (TNn) in hot to warm moist, tepid to cool sub moist, and hot to warm semi-arid AEZ. This result indicated that TNn would likely increase at a higher rate than the maximum temperature in many AEZs. The highest and negative -0.0730°C/year ($p < 0.001$) trend in TNn was reported in the hot to warm moist. Except for hot to warm semi-arid, the significant increase trend ($p < 0.001$) for the warmest night (TNx) was observed in other AEZs. The magnitude of change was reported to be highest at 0.075°C/year for the cold to very cold humid (Table 3.2). The highest positive value of TNx was observed in 1988, 1993, 1998, and 1993 (Figure 3.3g - j) for cold to very cold humid, tepid to cool humid, hot to warm moist, and hot to warm arid, respectively. However, tepid-to-cool sub-moist and hot to warm semi-arid AEZ experienced the highest negative anomalies in 1988 and 1991, respectively (Figure 3.3k - i). The highest positive value of TNn was observed in

2009 (Figure 3.3a) for cold to very cold-humid. Negative anomalies were commonly observed in the 1990s and 2000s for tepid to cool sub-moist and hot to warm semi-arid (Figures 3.3e and f). The results contrast with recent studies conducted in different parts of the world (Omondi et al., 2014; Esayas et al., 2018; Etana *et al.*, 2021), which showed an increasing trend in the coldest night (TNn). However, the same studies (Esayas *et al.*, 2018; Etana *et al.*, 2020) reported a significant increase in TNx. The difference between results could result from differences in the extent of periods and area conceptualization (i.e., agro-ecology vs. watershed) based studies. Furthermore, the significant increasing trends in TNx on most agro-ecologies are a clear indicator of a warming pattern in the sub-basin, which could reduce agricultural production (Ferrelli et al., 2020).

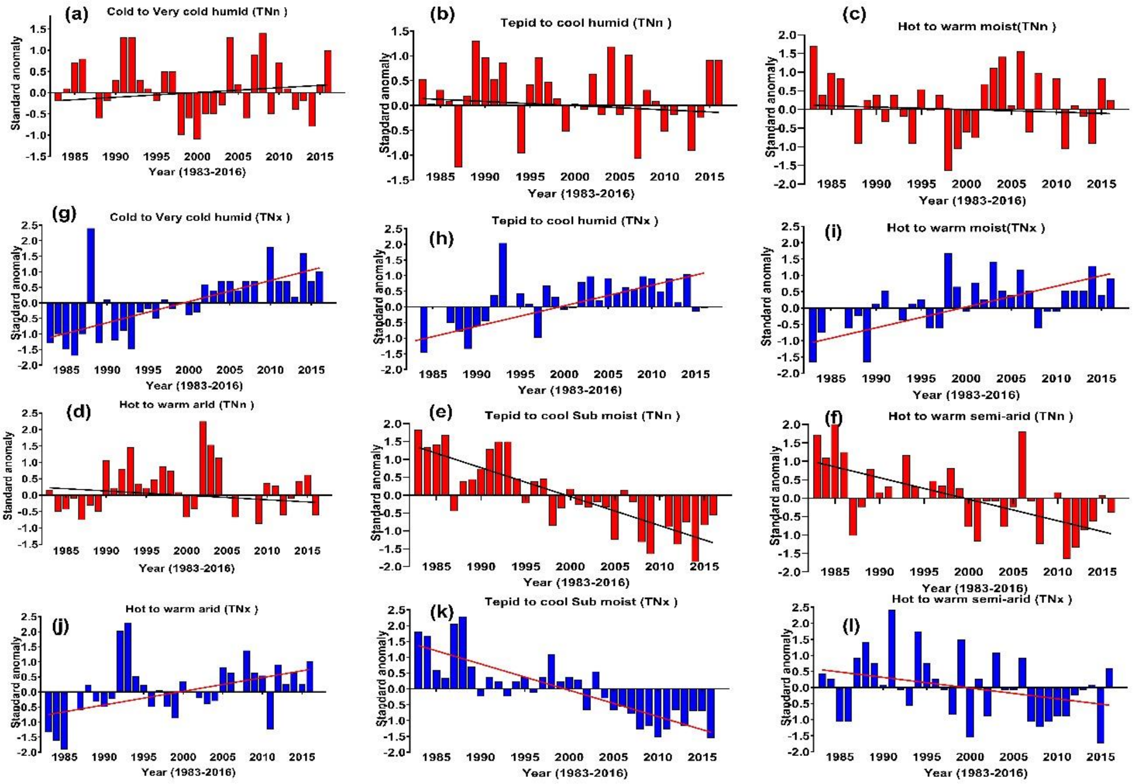

Figure 3.3. Coldest night (TNn) (a-f) and Warmest night (TNx) (g-l) over agroecological zones for the period 1983-2016.

Cool days and Cool nights

The TX10p and TN10p indices denote days with Tmax and Tmin less than the historical 10th percentile value, respectively. Concerning the frequency of cool nights (TN10p), results show a significant decrease in the cold to very cold humid, tepid to cool humid, hot to warm moist, and hot to warm arid agro-ecology zones. However, a positive and significant ($p<0.001$) trend was observed at tepid to cool sub-moist and hot to warm semi-arid (Table 3.2). Berhane *et al. (*2021) reported a statistically significant decreasing trend in studied stations in semi-arid areas of Western Tigray between 1983 and 2016. Similarly, Gebrechorkos *et al.* (2020) found a significant decreasing trend in TX10p and TN10p in their studies over Ethiopia, Kenya, and Tanzania from 1981-to 2016. On the other hand, except for tepid to cool humid, a significant ($P<0.001$) decreasing trend in the frequency of cool days (TX10p) was observed in studied agro-ecology zones (Table 3.2). The magnitude of change in the cool days (TX10p) was reported to be highest and positive 0.050°C/year in the tepid to cool humid ($p < 0.001$). The magnitude of change on the cool days (TN10p) was reported to be highest and positive at 0.057 ° C/year in the hot to warm semi-arid agro-ecology zone ($p < 0.001$) (Table 3.2). A recent study conducted in different parts of the country (Esayas et al., 2018; Gari *et al.,* 2018; Shuai et al., 2018) agrees with our study. Furthermore, (Teshome and Zhang, 2019) predicted a decrease in the frequency of cold nights (TN10p) by considering different climate change scenarios, a similar case to what has been projected globally (IPCC, 2021).

The TN10p anomalies show a reduction in negative anomalies since the beginning of the 2000s in the cold to very cold humid, tepid to cool humid, and hot to warm moist agro-ecologies (Figure 3.4a - c). On the contrary, significant, and positive anomalies are seen for tepid to cool sub-moist and hot to warm semi-arid in the 2000s and 2010s, respectively (Figure 3.4e and f). For all agro-ecologies, except hot to warm wet, the frequency of TX10p anomalies has consistently decreased since the early 2000s (Figure 3.4i).

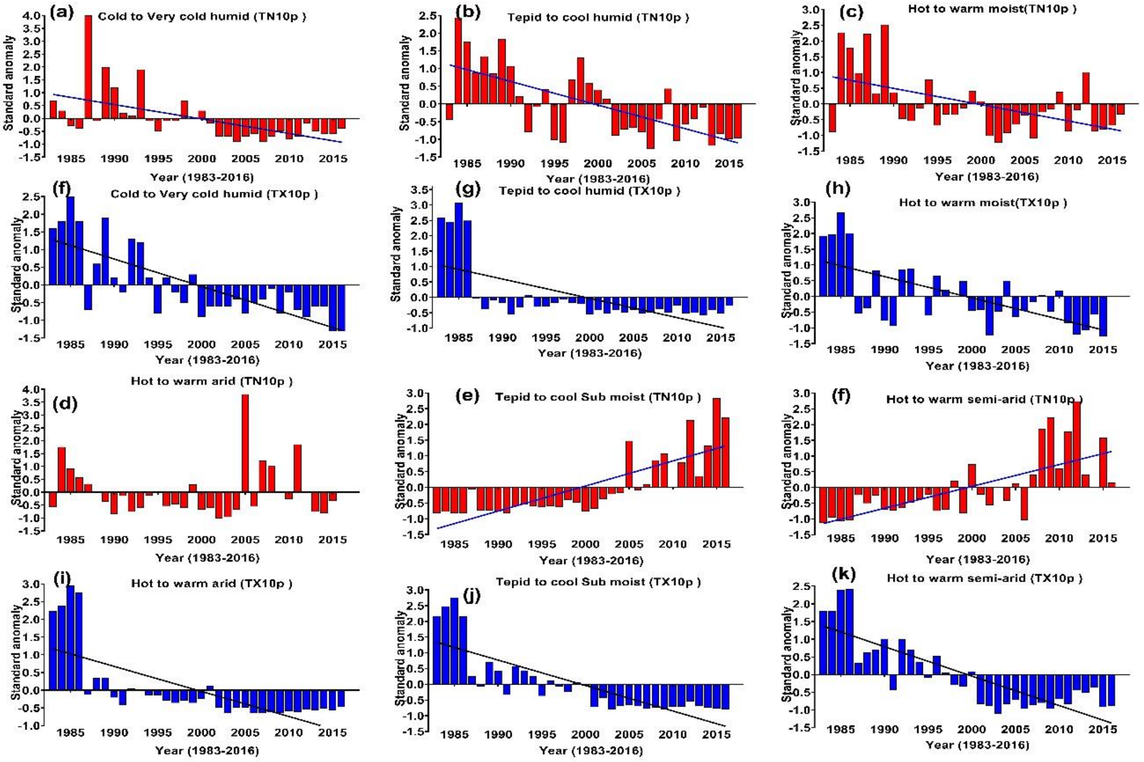

Figure 3.4. Cool nights (TN10p) (a-f) and Cool days (TX10p) (g-l) over agro-ecological zones for the period 1983-2016

Warm days and Warm nights

The increasing trends in the frequency of warm days (TX90p) were observed at 3 of the 6 AEZs ($p<0.001$) (Table 3.2). Significant positive trends are evident at all stations. Cold to very cold humid, hot to warm moist, and hot to warm arid showed significant decreasing trends in TX90p. Unlike the case in TX90p, all AEZs show increasing trends in the frequency of TN90p. The magnitude of change on TX90p was reported to be highest and positive at 0.075°C/year in warm to warm arid ($p < 0.001$) and lowest (0.040°C/year) in humid to warm (Table 3.2).

Similarly, the magnitude of change in TN90p was highest for the cold to very cold humid (0.080°C/year) at ($p <0.001$) and lowest (0.049°C/year). The results are consistent with the observed change in other parts of Ethiopia and elsewhere. Esayas *et al.* (2018) reported a significant increasing trend in the frequency of warm days and warm nights in lowland and highland agro-ecologies of Southern Ethiopia. The number of warm days and nights in the Lake Victoria region increased during 1971-2000 (Luhunga and Songoro, 2020). A global study (Vogel et al., 2019) found that an increase in TX90p and TN90p trends is typically correlated with a decline in crop yields due to the seasonality of crop production. This report points out the impact of increasing warm day and night trends on crop production and productivity across agro-ecologies.

In most agro-ecology zones, the annual number of warm days and nights is increasing, suggesting that significant increase in warming. When we compare the TN90p and TX90p anomalies, the TN90p peaked in 2014, 2004, 2004, and 2006 for the cold to very cold humid, tepid to cool humid, hot to warm moist, and hot to warm arid, respectively (Figure 3.5a - d). Overall, warming anomalies are consistently increasing in all AEZs after 2008.

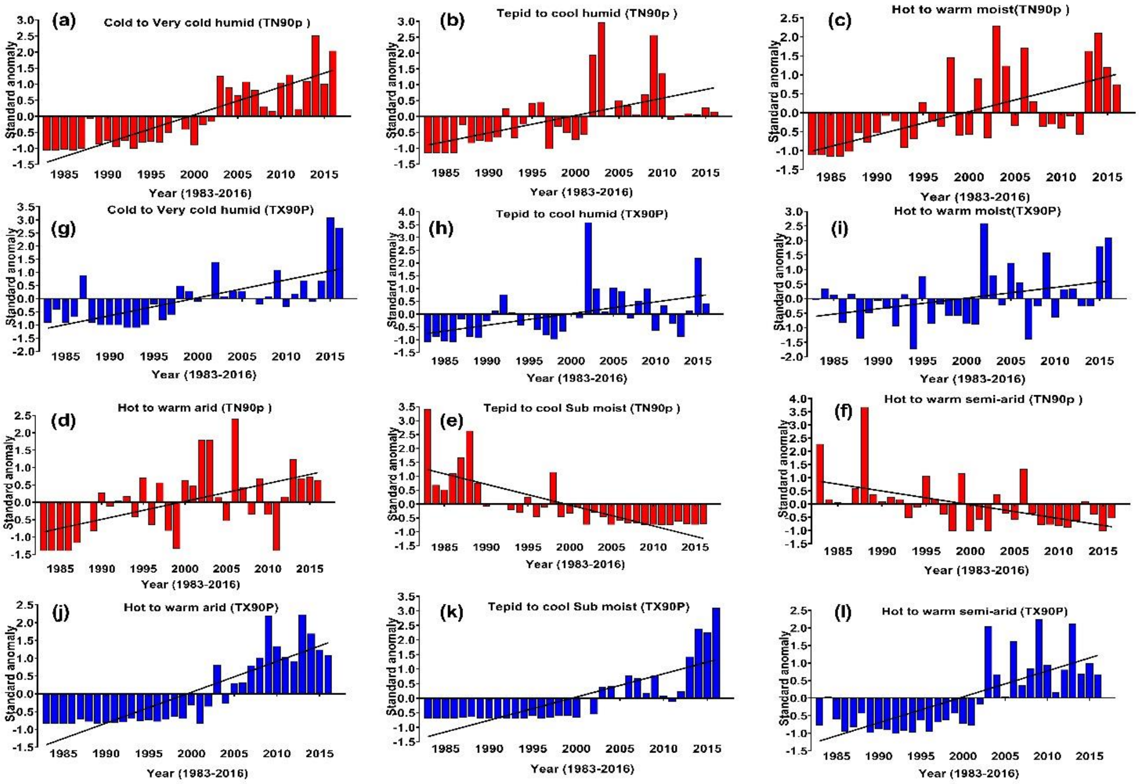

Figure 3.5. Warm nights (TN90p) and Warm days (TX90p) over agroecological zones for the period 1983-2016

Warmest day and Coldest day

Concerning the warmest day (TXx), significant positive trends were observed in all ago-ecology, except in hot to warm moist, where the trend is insignificant and decreasing (Table 3.2). The trend in (TXx) is highest for tepid to cool sub moist, with the magnitude of change being 0.089 °C/year ($p < 0.001$). At the same time, the lowest magnitude of change was observed in hot to warm moist to be -0.008°C/year. The coldest day (Tis substantially increasing in all agroecological zones, with the highest magnitude (0.081°C/year) for tepid to cool sub moist and hot to warm semi-arid. The lowest (0.024°C/year) change is observed for hot to warm moisture. The annual TXn and TXx annual show significant warming anomalies for 1983–2016 in most agroecological zones (Figure 3.6a - l).

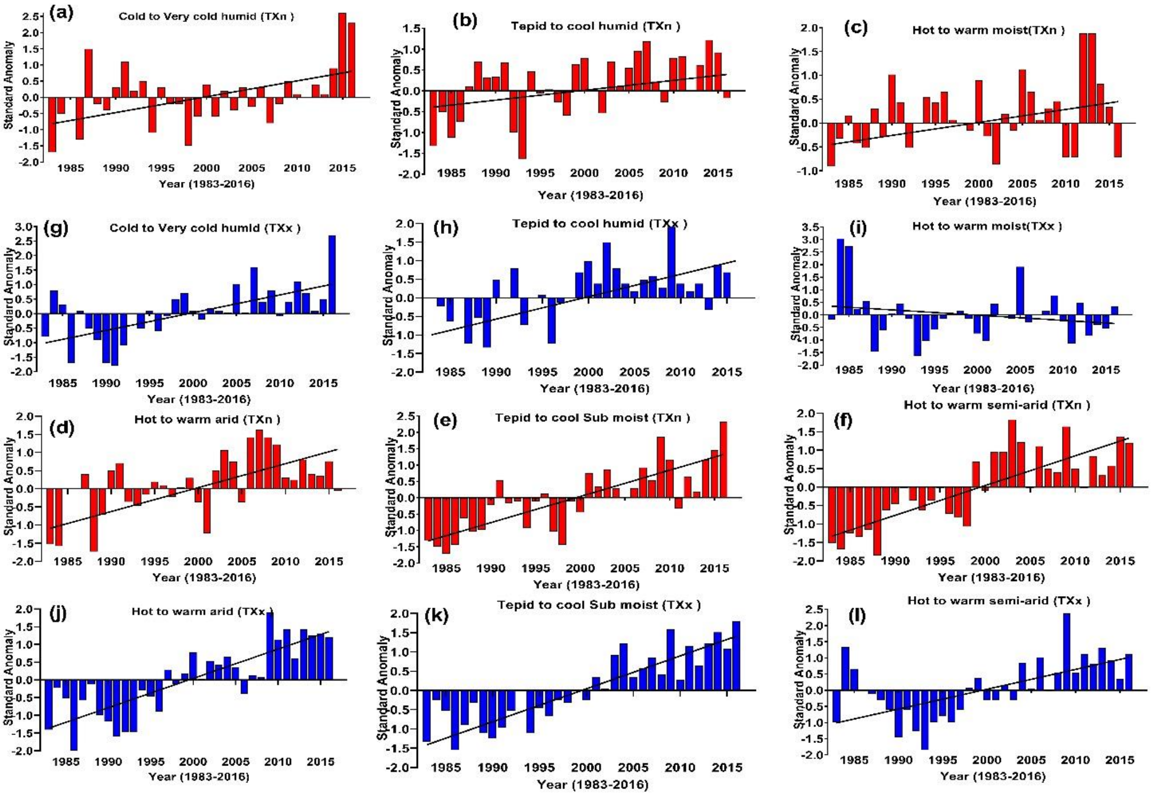

Figure 3.6. The warmest day (TXx) and Coldest day (TXn) over agroecological zones for the period 1983-2016

The findings corroborate previous studies for different parts of Ethiopia and elsewhere. For example, Shawul and Chakma (2020) investigated a decreasing trend in their study over the Upper Awash Basin. However, Tadese *et al.* (2020) testified a non-significant trend in TXn in all the sampled stations in the country. Chen *et al*. (2021) studied variations in extreme temperature in China and found a significant increasing trend from 1966 to 2015. The increase in TXx across the agro-ecology zone is another indicator of changing climate in the sub-basin. A growing trend in TXx in the main cropping season could reduce agricultural yields (Wu *et al.*, 2017).

Diurnal temperature range and Number of summer days

Diurnal temperature range (DTR) trends are significantly increasing in the tepid to cool humid, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid zones (Table 3.2), indicating that the daily maximum and minimum temperatures are significantly changing. Only hot to warm, moist stations showed an insignificant decreasing trend in DTR, meaning that daily maximum and minimum temperatures are not changing in opposite directions at many of the stations studied. Compared with other agro-ecologies, the tepid to cool humid and cold to very cold humid recorded the highest (0.120°C/year) and lowest (0.013 °C/year) magnitude change of DTR, respectively. Esayas *et al*. (2018) reported an insignificant decreasing trend (-0.015°C/year) in the DTR of the midland AEZ of Southern Ethiopia. Regarding trends in the number of summer days (SU), all AEZ in the study shows a significant increase (Table 3.2). This result indicates that the number of days by which the daily temperature is above 25°C is significantly increasing. Compared with other agro-ecologies, the greatest and lowest magnitude change of SU was 0.22°C/year and 0.034 °C/year ($p < 0.001$) in the tepid to cool humid and hot to warm arid, respectively (Table 3.2). The annual number of DTR and SU shows a significant change from 1983–to 2016 in most agro-ecology zones (Figure 3.7a - l).

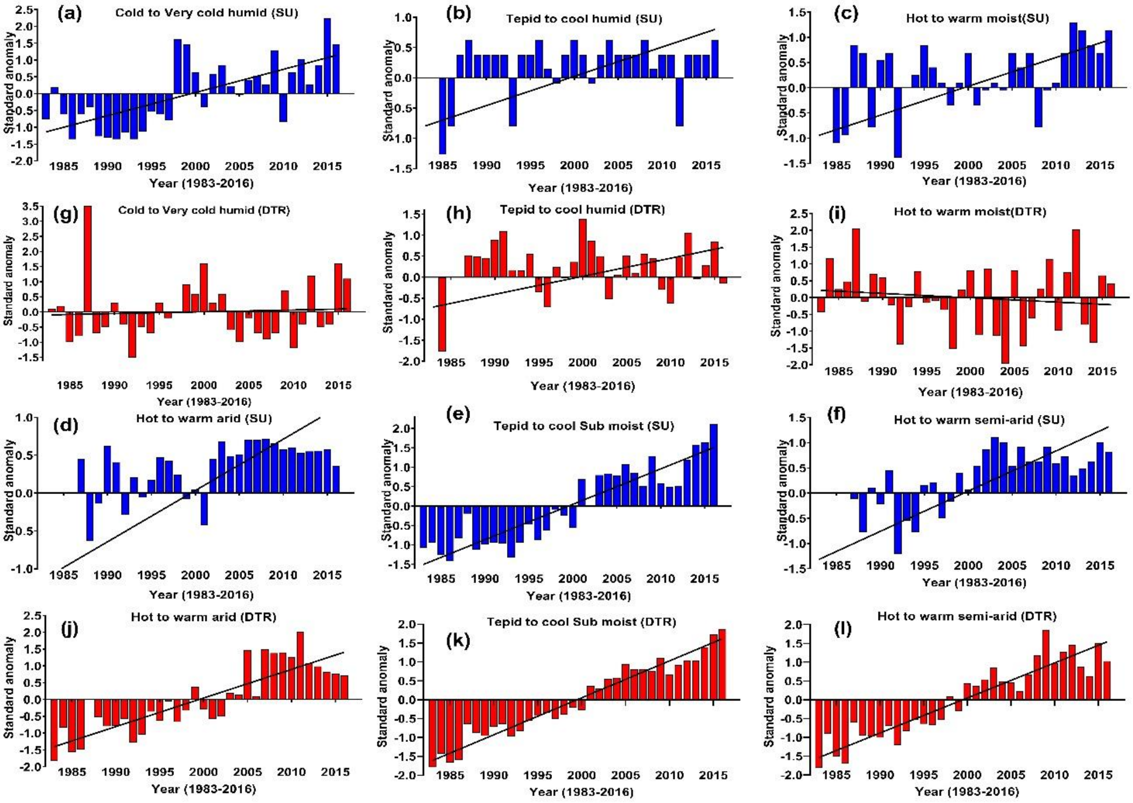

Figure 3.7. Diurnal temperature range (DTR) and Number of summer days (SU) over agroecological zones for the period 1983-2016

Cold spell duration indicator and Warm spell duration indicator

The CSDI and WSDI, the cold spell duration and warm spell duration indices, are annual counts of at least six consecutive days with Tmin greater than the historical 90th percentile value and Tmax less than the historical 10th percentile value; five of the six agro-ecology zones showed significant increasing trends in the WSDI. On the other hand, hot to warm moist shows no trend (Table 3.2). Compared with other agro-ecologies, the highest and lowest magnitude change of WSDI was 0.200°C/year and 0.020 °C/year ($p < 0.001$) in the tepid to cool humid and hot to warm semi-arid, respectively. Regarding the CSDI, a significant positive trend was observed in tepid to cool sub moist. In contrast, significant decreasing trends were observed in tepid to cool humid and hot to warm moist (Table 3.2), indicating a decrease in the number of consecutive cool days at the stations. The highest magnitude of CSDI was detected in tepid to cool sub moist (0.027°C/year). Negative and highest at -0.031°C/year ($p<0.001$) was recorded at hot to warm moist. When we compare the WSDI and CSDI anomalies, the WSDI reaches its peak in 2016, 2002, 2013, 2016, and 2013 for cold to very cold humid, tepid to cool humid, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid, respectively (Figure 3.8a - f).

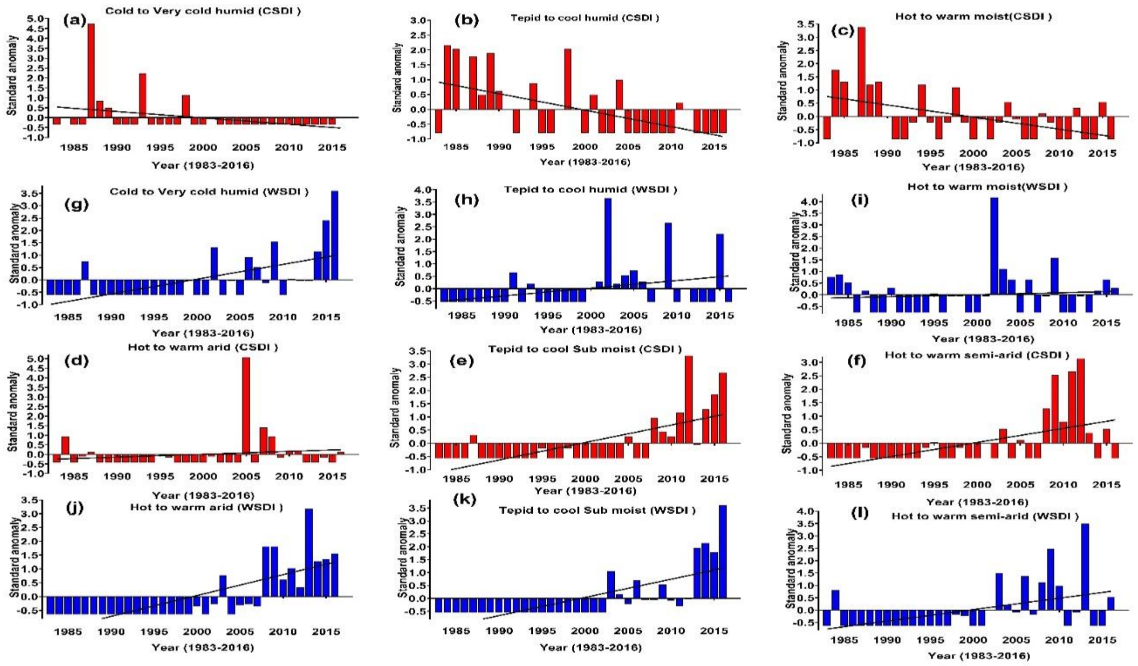

Figure 3.8. Warm spell duration indicator (WSDI) and cold spell duration indicator (CSDI) over agro-ecological zones for the period 1983-2016

The CSDI peaked in 1987, 1984, 1987, 2005, 2012, and 2012 in the cold to very cold humid, tepid to cool humid, hot to warm moist, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid, respectively (Figure 3.8g-l). It is known that the development and yield of crops depend on factors like temperature, precipitation, soil moisture and fertility, crop pest and diseases, and other crop management practices. Overall, the increase in trends of warm and cold temperature extreme events coupled with a lack of preparedness for increasing trends affects agricultural productivity and further farmers whose livelihood depends on it.

Table 3.2 Trends of ET_SCI extreme indices

Code	**Cold to Very cold humid [AEZ_1]**	**Tepid to cool humid [AEZ_2]**	**Hot to warm moist [AEZ_3]**	**Hot to warm arid [AEZ_4]**	**Tepid to cool sub moist [AEZ_5]**	**Hot to warm semi-arid [AEZ_6]**
	(MK)Sens Slope	(MK)Sens Slope	(MK)Sens Slope	(MK)Sens Slope	(MK)Sens Slope	(MK)Sens Slope
Temperature Indices						
TXx warmest day	(0.419) 0.056***	(0.400) 0.040***	(-0.073) -0.008 ns	(0.615) 0.082***	(0.699) 0.089***	(0.480) 0.073***
TNx warmest night	(0.606) 0.075***	(0.470) 0.060***	(0.455) 0.056***	(0.385) 0.049***	(-0.636) -0.080***	(-0.228) -0.033ns
TXn	(0.308) 0.047**	(0.330) 0.030***	(0.196) 0.024ns	(0.435) 0.066***	(0.631) 0.081***	(0.586) 0.081***
TNn coldest night	(0.005) 0.000ns	(-0.130) -0.010ns	(-0.240) -0.030*	(-0.025) -0.004ns	(-0.583) -0.080***	(-0.430) -0.061***
TN10p	(-0.456) -0.035***	(-0.470) -0.070***	(-0.291) -0.041**	(-0.082) -0.008ns	(0.724) 0.050***	(0.544) 0.057***
TX10p	(-0.549) -0.070***	(0.500) 0.050***	(-0.438) -0.069***	(-0.622) -0.033***	(-0.709) -0.057***	(-0.599) -0.077***
TN90p	(0.722) 0.080***	(-0.490) -0.020***	(0.472) 0.049***	(0.405) 0.053***	(-0.699) -0.048***	(-0.380) -0.040**
TX90P	(0.472) 0.056***	(0.390) 0.040***	(0.184) 0.028 ns	(0.768) 0.075***	(0.713) 0.054***	(0.528) 0.065***
WSDI	(0.430) 0.024***	(0.050) 0.200***	(0.041) 0.000ns	(0.583) 0.041***	(0.545) 0.026***	(0.346) 0.020**
DTR	(0.111) 0.013ns	(0.320) 0.120**	(-0.071) -0.015ns	(0.620) 0.082***	(0.879) 0.098***	(0.772) 0.094***
CSDI	(-0.159) 0.000*	(-0.260) -0.040*	(-0.283) -0.031*	(0.116) 0.000ns	(0.430) 0.027***	(0.340) 0.000**
SU	(0.481) 0.073***	(0.050) 0.220***	(0.364) 0.055*	(0.513) 0.034***	(0.720) 0.090***	(0.620) 0.069***
Rainfall indices						
RX1day	(-0.194) -0.036ns	(-0.090) -0.010ns	(-0.127) -0.013ns	(0.025) 0.005ns	(-0.121) -0.018ns	(-0.077) -0.010ns
RX5day	(-0.239) -0.026*	(-0.120) -0.010ns	(-0.123) -0.022ns	(0.139) 0.027ns	(-0.082) -0.011ns	(0.011) 0.001ns
R10mm	(-0.210) -0.025ns	(-0.048) -0.006ns	(-0.385) -0.049**	(0.189) 0.034ns	(-0.282) -0.032*	(0.094) 0.011ns
R20mm	(-0.257) 0.000*	(-0.300) -0.120***	(-0.184) -0.023ns	(0.121) 0.015ns	(-0.087) 0.000ns	(-0.002) 0.000ns
CDD	(0.175) 0.021ns	(0.320) 0.040**	(0.378) 0.042**	(0.135) 0.019ns	(0.258) 0.035*	(0.077) 0.012ns
CWD	(0.258) 0.032*	(-0.060) 0.000 ns	(0.135) 0.016 ns	(0.068) 0.000 ns	(0.207) 0.022 ns	(0.053) 0.006 ns
R95p	(-0.155) -0.010ns	(-0.170) -0.020ns	(-0.332) -0.037**	(0.098) 0.014ns	(-0.232) -0.020*	(0.011) 0.000ns
R99p	(-0.235) 0.000**	(-0.180) 0.000ns	(-0.080) 0.000ns	(0.027) 0.000ns	(-0.134) 0.000ns	(0.045) 0.000ns
SDII	(-0.159) -0.014ns	(-0.220) -0.030ns	(-0.178) -0.021ns	(0.134) 0.024ns	(-0.171) -0.023ns	(-0.053) -0.006ns
PRCPTOT	(-0.201) -0.025 ns	(-0.360) -0.040***	(-0.237) -0.029*	(0.141) 0.021 ns	(-0.225) -0.036 ns	(0.023) 0.004 ns
Drought Index						
SPEI 12	(-0.330) -0.052**	(-0.410) -0.050***	(-0.275) -0.040*	(-0.390) -0.058**	(-0.695) -0.088***	(-0.497) -0.068***
*** p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001.**						

3.4.3. Observed changes in precipitation extremes.

Consecutive wet days, consecutive dry days, and simple daily intensity index

The annual spatiotemporal trends of extreme precipitation indices across studied agro-ecologies are presented in Table 3.2. The maximum number of CWD (≥ 1 mm) did not show a significant trend in most studied AEZs. Except for cold to very cold humidity, all regions of AEZ show an insignificant increasing trend. Though the AEZ are found in different basin locations, the CWD trend result was negligible. Previous research (Tadese *et al.*, 2020) made the same observation, where different eco-environments did not show significant trends in most studied areas. In contrast, a study by Mohammed *et al.(*2018) in the northern highlands of Ethiopia shows a significant and increasing trend in Ambamariam, Mekaneselam, and Dessie stations. Unlike CWD, the maximum number of consecutive days when precipitation < 1 mm (CDD) shows a significant increasing trend in tepid to cool humid, hot to warm moist, and tepid to cool sub moist and non-significant increasing trend in the cold to very cold humid, hot to warm arid and hot to warm semi-arid. The increasing trend in CDD indicates increasing dryness across agroecological zones. When the trends in CDD are higher during the cropping season, the consequence for rain-fed agriculture is adverse. Compared with other agro-ecologies, the significant change of 0.032°C/year ($p < 0.05$) magnitude for CWD was recorded in the cold to very cold humid AEZ. The insignificant and lowest trend in the CWD was observed in tepid to cool humid and hot to warm arid AEZ (Table 3.2). The result presented in tepid to cool humid, hot to warm moist, and tepid to cool sub moist agro-ecology is consistent with (Berhane *et al.*, 2020), who found a significant increase in CWD in Dedebit, Maygaba, Maytsebri, and Sheraro of Western Tigray.

The highest CWD in the cold to very cold humid, tepid to cool humid, hot to warm moist, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid was observed in 2016, 2010, 1998, 1992, 1993, and 1993 respectively (Figure 3.9g - l). On the contrary, the highest CDD was observed in 1997, 2012, 2016, 2013, 2000, and 2012 in the cold to very cold humid, tepid to cool humid, hot to warm moist, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid respectively (Figure 3.9a - f). The SDII did not show a significant trend in all the zones. All AEZ, except for the hot to warm arid, show an insignificant negative trend (Table 3.2). The highest SDII was recorded in 1984, 1985, 1985, 1998, 1985, and 2016 for cold to very cold humid, tepid to cool humid, hot to warm moist, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid respectively (Figure 3.9A-F). In contrast, Muluneh *et al.*(2017) the central rift valley of Ethiopia reported a significant increase in SDII in most studied stations. The negative and insignificant trend implies that the trends of daily precipitation have been declining in most observed agro-ecologies.

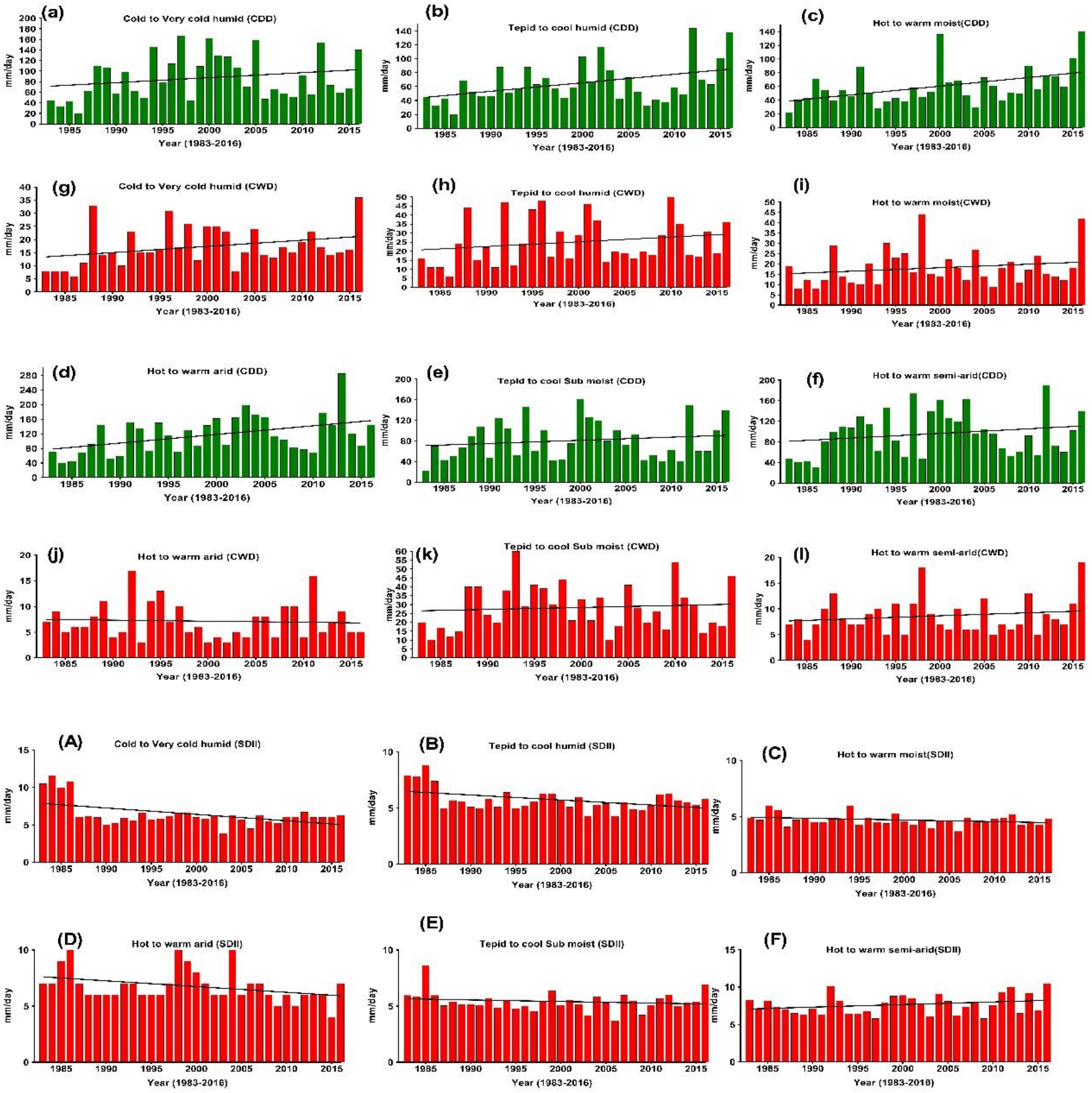

Figure 3.9. Consecutive wet days (CWD), Consecutive dry days (CDD), and Simple daily intensity index (SDII) over agroecological zones for the period 1983-2016,

Number of heavy and very heavy precipitation days

Trends in R10mm show variation across studied agro-ecology. Significant decreasing trends were observed for hot to warm moist and tepid to cool sub moist with decreasing magnitude of -0.049 days/year ($p < 0.01$) and -0.032 mm ($p < 0.05$), respectively (Table 3.2). On the other hand, cold to very cold humid, tepid to cool humid, hot to warm arid, and hot to warm semi-arid show a non-significant trend. The highest R10mm was recorded in 1984, 1985,1985,1998,1985, and 2002 for cold to very cold humid, tepid to cool humid, hot to warm moist, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid, respectively (Figure 3.10a - f). An increasing, but not significant, trend of R10mm was observed in hot to warm arid and hot to warm semi-arid, while negative trends in R10mm were observed among the remaining agro-ecologies (Table 3.2).

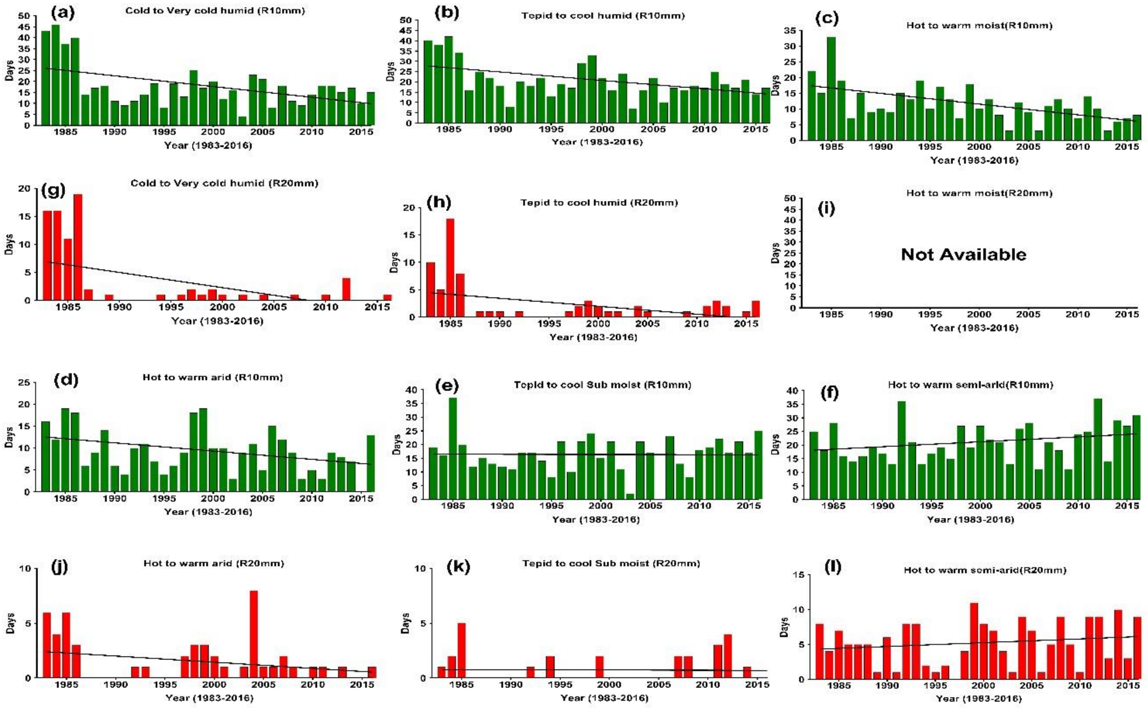

Figure 3.10. Number of heavy (R10mm) and very heavy (R20mm) precipitation days over agroecological zones for the period 1983-2016

Similarly, trends in R20mm show variation across the studied agro-ecology. Significant and decreasing trends were observed with decreasing magnitude of -0.120mm ($p<0.001$) in tepid to cool humid agro-ecology (Table 3.2). The remaining AEZs show an insignificant trend. The highest R20mm was recorded in 1986,1985,2004,1985, and 1999 for cold to very cold humid, tepid to cool humid, hot to warm arid, tepid to cool sub moist, and hot to warm semi-arid, respectively (Figure 3.10g-l). An increasing but insignificant trend of R20mm was observed in hot to warm arid, while divergent trends in R20mm were observed among other agro-ecologies (Table 3.2). The decreasing trend in R10mm and R20mm infer an increase in dry days and a decrease in the magnitude of precipitation. A decreasing trend in the number of heavy and very heavy precipitation suggests potential risks related to drought in most agro-ecologies. The results are consistent with the findings of Muluneh et al. (2017), who found decreasing trend in Addis Ababa, Combolcha, and Jimma stations.

Maximum precipitations of one day and five days

The spatial change in Rx1day and Rx5day precipitation indices values generally revealed variations across agro-ecologies. For the RX1day and RX5day indices, there is a sign of change across agro-ecologies between 1983 and 2016. Among the studied agro-ecology, only hot to warm arid had positive and significant trends (0.005 mm/year). In contrast, others had negative and non-significant trends in annual maximum consecutive 1-day precipitation (Rx1day) (Table 3.2). The trends in Rx5day show a negative and significant trend for cold to very cold humid, while tepid to cool humid, hot to warm moist, and tepid to cool sub moist were negative and insignificant. Hot to warm arid and hot to warm semi-arid show a positive and negligible trend in Rx5day (Table 3.2). Compared with other agro-ecologies, the significant magnitude change of Rx5day was recorded at -0.026 mm/year ($p < 0.05$) in the cold to very cold humid (Table 3.2). The higher value and negative trend in Rx1day and Rx5day across the studied AEZ indicate dry years (Figure 3.11(a-l)). Comparing cold to very cold AEZ study's result with (Worku *et al.*, 2019), who studied extreme climate events in Jema Sub Basin, Upper Blue Nile Basin, show a significant decreasing trend in Alemketema Station.

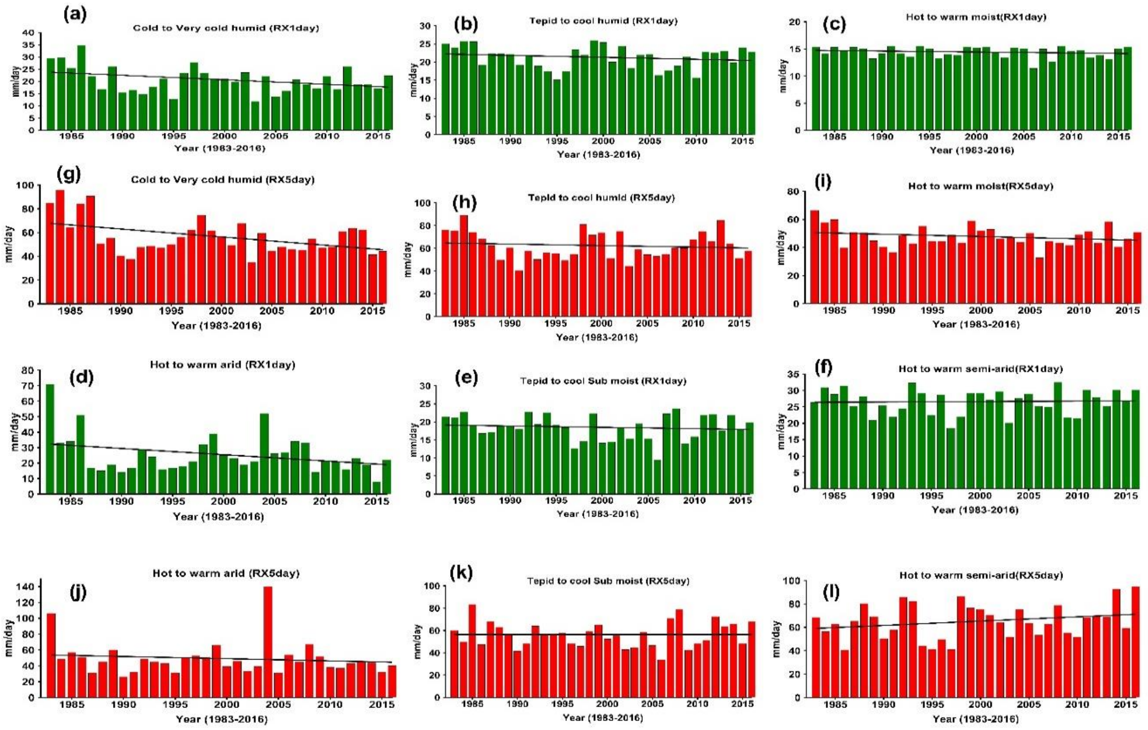

Figure 3.11. Maximum precipitations of 1 day (Rx1DAY) and 5 days (Rx5DAY) over agro-ecological zones for the period 1983-2016

Very wet days and extremely wet days

Table 3.2 shows the computed R95p and R99p as annual totals of wet-day precipitation amounts that exceed the 95th and 99th percentiles from 1983–2016. There were no significant trends in R95p in the studied agro-ecology, except hot to warm moist and tepid to cool sub moist, where a significant decreasing trend was observed. Despite the lack of statistical significance, the trends in R95p were positive in hot to warm arid (0.014 mm/year) (Table 3.2). Similarly, the trends in R99p were not significant in all agro-ecologies (Table 3.2).

Furthermore, the frequency of R95p anomalies, the negative anomalies are consistently declining since the beginning of the 1985s in the cold to very cold humid, tepid to cool humid and hot to warm moist and tepid to cool sub-moist agro-ecologies (Figure 3.12a-c and h). On the contrary, positive anomalies are seen for hot to warm arid (Figure 3.12g). Regarding the frequency of R99p, the anomalies are consistently declining for all agro-ecologies (Figure 3.12d-f and j-l). This result inferred minor variation in the distribution of wet and extreme wet days across the agro-ecology understudy over the study periods. Previous research (Bulti *et al.*, 2021) in Adama city and (Reser and Bradley, 2020) in Debre Zeyit and Kulumsa station of the central highland of Ethiopia also shows an insignificant trend.

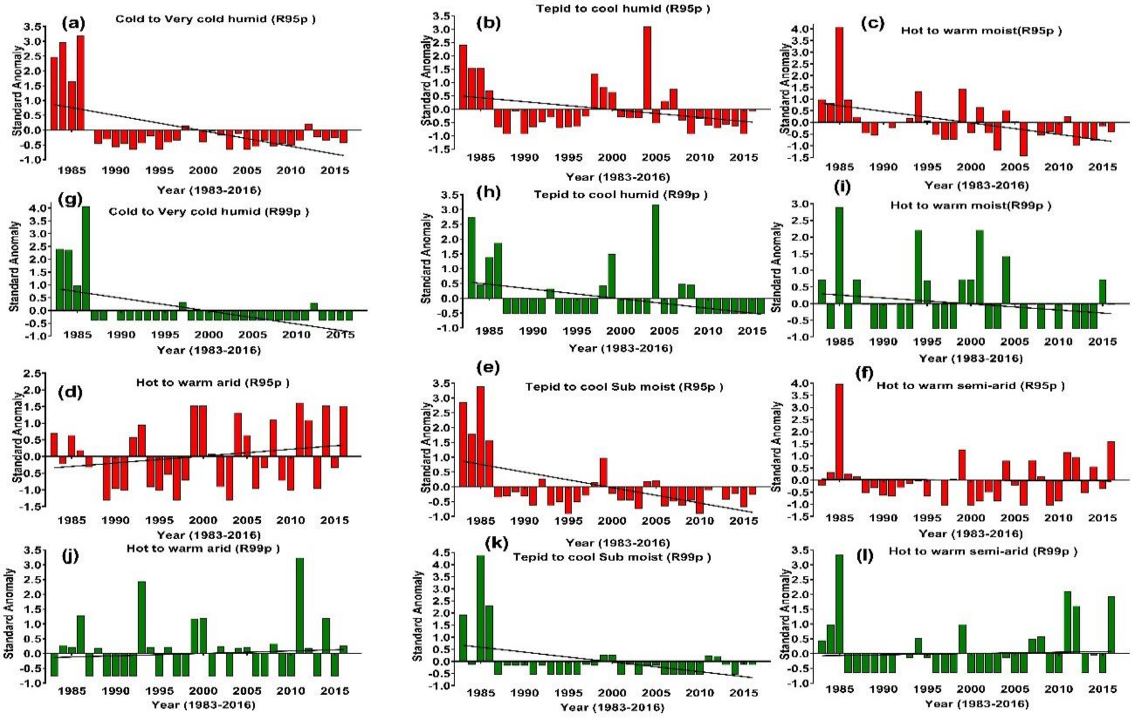

Figure 3.12. Very wet days (R95p) and Extremely wet days (R99p) over agroecological zones for the period 1983-2016

Annual total precipitation in wet-day

Table 3.2 shows the computed PRCPTOT (>1 mm/day), which greatly varies across agro-ecologies. Results show that only tepid to cool humid and hot to warm moist had negative and significant trends, while cold to very cold humid and tepid to cool sub moist had negative and insignificant trends in PRCPTOT. Hot to warm arid and hot to warm semi-arid had positive and non-significant. Compared with other agro-ecologies, the greatest significant magnitude change of (PRCPTOT) was recorded at -0.040 mm/year ($p < 0.001$) in cold to very cold humid

(Table 3.2). Our results revealed a mixture of drying and wetting trends in the long-term context of the annual PRCPTOT in the studied agro-ecology. Our results in the cold to very cold humid and tepid to hot moist agro-ecologies are consistent with (Omondi *et al.*, 2014), who noted a significant and decreasing trend over the Horn of Africa.

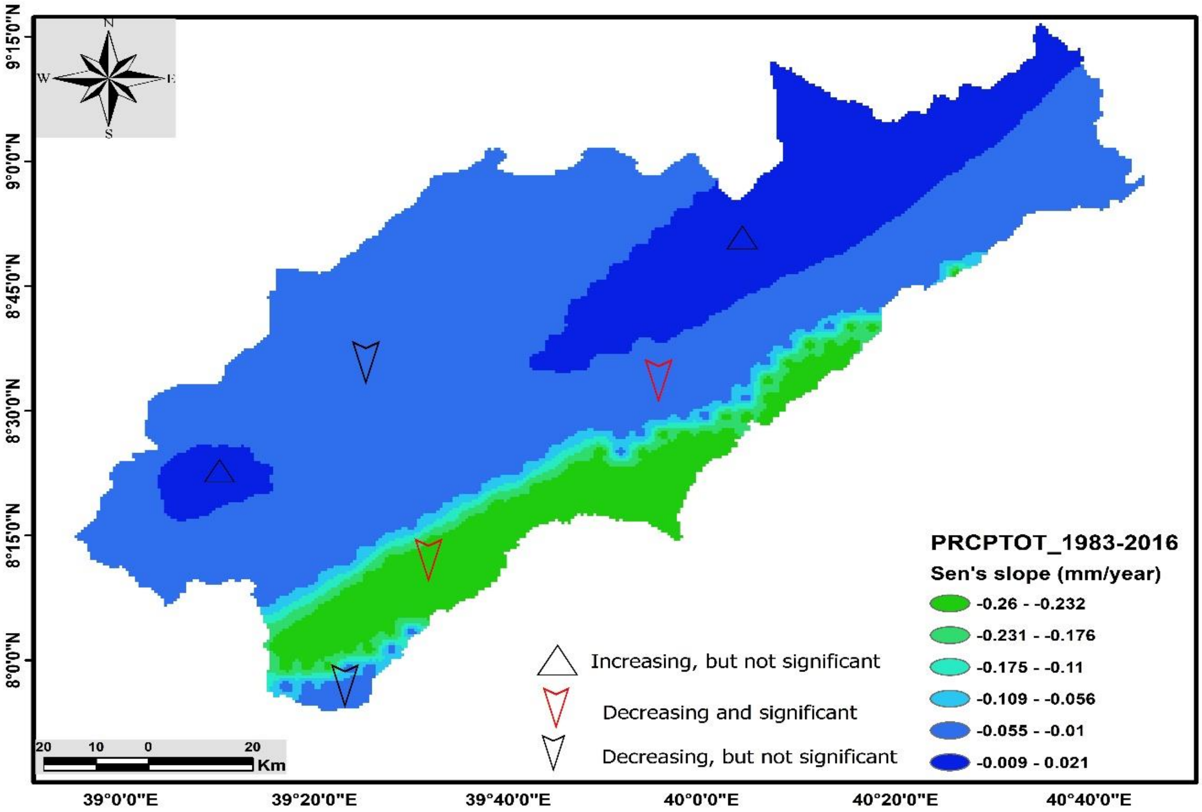

Figure 3.13. Annual total wet-day PRCPTOT (>1mm/day) over agroecological zones for the period 1983-2016

Generally, the significant change in extreme rainfall indices across studied agro-ecologies can be explained by natural variability and a high response to increased global greenhouse gas emissions (Myhre *et al.,* 2019; Halimatou *et al.,* 2017). Therefore, the decrease in rainfall and extreme events in some agro-ecologies impact farmers' livelihoods. Elsewhere, increased frequencies of extreme rainfall events, such as long dry or wet spells, result in weaker productive systems (Vogel *et al.,* 2019; Halimatou *et al.,* 2017).

3.4.4. Drought indices

For the SPEI 12 index, there is a sign of change across agro-ecologies between the years 1983 to 2016. The study revealed that all study agro-ecology experienced negative and significant trends (Figure 3.14 (a-e). A significant and negative annual SPEI trend indicates an increase in drought across agro-ecology. Compared with other agro-ecologies, the biggest significant magnitude changes of (SPEI-12) were recorded at -0.088°C/year ($p < 0.001$) in the tepid to cool sub-moist agro-ecology (Table 3.2). The frequency of annual wet, normal, and dry events across agro-ecologies for the period 1983–2016 are described in **(Annex H, Table 3.3).** The most extreme annual wet event was observed in tepid to cool sub-moist agro-ecology. The stronger value for normal events was observed in the hot to warm semi-arid agro-ecology. The most frequent annual extreme dry event was observed in hot to warm moist, hot to warm arid, and tepid to cool sub-moist agro-ecologies **(Annex H, Table 3.3).** The results from the SPEI-12 in this study area agree with recent studies conducted in the Awash basin (Maru *et al.*, 2021). The increase in drought frequency across agro-ecologies can be related to an increase in extreme mean temperature indices and a decrease in mean and extreme precipitation indices across studied agro-ecology. The increasing frequency of drought events across agro-ecology can affect agricultural production by limiting soil water availability for different crops and reducing crop yields (Lu *et al.*, 2020).

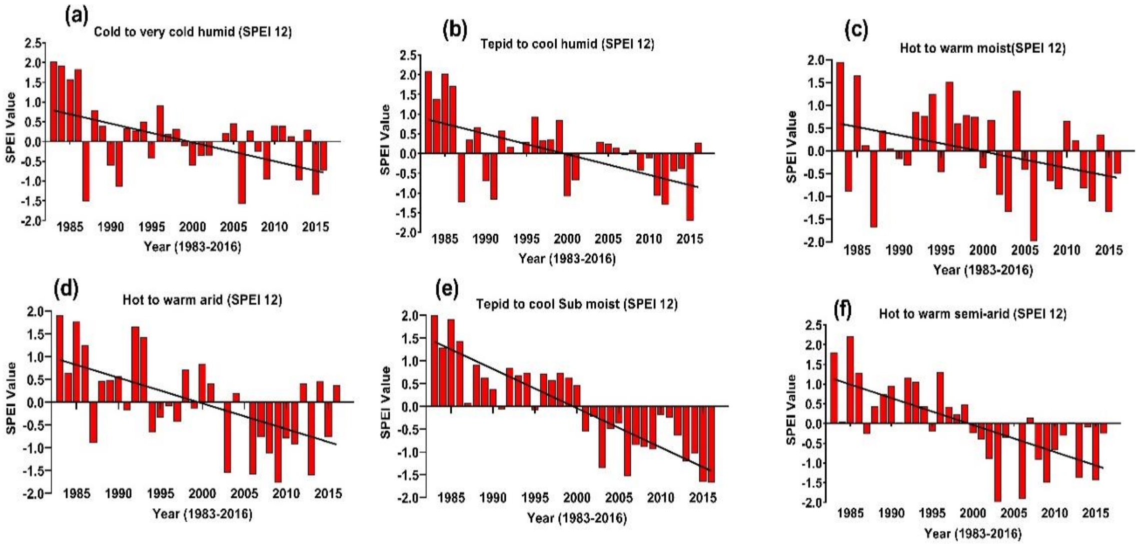

Figure 3.14. Annual trends of SPEI over agroecological zones for the period 1983-2016

3.5. Farmers’ perception and agricultural implications of climate extremes

Farmers from different agro-ecology zones perceived climate change, variability, and extreme events over the last two decades. Most interviewed key informants, focus group discussants, and surveyed sample farmers in different agro-ecology (89.3%) perceived changes in climate **(Annex I, Table 3.4)**. Focus group discussants indicated that the main source of information for climate change came from personal experience, radio broadcasts, and training given at different times by development agents. Furthermore, they elaborated on the changes in climate through changes in rainfall pattern, amount, and length of the rainy and dry seasons. One focus group discussant from hot to warm semi-arid stated the change and its impacts brought in his village as,

> "Climate in our area is changing. Compared to our youth time, the rain does not come on time…., sometimes we experienced unexpected rainfall. The late rain during the main season is harming our agriculture".

The results of the descriptive statistics between farmers' perceptions and a few chosen climate indices are displayed in **(Annex I,** and **Table 3.4).** The outcome demonstrates the studied area's climate change, variability, and extreme events. The study also showed that precipitation patterns throughout agro-ecologies have changed. Most respondents, from cold to very cold humid, tepid to cool humid, hot to warm moist, and hot to warm arid, perceived that temperature has increased in their area. Compared to farmers' perception, the Mann-Kendall trend analysis of temperature (Tmax and Tmin) result shows a significant increase in all agro-ecology except for hot to warm semi-arid, where temperature decreases (Table 3.2 and Figure 3.3). This result agrees with research conducted in different parts of the country and another part of the world, where researchers reported an increase in temperature (Mihiretu *et al.,* 202; Zhang *et al*., 2020; Roy *et al.,* 2021) and its convergence with climate data. Most farmers across agro-ecologies believed that the annual rainfall had decreased. This result is highly consistent with meteorological data. The total rainfall (TRF) trend analysis shows a significant decrease in all agroecologies except hot to warm semi-arid (Table 3.2 and Figure 3.3). The consistency between farmers' perceptions and meteorological data can facilitate farm adaptation.

Key informant interview conducted with woreda agricultural office heads in the study area shows that all informants know about changing rainfall, temperature, and extreme climate events. Key informants from Lode Hitosa woreda stated that;

> "Recently, we are observing changes and variation in climatic elements, which we believe as one of the contributors to the reduction of crop yields" The key informant further elaborated on the situation as "the variability in rainfall and temperature is affecting crop productivity by introducing crop pests and disease."

A key informant from the Merti Woreda Agriculture office stated that;

> "It is observable that there is climate change and variability in our woreda. Because of woredas' agroecological location, where almost half of the area is in lowland, frequent drought experience, crop pest and disease, the animal disease is the main indicator of climate change in the woreda".

Annex I and **Table 3.4** also show farmers' perceptions of the number of warm days and cold nights. The study revealed that farmers from different agro-ecologies perceived an increase in warm days (76.6%) and cold nights (63.3%). However, the result was wide-ranging between agro-ecologies **(Annex I,** and **Table 3.4).** All (100%) sample respondents from Hot to warm semi-arid agro-ecology and 82.9% from Hot to warm semi-arid perceived a change in the number of warm days. The result agrees with studies conducted by Mihiretu *et al.* (2020), where farmers perceive several Warm days. However, there is a divergence between farmers' perceptions and meteorological data on several cold nights. Farmers from hot to warm moist and hot to warm semi-arid agro-ecology zone perceived an increase and decrease in the number of cold nights. This result deviates from the meteorological data. Hot to warm moist and hot to warm semi-arid agro-ecologies indicated a reduction and an increase in the number of cold nights (Table 3.2). It can be assumed that determinants affect farmers' perceptions of climate change and extreme occurrences, given the convergence and divergence between meteorological data and farmers' perceptions (Mekasha et al., 2014; Mihiretu et al., 2020).

The descriptive statistics show that about 68.3% of farmers in the entire agro-ecology perceived an increase in drought frequency in their area. However, there is variation across agro-ecologies, where 75.9%, 65.6%, 62.4%, 60.7%, 61%, and 54.2% of farmers from tepid to cool sub moist, hot to warm semi-arid, tepid to cool humid, cold to very cold humid, hot to warm arid, and Hot to warm moist perceived an increase in drought years respectively **(Annex I, Table 3.4).**

One focus group discussant from tepid to cool humid stated the occurrence of frequent drought in his village as:

> "In previous years, our area is known with better rainfall, even several times of summer season; rainfall did not allow us to out from our tukul. But, in recent years, the rain has significantly decreased, and rainfall amount we used to see in the arid area is coming to us".

The SPEI-12 computed from all meteorological data show an increase in drought frequency in the last three decades **(Annex J, Table 3.5**). Similarities between meteorological data (increase in drought frequency) and farmers' perceptions can be due to farmers' experiences with consequences during drought years (Manalo *et al*., 2020; Neisi *et al*., 2020; Zhang et al., 2020; Roy *et al.,* 2021).

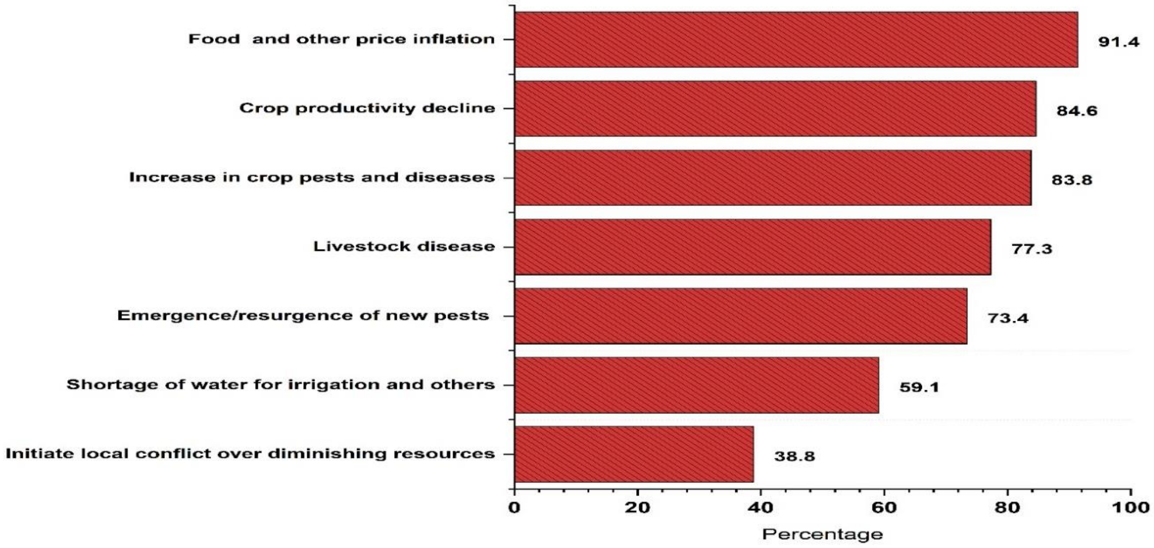

Figure 3.15. Perceived impacts of climate change, variability, and extreme events (%)

Regarding the perceived impacts of climate change, variability, and extreme events, farm households perceived effects, including food and other product inflation (91.4%), a decrease in crop productivity (84.6), an increase in crop pests and diseases (83.8), increase in livestock disease (77.3), emergence of new pests and weeds (73.4), shortage of water for irrigation (59.1) and initiating conflict over decreasing resources (38.8) (Figure 3.15). Similarly, a key informant interview with the Woreda Agricultural office and Development Agents (DA) shows visible effects of climate change, variability, and extreme events. The development agent from Gado Arba kebele stated the impacts as follows:

> “There are multiple effects of climate change, among others, reduction in agricultural production, introduction and expansion of crop pests like armyworm, cutworms, yellow rust, aphids and smut, livestock diseases like Blackleg, anthrax, lumpy skin disease, human disease like malaria, frequent occurrences of drought years, and scarcity of water for irrigation are visible effects of climate change in the kebele.”

This statement shows that climate change and extreme events are evident in all studied agro-ecology. Studies conducted in different parts of the country (Mekuyie and Mulu, 2021) and other parts of the world (Cuni-Sanchez *et al*., 2019; Poudyal *et al*., 2021; Talanow *et al.*, 2921) recognized perceived and actual impacts of climate change and extreme events on agricultural production.

3.6. Conclusion

The need for information on local temperature and precipitation extremes has significantly increased due to its wide range of livelihood impacts. The studied major agroecological zones are experiencing climate change and extreme events, which are either the same or vary between them. Overall, increasing maximum and minimum temperature and decreasing total rainfall signify that the study agro-ecologies are experiencing warming.

The growing trend of warm extreme temperature events in the cold to very cold humid, tepid to cool humid, and tepid to cool sub moist agro-ecology possibly affect agricultural production and productivity. Overall, the magnitude and direction of change differ across studied agro-ecologies. In general, warm extreme temperature indicators like TXx, TNx, TN90p, TX90p, and WSDI in the studied agro-ecology zone show a significant increasing trend. However, WSDI, TX90p, and TXx indicated a non-significant decreasing trend in hot to warm moist agro-ecology zones. Extreme cold temperature indicators: TNn, TN10p, TX10p, and CSDI show significantly decreasing trends in most agro-ecology zones. However, indicators like TXn and TX10p show a significant increasing trend in tepid to cool-humid climates.

Extreme precipitation indicators such as RX1day, RX5day, R10mm, R95p, R99p, and PRCPTOT show a decreasing trend in most agro-ecology zones. However, extreme precipitation indices indicated a non-significant increasing trend in the hot to warm arid agro-ecology zone. The increasing trend of extreme precipitation events in hot to warm semi-arid and hot to warm arid agro-ecology can be taken as an advantage for the community whose livelihood depends on rainfed agriculture. It can boost crop and vegetation productivity in the study of agro-ecology. Nevertheless, the decreasing trend of extreme precipitation events in the cold to very cold humid, tepid to cool humid, and tepid to cool sub moist agro-ecology possibly indicate the increase in the number of consecutive dry days (CDD), which is an indicator of drought occurrences in most agro-ecologies which they never experienced in prior years. In addition, the study compared agro-ecology-based farmers' perceptions of climate change trends and some selected extreme indicators. The study revealed similarities in farmers' perception with meteorological data results.

In conclusion, the spatiotemporal differences in temperature and extreme precipitation indices in the Awash-Awash sub-basin indicate varying implications for agriculture and crop productivity. The increasing trend in extremely warm and decreasing trends in extreme cold indicators may influence crops' physiological processes and productivity. Similarly, the shift in trends of extreme precipitation can disrupt agricultural productivity and possibly affect farmers whose livelihood mainly depends on rainfed agriculture. The agro-ecology-specific study result shows crucial information to the policy developers, decision-makers, and farmers about the possible impacts of climate change and extreme events that lead to developing agro-ecology-based adaptation measures. Furthermore, agro-ecology-based vulnerability assessment to extreme climate events in the sub-basin can provide the opportunity to minimize the high cost of crisis management, thereby increasing the adaptive capacity of farmers for sustainable production. As the effect of change in mean and extreme climate on agriculture is complex, future research is required to explore the impacts of seasonal variations of extreme climate events on crop and livestock resources.

CHAPTER FOUR

4. Disentangling climate from human-induced Net Primary Productivity and its agricultural implication in Awash Basin, Ethiopia

Abstract

Exploring vegetation responses to human and climate-induced change and its feedback is crucial for understanding the terrestrial ecosystem dynamics and sustainable development. The study's main objective is to quantify the relative contribution of climate and human-induced Net Primary Productivity (NPP) and its implications on agriculture in the Awash Basin. Seasonal and annual trends and correlation between total rainfall (TRF) and NPP data (1982-2018) were used to disentangle climate from human-induced change. The Rain Use Efficiency (RUE) and Residual Trend Analysis (RESTREND) were also computed to support the analysis. The study revealed that the spatial heterogeneity of TRF in the basin influenced the NPP, RUE, and RESTREND results. The study shows that climate change decreased about 39.9% of NPP area, while human activities increased about 14.9 % of NPP area. Human activities that caused the increase in the NPP area are mainly found in areas where large-scale and small-scale irrigation activities are practiced. Human activities in land use and land cover transition, including expansion of bareland areas, rainfed agricultural lands, and vegetation losses, resulted in NPP reduction. The result of the study also indicated that the seasonal variation in NPP and TRF in the basin threatens farmers whose livelihood depends on rainfed agriculture. Generally, the declining rate of NPP in the Basin suggests that land degradation is increasing, resulting in reduced ecosystem service. Therefore, addressing the local conditions and factors driving the change is important when managing the basin's vegetation productivity.

Keywords: Climate change, land use and land cover change, net primary productivity, agriculture, residual trend, Ethiopia

4.1. Introduction

In recent decades, the earth has been experiencing rapid changes in its ecosystem (Ran *et al.,* 2021; Ma *et al.,* 2022). Changes in atmospheric composition, climate, land use and cover, and the hydrologic cycle are some examples of anthropogenic changes in global and regional terrestrial ecosystems (Koutsoyiannis, 2020; Malhi *et al.,* 2020; Hu *et al.,* 2021; Zhang *et al.,* 2021). According to the sixth IPCC, the average global surface temperature increased from 0.8°C to 1.3°C between 1850-1900 and 2010-2019 (Masson-Delmotte *et al.,* 2021). Climate changes have an impact on ecological processes such as Gross Primary Productivity (GPP) and Net Primary Productivity (NPP) (Michaletz *et al.*, 2014; Wu *et al.*, 2020). NPP is an important indicator of biomass dynamics through its indicator of abundant vegetation, climate change, and human interference, such as LUCC (Dangal *et al.,* 2016). Besides climate change and global carbon balance, understanding the relationship between NPP and climate variables is important. The variation in NPP is related to mean and extreme climate events such as temperature, precipitation, solar radiation, and air pressure (Wang *et al.,* 2013; Zheng *et al.,* 2020; Yan *et al.*, 2021a), soil moisture (Li *et al.,* 2020a), and drought (Zhang *et al*., 2020a) conditions. Pan *et al.* (2020) observed that terrestrial NPP is more sensitive to temperature in the middle and high latitudes, while precipitation is the most important factor in the low latitudes. According to Guo *et al*. (2021), precipitation has a significant positive impact on NPP in arid and semi-arid regions, whereas temperature has a negative impact on NPP. However, some aspects of these relationships need to be investigated further, owing to differences in localities and timelines (Yan *et al.,* 2021a).

Furthermore, ecosystem attributes and human activities influence NPP through transformation activities that improve production and livelihoods. LUCC is the most human-specific activity (Li *et al.,* 2020). The population growth and corresponding human needs have increased human pressure on the ecological system, resulting in a slew of potential ecological and environmental issues (Ganivet, 2020; Pham *et al.,* 2020; Pan *et al.,* 2021). NPP dynamics can be monitored to some extent, but identifying the drivers and their contributions to the changes is challenging (Wessels et al., 2007).

Distinguishing between climatic drivers and human impacts on ecosystems has long been a source of contention in arid and semi-arid regions because ecosystem dynamics and climate variability are inextricably linked and difficult to separate (Wessels et al., 2007). Increased human activity and climate change can cause ecological and economic damages in semiarid and arid ecosystems. As a result, accurate assessment and separation of the contributions of climate change and human activity to ecological changes are critical for ecological regulation and management (Chen et al., 2019).

Recent studies (e.g., Evans and Geerken, 2004; Li *et al.,* 2012) have used remotely sensed indices, such as the NDVI-based residual trend (RESTREND) method, to identify climatic and human influences on vegetation dynamics in arid and semiarid regions. Satellite imagery was frequently used to characterize the seasonality of vegetation (Donmez *et al*., 2016). Furthermore, because NPP is a sensitive indicator of both human activity and climate change, it has been widely used to differentiate climatic from anthropogenic influences on ecosystems (Wang *et al.*, 2013; Azhdari *et al.*, 2020; Guo *et al*., 2020; Wang *et al*., 2021; Zarei *et al.*, 2021; Wei *et al*., 2022). Generally, recent studies have focused on the global or national scale, yet NPP varies greatly in space and time due to differences or inconsistencies in natural and anthropogenic factors.

The Awash River basin is covered with different LULC types and is one of the most sensitive to climate and LULCC in Ethiopia (Taye *et al.*, 2018; Tadese *et al.*, 2020a2018; Damtew *et al.*, 2022a). Large areas of the basin are covered by arid and semi-arid types of climate and are characterized by a high rate of agricultural expansion at the expense of vegetation (Tadese et al., 2020b; Damtew et al., 2022b), variability of mean and climate extremes (Shawul and Chakma, 2020) including recurrent drought (Maru et al., 2022) and seasonal floods (Wondim, 2016; Namara et al., 2022) along the river banks. Studies have also indicated that LULC transition alters the NPP of the ecosystems (Duveiller et al., 2018).

A few studies have been conducted in Ethiopia's northern highlands to investigate trends and relationships between hydrological variables and NPP. Despite extensive research in other parts of the world (Azhdari *et al.*, 2020; Guo *et al*., 2020), the quantitative relationship between climate change and NPP in the Awash basin remains unclear. Furthermore, studies have also shown that based on the seasonal nature of vegetation productivity, seasonal trend analysis is very important to identify changes in vegetation productivity and monitor areas prone to ecosystem degradation (Teferi *et al*., 2015). Besides, systematic analyses on differentiating human and climate-induced drivers of NPP are still lacking in the Basin. Understanding the response of NPP to climate change is particularly important because the Basin is known for its vulnerability to climate change (Yadeta *et al*., 2020), proneness to drought events (Maru *et al.,* 2021), and LULCC (Tadesse *et al*., 2020). Thus, this research explores the Spatio-temporal variability of NPP and climate in the Awash Basin and disentangles the relative impacts of human activities and climate change on vegetation NPP and its agricultural implication in the Basin.

4.2. Materials and Methods

4.2.1. Study area Description

The Awash River basin is one of the 12 major river basins in Ethiopia and is located between latitude 7°23’ N and 12°8’ N and longitude 37°55’ E and 43°18’ E. The basin has an estimated 11,200 sq. km and a population of 18.3 million people (AWBA, 2017). Its landscape changes from peak mountains on the upper Basin's boundaries to a decline in elevation as it moves toward the northeast. The slope gradient varies from flat terrain on the bottom of the rift valley to mountainous and steep slopes on the rift valley escarpments.

From its source in Dendi woreda, the Oromia region, Awash flows North East following the direction of topography that ranges from 205 m.a.s.l at Awash terminal to 4,180 m.a.s.l at Keleta Watershed. The main river has a total length of 1250 km (Tadese et al., 2019). Tributaries like Akaki, Kebena, Mojo, Kassam, and Mile rivers are perennial, while many other tributaries appear during the rainy seasons with an estimated mean annual runoff of 4.6 km3.

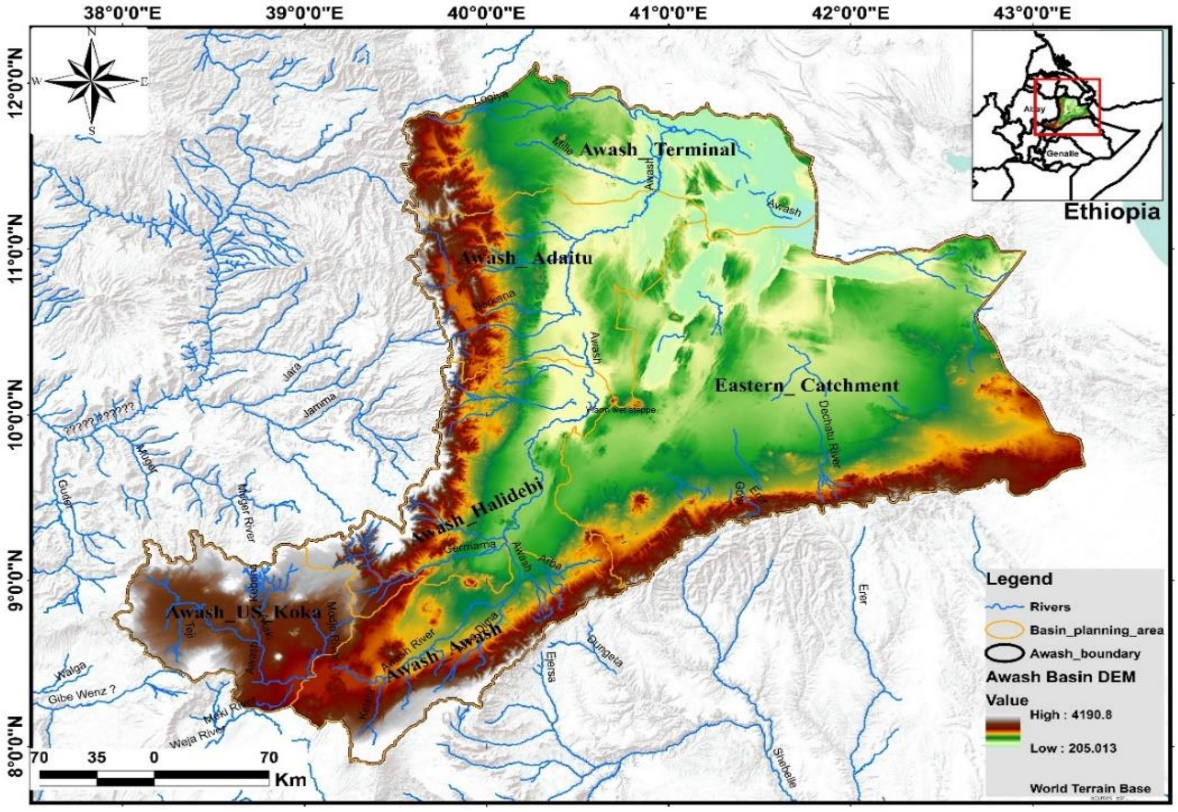

Figure 4.1 Map of the study area

Due to extensive irrigation water usage and limited water storage capacity, the Basin has high water demand and low supply making the Basin one of the vulnerable basins to climate variability and change in the country. The Awash River is also known as the most polluted river in the country due to several industries and towns in the basin (Aregahegn and Zerihun, 2021).

The trade winds, including Atlantic Equatorial westerlies, southerly and Easterly India Ocean currents, and the southwards and northward movement of the Inter-Tropical Convergence Zone (ITCZ) have a great influence on the climate of the Basin (Halcrow, 1989). The yearly precipitation of the basin ranges from 160 mm in lowlands to above 1600 mm of the basin, whereas the average temperature ranges from 16.7 to 29°C (Amare et al., 2017). According to traditional agro-ecology classification, about 58% of the basin is covered by bereha (semi-arid and desert), followed by kolla, where 22% coverage in the area, and the rest is covered by woinadega and dega agro-ecology (MOA, 1998). The dominant soils of the Basin include Leptosol (34.5%), Fluvisol (22.6%), Cambisols (14.2%), Solonchack (7.2%), and Vertisols (6.8%) (FAO 1998).

4.2.2. Data sources

NPP is the most used remote sensing dataset for vegetation and land degradation monitoring (It is also used as a sensitive indicator of interannual precipitation variability. The NPP was estimated by using the improved Multisource Data Synergized Quantitative-Net Primary Productivity (MuSyQ-NPP) algorithm, which is a Light Use Efficiency Model (LUE) that considers the effect of the fraction of diffuse solar radiation on LUE of estimating vegetation productivity (Sun et al., 2020). It gives the best estimate in cloudy areas, including tropical evergreen forests (Yu *et al.*, 2018; Wang *et al.*, 2021). The product has a spatial resolution of 0.05° and eight days of temporal resolution that come from the fraction of absorbed photosynthetically active radiation (FPAR) products and long-term series of global land and terrestrial satellite (GLASS) leaf and index (LAI) computed for the period between 1981 and 2018. Global data can be accessed freely at https://zenodo.org/record/3996814#.YrcWNnZBzrc. Daily total precipitation records were sourced from the Enhancing National Climate Services (ENACTS) dataset (http://www.ethiomet.gov.et). An observed dataset running from 1982 to 2018 with a spatial resolution of 0.0375° and daily temporal resolution was provided by National Meteorological Agency (NMA). The dataset is a blend of precipitation estimated from ground-based observation collected from NMA and EUMET-SAT. The estimated dataset has demonstrated strong performance when considering station location (Dinku *et al.*, 2014, 2022).

4.2.3. Method of data analysis

This study used Pearson Correlation Coefficient to test for a linear relationship between NPP and total rainfall. The coefficient is widely used in science to measure the degree of linear association between two variables (Zhao *et al.,* 2019; Hao *et al.,* 2021; Yan et al., 2021b). Mathematically, it can be presented by Equation 1;

$$\boldsymbol{r_{xy}} = \frac{\sum_{i=1}^{n}(X-\bar{x})(Y-\bar{y})}{\sqrt{\sum_{i=1}^{n}(X-\bar{x})^2}\sum_{i=1}^{n}(Y-\bar{y})^2} \tag{1}$$

X and Y, $\bar{\boldsymbol{x}}$ $\bar{\boldsymbol{y}}$ is NPP i^{th} season, Yi is climatic elements (precipitation) of the i^{th} season; Xm is the mean NPP for all seasons; Ym is the average precipitation for all seasons.

Rain Use Efficiency

The Rain Use Efficiency (RUE) ratio of NPP to rainfall is the critical indicator of land degradation in semi-arid and arid regions, where rainfall is considered a major limiting factor for vegetation growth (Bhandari *et al.,* 2015; Chang *et al.,* 2018). It has also been regarded as a crucial technique for figuring out how the NPP reacts to changes in annual precipitation. RUE is expressed by Equation 2;

$$\mathbf{RUE} = \frac{\sum_{1}^{i}\mathbf{NPP_i}}{\sum_{1}^{i}\mathbf{RF_i}} \tag{2}$$

Where NPP is the Net Primary Productivity of the season under investigation, **RF** is rainfall measured during the season, and **i** is the month under investigation.

NPP and climate trend analysis

Mann Kendall test (Mann,1945; Kendall, 1975) was applied to detect the changing trends in NPP across the study region. It is a non-parametric test that can address the time series with temporal variation, having missing values, tied values, or outliers. It is widely used in climate and hydrology to evaluate the significance of trends in time series (e.g., Baig *et al*., 2022; Damtew *et al*., 2022b; Wei *et al*., 2022). The seasonal Kendall test was applied to the individual pixel NPP time series to determine the spatial distribution of shifting trends. The significant and positive Kendall test statistics (Tr) value indicates an increasing trend, while the significant and negative τ value suggests a decreasing trend. Therefore, the method was adopted to explore the trends in NPP, maximum temperature, and total precipitation in the study area. Mann-Kendall trend test is expressed by Equation. 3;

$$\mathbf{Tr} = \sum_{\mathbf{i=1}}^{\mathbf{N-1}} \sum_{\mathbf{j=i+1}}^{\mathbf{N}} \mathbf{sgn}\left(\mathbf{a_j} - \mathbf{a_i}\right) \tag{3}$$

Where Tr is Mann Kendall test statistics, ai and aj are the sequential data values of the time series in the years i and j (j > i), and N is the time series length. A negative S value indicates a decreasing trend, and a positive value indicates an increasing trend in the data series. The sign function *sgn* is given by Equation 4;

$$\boldsymbol{sgn(a_j - a_i) = \begin{cases} +1 \; if \; (a_j) > 0 \\ 0 \; if \; (a_j - a_i) = 0 \\ -1 \; if \; (a_j - a_i) < 0 \end{cases}} \tag{4}$$

If the data is independent and normally distributed, the variance of the S statistic is given by Equation. 5;

$$\boldsymbol{Var\ (S) = \frac{1}{18}\left[Pn(Pn-1)(2Pn+5) - \sum_{i=1}^{T} v_i(\,(v_i-1)(2v_i+5)\right]} \tag{5}$$

Pn is the number of points, T is the number of tied groups in the data set, and vi is the number of data points in the tied group. A tied group consists of sample data with the same value; there is no difference in the values being compared. The summation aspect of Equation. 5 can be ignored if there are no tied groups. F and Var(F) values will be used to compute the test statistic Z by Equation 6.

$$\boldsymbol{Z} = \begin{cases} \dfrac{\boldsymbol{F-1}}{\sqrt{\boldsymbol{Var(F)}}} & \boldsymbol{if\ F} > 0 \\ \mathbf{0} & \boldsymbol{if\ F} = 0 \\ \dfrac{\boldsymbol{K+1}}{\sqrt{\boldsymbol{Var(F)}}} & \boldsymbol{if\ F} < 0 \end{cases} \tag{6}$$

The Z value is used to calculate the statistically significant trend. A negative or positive value of Z represents decreasing or increasing trend, respectively. The significance is tested at the 95% confidence level. The null hypothesis is not accepted at the significance level of α if |Z| ≥ Z_(α/2), where Z_(α/2) is the critical value of the standard normal distribution with a probability exceeding α/2, and shows that the trend is significant. If |Z| < Zα/2, the null hypothesis is accepted, and the trend is insignificant.

Sen's slope estimator is applied when the trend is assumed linear, showing the quantification of changes per unit time (slope). It is given by Equation 7;

$$\boldsymbol{T_s = \frac{Y_a - Y_b}{a - b}} \tag{7}$$

Ts is the estimate at year Ya, and Yb are considered data values at the time a and b (a > s) correspondingly.

Calculation of NPP actual, NPP predicted, and NPP residual

Residual Trend (RESTREND) is the difference between the observed NPP and the NPP predicted by climate variables using regressions calculated for each pixel (Evans and Geerken, 2004; Li *et al.,* 2012). According to Wessels *et al.* (2007), the method consents individual production total rainfall relationships to be developed for individual pixels, after which negative trends in the residuals (observed production predicted by precipitation) through time are identified. The method assumes that water is the most limiting factor to vegetation productivity in most dryland ecosystems. There is a strong correlation between vegetation productivity and climatic variables (total rainfall) (Evans and Geerken, 2004; Wessels *et al.,* 2007). The method follows three steps. First, pixel level ordinary least square (OLS) regression models of NPP against precipitation was computed using total and seasonal data. The OLS reduces the sum of the squared residuals and is commonly used in environmental studies and calculated by Equation (8).

$$\boldsymbol{V_i = A_{i-p} \times P + B_{i-p}} \tag{8}$$

where V_I= NPP, $A_{i-p}$the slope coefficient, P= annual precipitation, and B_{i-p}= intercept. Based on Equation (8), the predicted value of inter-annual NPP (V_{i-pred})for each pixel was calculated from the observed precipitation values (P). The NPP residual ($RESI_i$), i.e., the difference between observed NPP V_{i-obs}) and predicted NPP (V_{i-pred}) ($RESI_i$)= $V_{i-pred} - V_{i-obs}$), were calculated for each pixel, i. Following this, the trend of the NPP residuals for an individual pixel was computed on the time series of NPP residuals through linear Equation 9.

Second, the linear model's residual difference between the observed NPP and the predicted NPP was calculated. This model is called RESTREND residuals. For each pixel i, the relationship between NPP and climate factor (precipitation) was estimated using linear regression analysis:

$$\boldsymbol{RES_i = A_{i-re} \times t + B_{i-res}} \tag{9}$$

where RES_i= NPPI residual, A_{i-re}= NPP residual trend, and B_{i-res} = constant. The trend of NPP residuals over 37 years is the clue for isolating human-induced vegetation degradation from climate-driven impacts. If there is a significant temporal trend of RESi, then the decreasing NPP would additionally be derived by other hidden factors (i.e., human activities) besides the climate variable. Otherwise, the decreasing NPP would be caused by only the climate factor (rainfall) considered in Equation 9. Third, another linear regression of the RESTREND residuals against time will be carried out. If there is no trend in the residuals over time, climate factors are thought to be responsible for the observed changes in the vegetation. However, a trend toward decreasing residuals indicates that the vegetation is degrading, most likely due to human activity (e.g., deforestation due to agricultural land expansion, overgrazing, urbanization); and an increasing trend in the residuals suggests improved vegetation conditions which may be attributed to conservation and restoration efforts.

Establishing scenarios and quantitative assessment method

The relationship between NPP and climatic variables has the potential to distinguish between climate and human-induced vegetation change (Jiang *et al.*, 2022). The relative contribution of human activities and climate change vegetation productivity in the Basin was assessed and separated by comparing the slopes of NPP and the correlation between slopes of NPP and TRF (Li *et al*., 2012; Burrell *et al.*, 2017; Irisarri *et al*., 2021; Zhao *et al.,* 2021). All the slopes were calculated by Equation 7, and four scenarios were established (Figure 4.2). A NPP Actual (NPPA) slope> 0 suggests that Basin NPP increased, and vice versa. First, pixels of positive and negative trends in NPP Actual (NPPA) were identified. Second, pixels of positive correlation (+R) and negative (-R) between NPP and rainfall were computed. Third, pixels with a (-NPP) and (+R) were identified as climate-induced decline (drought). Fourth, pixels with negative (-NPP) and (-R) were classified as human-induced decline (deforestation due to agricultural land expansion, overgrazing, urbanization). Fifth, pixels with (+NPP) and (+R) were assigned to climate-induced increases in vegetation productivity. Finally, pixels with

(+NPP) and (-R) were assigned to human-induced increase in vegetation productivity, which can be attributed to conservation and restoration efforts.

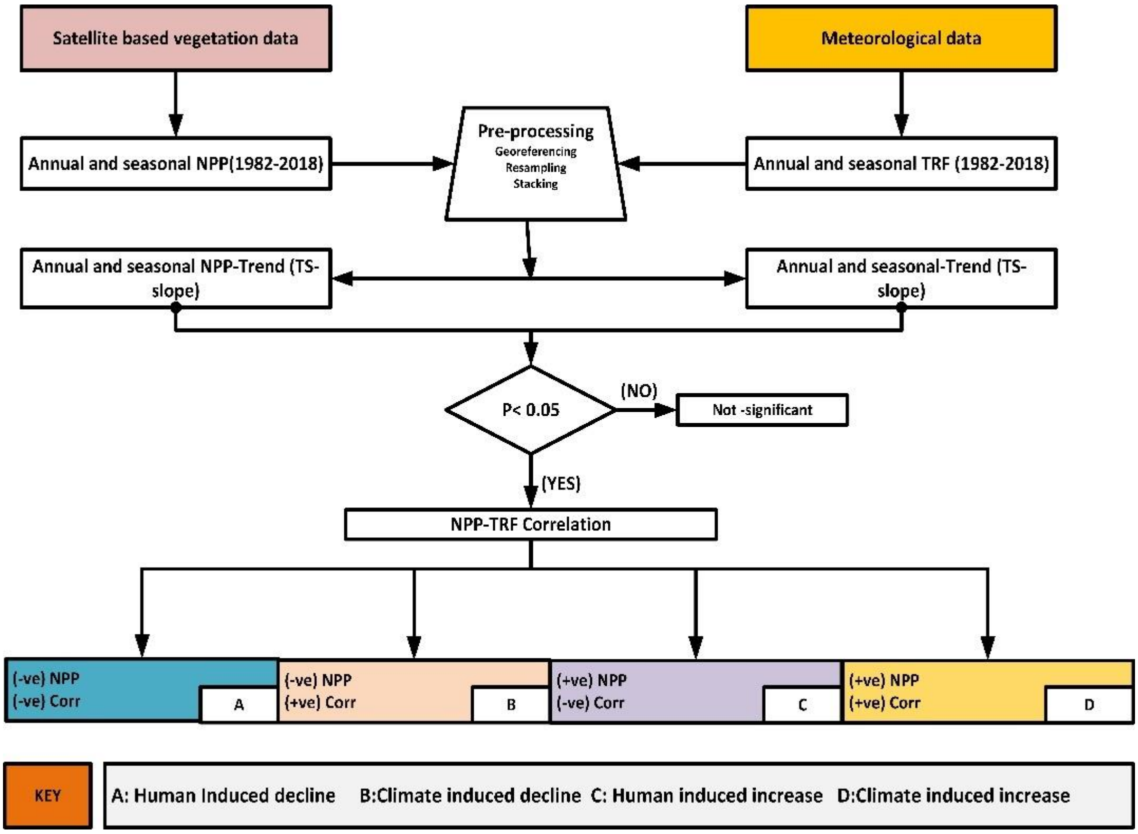

Figure 4.2 Flowchart to discriminate between climate and human-induced NPP change. Adopted from Evans and Geerken (2004), Wessels *et al.* (2007), and Chen *et al.* (2019)

4.3. Results and Discussion

4.3.1. Spatio-temporal analysis of seasonal and annual mean of NPP and TRF

Figure 4.3 shows the spatio-temporal distribution of seasonal average NPP and TRF from 1983 to 2018. The Awash Basin's mean seasonal and annual NPP showed significant spatial heterogeneity. The mean annual NPP ranges from 0 to 118 gC/m^2. Albeit the amount of mean NPP across seasons varies, the high NPP areas are found in the highland forest, grassland, and croplands of Awash-Awash, Awash upper stream Koka, Awash-Adaitu, Eastern Catchment, and Awash Helidebi (Figure 4.3). The estimated mean annual NPP in the Basin was 36.5 gC/m^2/year. The maximum annual mean NPP occurred in 2000 (42 gC/m^2), and the lowest occurred in 1991 (25 gC/m^2). The lowest NPP values were recorded in lowland areas of the Basin where the land is covered with bareland and very low vegetation cover. The observed NPP distribution pattern in the basin indicated the sign of good vegetation coverage in limited areas of the basin. The study affirms that a high value of NPP is a good indicator of vegetation coverage, as observed by Wei *et al*. (2022). The high value of NPP across seasons in the basin can be explained by good vegetation coverage supported by suitable climatic conditions for the vegetation and human management by introducing a reserve forest/park. Global studies show an increase in terrestrial primary due to the fertilizing effect from human activities (Forzieri *et al.,* 2017), fertilization effect (Piao *et al*., 2020), forest regrowth, and longer growing seasons (Duveneck and Thompson, 2017). MODIS-based global NPP revealed variations of NPP across different vegetation types and climatic zones (Li *et al.,* 2020c). The lowest NPP are recorded in areas experiencing harsh climates and human activities (Guan *et al.*, 2017). The amount of NPP will most likely increase in areas with plentiful soil water and areas covered by forests and crops (Latta *et al*., 2010; Weiskopf *et al.,* 2020; Zhang *et al*., 2020b).

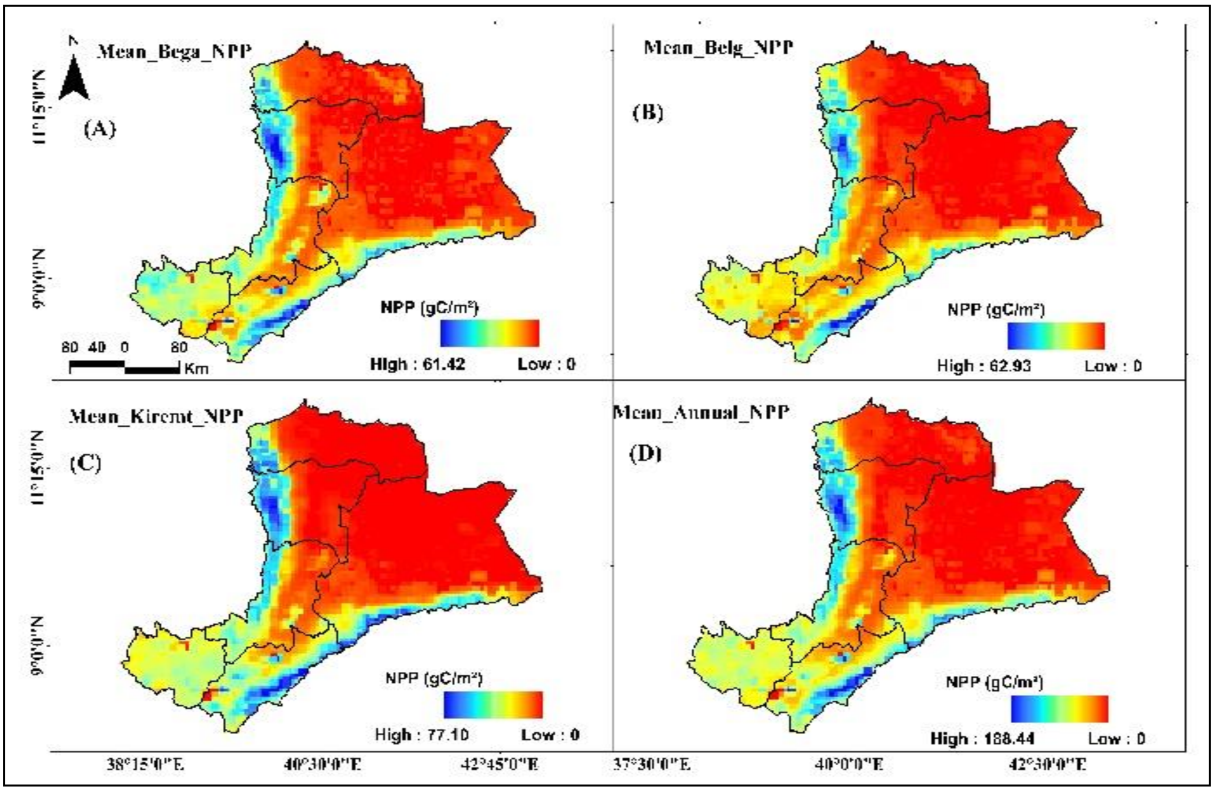

Figure 4.3 Annual and seasonal pattern of mean NPP in the Basin

Figure 4.4 presents the spatio-temporal variation of the study basin's mean annual and total seasonal rainfall. The observed average TRF distribution pattern in the Basin indicated a significant variation across seasons. The mean annual rainfall in the Basin is 571mm, while the highest and lowest rainfall was recorded in 1993 (733mm) and 363.6 mm in 2015, respectively. The highest TRF values are detected in highland areas of Awash Halidebi, Awash Upper Sub-basin Koka, and Awash-Awash sub-basin (Figure 4.4). At the same time, the lowest

TRF is found in lowland areas of the Basin, especially in the Eastern catchment and Awash terminal sub-basin (Figure 4.4). The mean annual and seasonal precipitation recorded in the Basin indicated the typical characteristics of the arid and semi-arid regions.

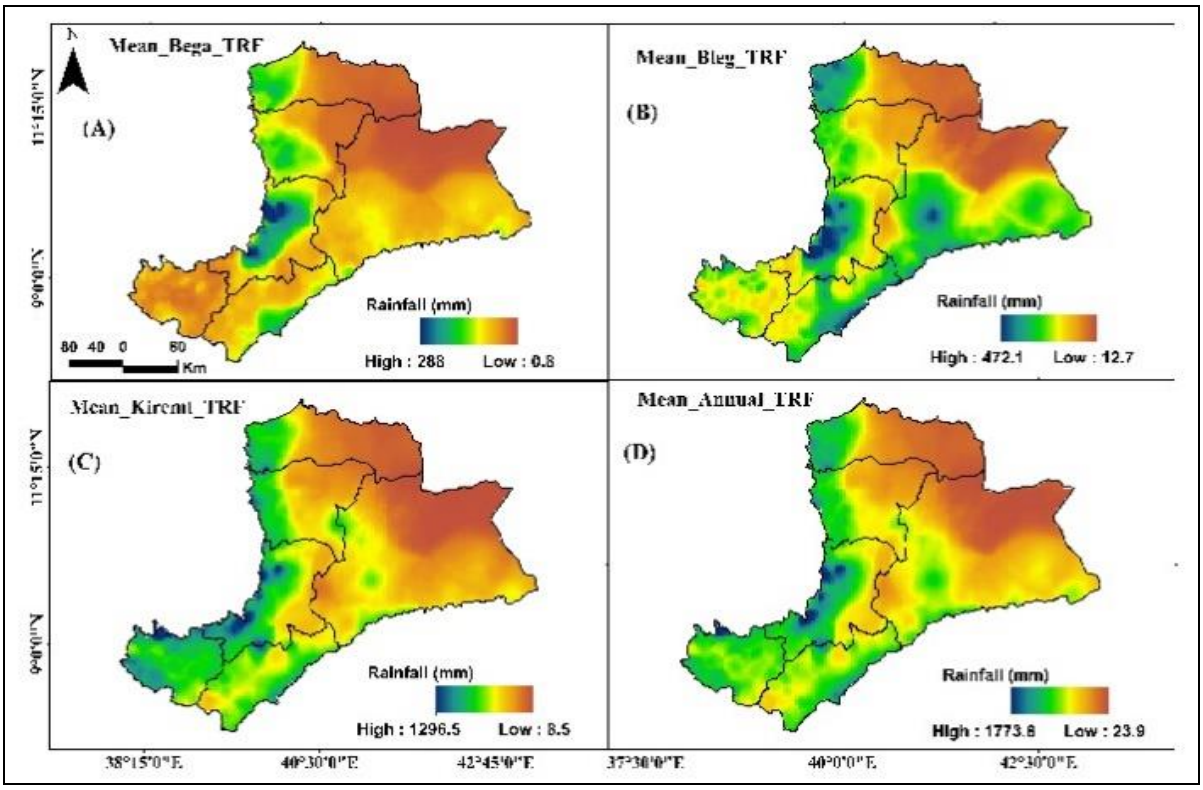

Figure 4.4 Annual and seasonal pattern of mean TRF in the Basin

4.3.2. Spatio-temporal analysis of trends of seasonal and annual NPP and TRF

Figure 4.5 depicts the spatio-temporal NPP and TRF tendencies as determined by the Mann-Kendall test and Sen’s slope estimator. Throughout the study period and seasons, different areas of the basin show variations in the NPP trend. The annual NPP trend analysis shows a significant decrease of over 56.6% of the basin. The annual average rate of NPP change ranges from -2.46 to 2.49 gC/m^2/year. The significant areal coverage of NPP in the Basin also varied seasonally. Approximately 35.4%, 38.4%, and 24.5% of land areas exhibited a significant ($P<0.05$) trend during the Bega, Belg, and Kiremt seasons, respectively. The average seasonal rate of NPP change ranges from -0.86 to 0.97 gC/m^2/year, -1.21 to 0.65 gC/m^2/year, and -1.09 to 1.13 gC/m^2/year for Bega, Belg, and Kiremt seasons, respectively (Figure 4.5). The seasonality trend of vegetation productivity is not rare for the Basin alone. In a study in the Abay basin, Teferi *et al.* (2015) found a significant trend change in vegetation productivity along with the year’s season.

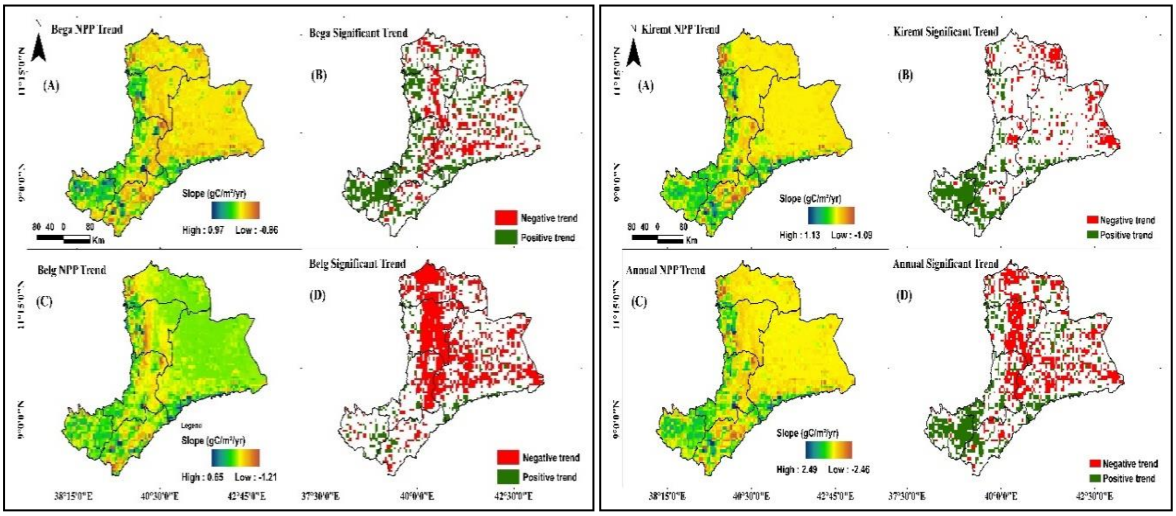

Figure 4.5 Annual and seasonal trends and significant spot areas of mean NPP in the Awash Basin during 1982-2018

Similarly, Tesfaye *et al*. (2017) in the highlands of northern Ethiopia found an increase in NPP during rainy and dry seasons. Areas in the Awash Upper Stream Koka and Awash and highland areas of the Awash Halidebi had strong and positive trends in NPP during the *Bega* and *Kiremt* season (Figure 4.5). A few areas in similar sub-basins had negative and significant trends indicating land use and land cover changes. However, a significant and negative trend in NPP has been observed in most areas of eastern catchment Awash Adaitu sub-basins (Figure 4.5). This trend is linked to the expansion of urban areas and land degradation in the sub-basins. Areas with a positive trend in the Eastern catchment, Awash Adaitu, and low lands of Awash Halidebi appeared to be associated with increased vegetation coverage due to the invasion of Prosopis Juliflora (Shiferaw *et al*., 2021; Ahmed *et al*., 2022) and expansion of cash crops (Damtew *et al*., 2022a) and irrigation land (Tola and Shetty, 2021). Generally, the declining NPP rate in the Basin suggests that land degradation is increasing, resulting in a reduced ecosystem service (Xing *et al.*, 2021).

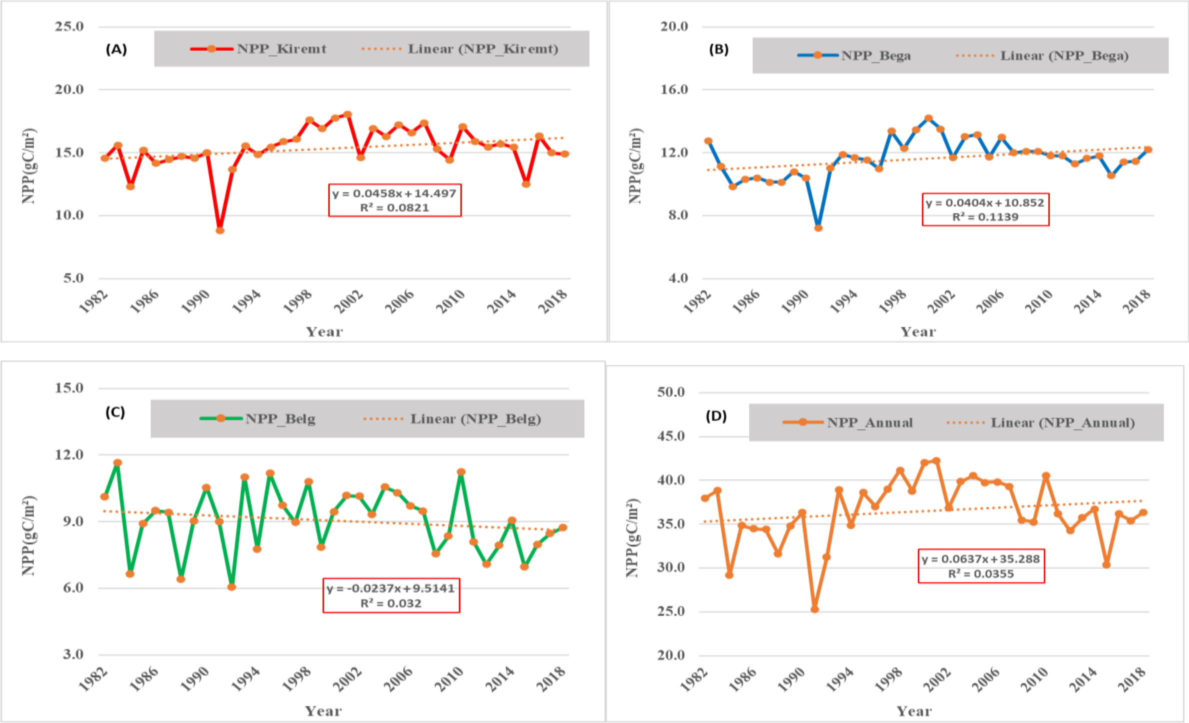

Figure 4.6 Seasonal trends of mean NPP in the Awash Basin during 1982-2018

The mean annual rate of change for total rainfall ranges from -29.17 to 15.52 mm/year. A significant and maximum decreasing trend was detected in the Awash Haldebi sub-basin. In contrast, a significant increasing trend was recorded in highland areas of the Awash and Awash Adaitu sub-basin (Figure 4.6). The annual significant ($p<0.05$) increase in the TRF was detected in about 37.4% of the basin area, out of which 83.5% shows a decreasing trend (Table 1, Supplementary material). During the Belg season, about 55.3% of the basin area recorded a significant negative trend. During the Kiremt season, out of the total basin area, 23.8% shows a significant trend, out of which 83.3% are covered with significant and positive (Figure 4.6 and Table 4.1 (Supplementary material)). The average seasonal rate of TRF change for *Bega*, *Belg*, and *Kiremt* seasons is -8.14 to 2.39 mm/year, -15.28 to 2.49 mm/year, and -13.06 to 14.67 mm/year, respectively (Figure 4.6). TRF grid and station-based analyses in different basin parts have also reported similar results (Damtew et al., 2022b; Duguma et al., 2021; Mulugeta et al., 2019; Taye et al., 2018). In general, annual trends of observed TRF in the Basin align with previous studies conducted in different parts of the country (Esayas *et al.*, 2018; Worku *et al.*, 2019; Nasir *et al.*, 2022).

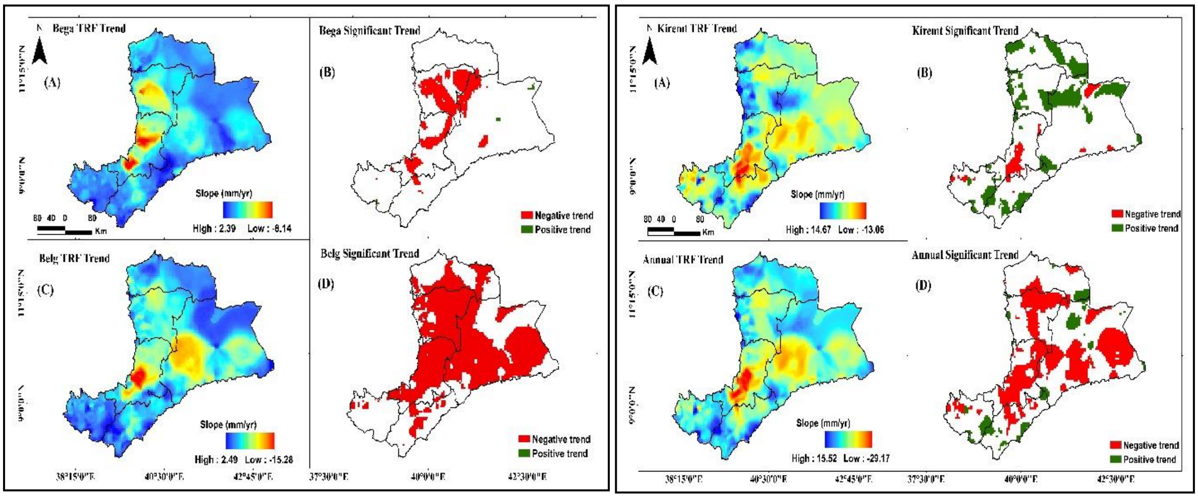

Figure 4.7 Annual and seasonal trends and significant spot areas of mean TRF in the Awash Basin, 1982-2018.

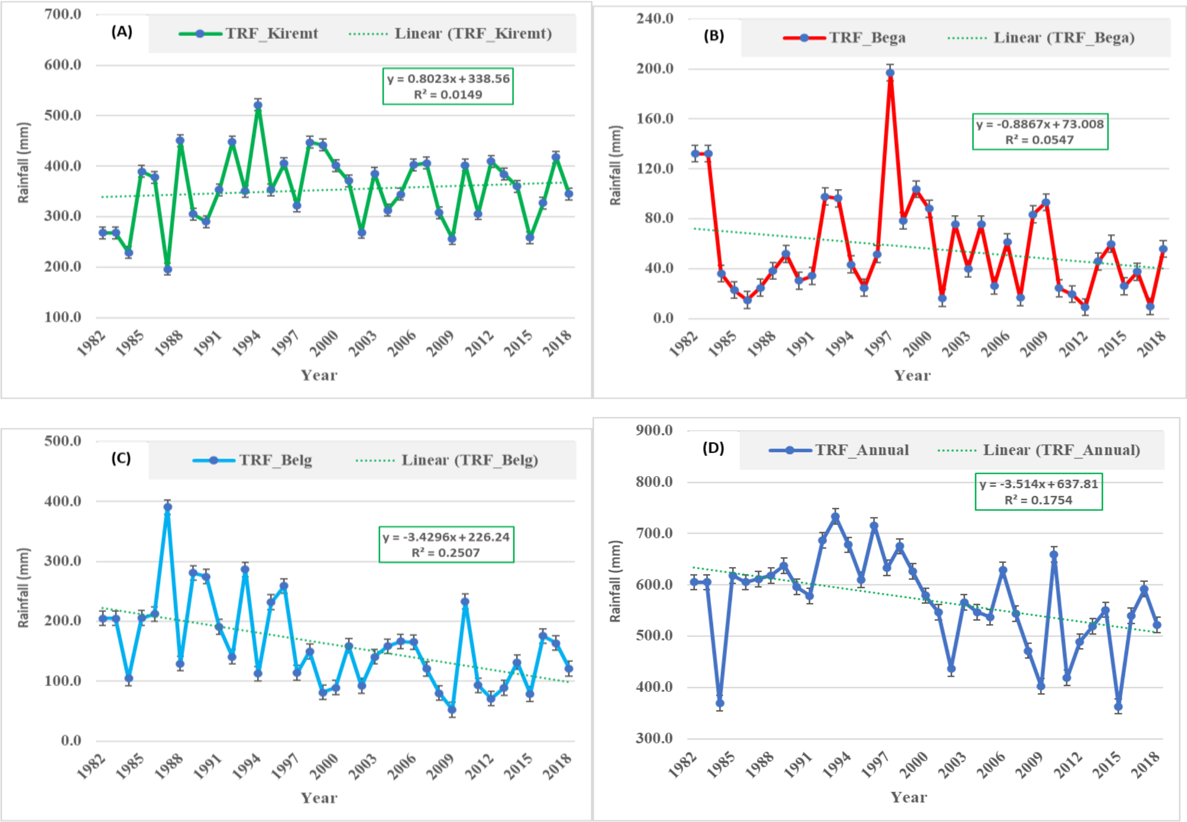

Figure 4.8 Seasonal trends of mean TRF (mm/year) in Awash River Basin, 1982-2018

4.3.3. Vegetation degradation indicators in the Basin

Spatio-temporal analysis of mean and trend of Rain Use Efficiency

The RUE, or the ratio of NPP to precipitation, may be an important determinant in arid and semi-arid ecosystems for assessing how primary productivity responds to variations in rainfall. Because of its strong correlation with rainfall, RUE showed seasonal variations. The spatial distribution of the mean RUE in the Basin is shown in Figure 4.8. In most parts of the Basin the mean RUE varies with season. During *Bega* season, the RUE ranges from 0 to 28.7 $gC/m^2/mm$. The highest mean during this season was seen in areas where intense soil and water conservation practices were being held in the basin.

Furthermore, the mean RUE during the Kiremt season across the basin is almost low. This low record can be due to increased rainfall during the Kiremt season (Figure 4.8). Bhadra *et al*. (2015) found a similar result in semiarid grasslands of inner Mongolia, where RUE decreased as annual and seasonal rainfall increased. Similarly, the RUE is almost non-existent in arid areas covered by rock-out crops and sands, with less vegetation coverage and low mean annual rainfall. During the Kiremt season, when the basin receives the total rainfall, approximately 67.5% of the area has a negative trend in RUE. Unlike the *Kiremt* season, the Belg season's RUE trends indicate a significant and positive RUE in the majority (72.1%) of its area (Figure 4.8 and Table 4.1).

Table 4.1 Annual and seasonal RUE percentage of the area where trends are significant or not and Positive or negative.

Variables	Percentage of area				
	Significant (%)	**Insignificant (%)**	**Positive**	**Negative**	**Total**
RUE_Annual_trend	100.00	-	53.88	46.12	100.00
RUE_Kiremt_trend	99.76	0.24	32.47	67.53	100.00
RUE_Bega_trend	99.93	0.07	54.56	45.44	100.00
RUE_Belg_trend	100.00	-	72.18	27.82	100.00

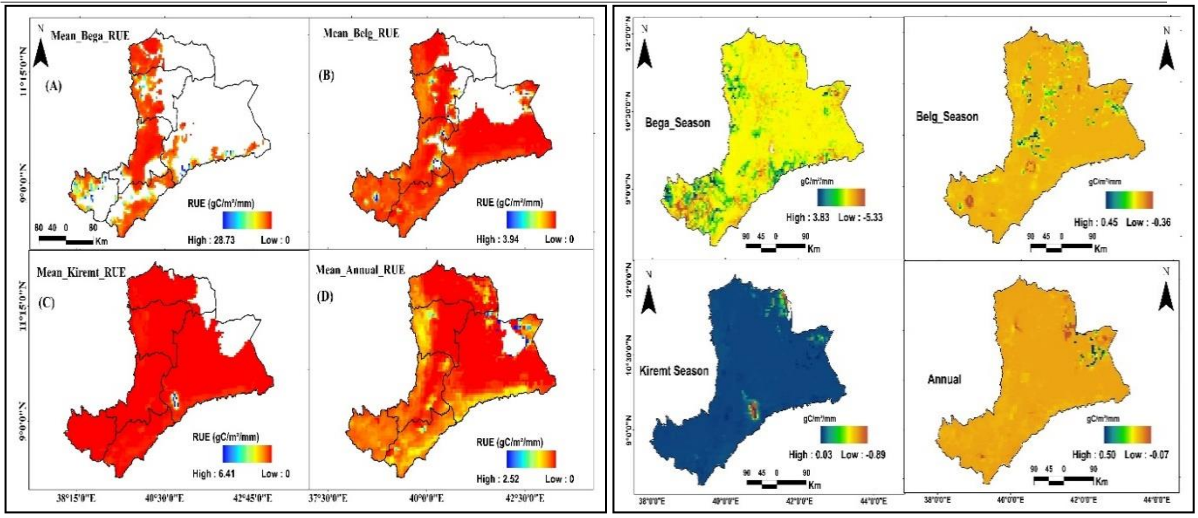

Figure 4.9. Spatiotemporal distribution of mean and trend RUE in Awash basin, 1982-2018

Spatio-temporal analysis of seasonal and annual Residual Trend Analysis

Residual Trend Analysis (RESTREND) calculated using regression model have identified the pixels with an increase or decrease in vegetation production per unit rainfall over the study period. Most of the basin area showed positive trends of residuals with time; an apparent increase in vegetation productivity per unit of rainfall (Figure 4.9 and Table 4.2). There were similarities in the geographic patterns of the residual (Figure 4.8) and the NPP trends (Figure 4.6). Areas with negative trends in NPP in Awash Adaitu, Awash-terminal, and Eastern catchment (Figure 6) also had negative residual trends (Figure 4.9). However, the magnitude of annual and seasonal residual trends show variation across the Basin. About 76.3% and 54.5% of the basin area had negative residual trends during the Belg season and Annual, respectively (Figure 4.9 and Table 4.2), suggesting the vegetation productivity indicators in the Basin during this time are declining. Studies (Tessema *et al*., 2020; Damtew *et al.*, 2022a) found that land use and land cover transition from shrubland to cultivated land in the Awash-Awash sub-basin is the major signal of change identified due to socio-economic and biophysical determinants. Furthermore, the RESTREND approach can determine human-induced land degradation in arid and semi-arid areas of the world (Wessels *et al*., 2007; Burrell *et al*., 2017).

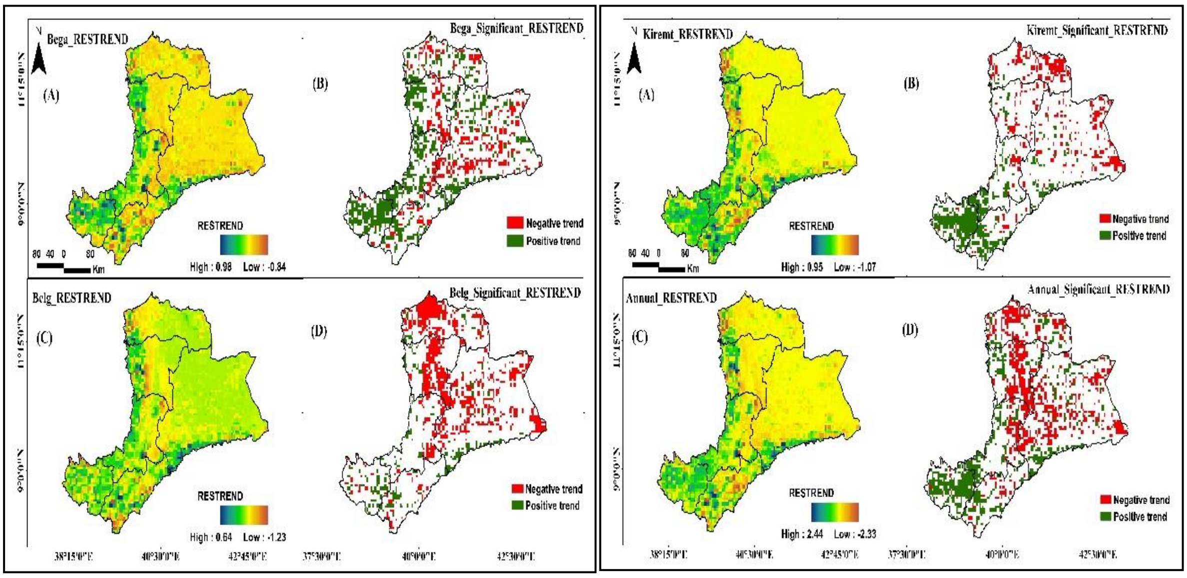

Figure 4.10 Spatiotemporal distribution of mean and trend RESTREND in Awash basin, 1982-2018.

The long-term status of land degradation varied across the river basin. In some spot areas eastern catchment, Awash Halidebi, and Awash Adaitu sub-basin, positive RESTREND value was noted. This result could be due to the vegetation restoration effort of national parks and reserves in the Basin. Conversely, a significant decreasing RESTREND was detected in the same sub-basins; this could be due to overgrazing, frequency of drought, expansion of irrigated land along the river course in the lower part of Awash River (Gedefaw *et al.,* 2019; Mersha *et al.,* 2021). The highland parts of the Awash upstream Koka, Awash Awash, and Awash Adaitu sub-basin showed a positive trend of residuals, indicating an apparent increase in vegetation productivity per unit rainfall (Figure 4.9 and Table 4.2). Spatially, the patterns of residuals were near like NPP (Figure 6), which could be due to vegetation in the area (Bekele et al., 2019). Global and regional studies (Zhuge *et al*., 2019; Adenle *et al.,* 2020; Li e*t al*., 2021) show that in the arid and semi-arid type of climatic zone, the rainfall and vegetation distributions usually are highly correlated to each. This result is comparable to our study, where the spatial homogeneity in this relationship at the basin level was enormous.

4.3.4. Disentangling humans from climate induced NPP changes

Spatio-temporal correlation between TRF and NPP in Awash River basin

The spatio-temporal correlation between TRF and NPP revealed apparent variation across seasons. With the differences in the river basin's climatic conditions, the NPP trends can have some seasonal characteristics. Annually, the correlation between TRF and NPP ranged from -0.59 to 0.74. Figure 4.10 showed that about 82.1% of the Basin exhibited a significant positive ($r>0.1$) NPP and TRF relationship during the Belg season of the 1982-2018 period. Furthermore, 74%, 67.7%, and 67.6% of the Basin exhibited significant positive TRF and NPP correlation during the Bega, Kiremt, and Annual times scale, respectively (Figure 4.10 and Table 4.3). This result revealed that the spatiotemporal pattern of TRF and NPP correlation are spatially heterogenous, and the high correlation values are located in lowland areas of the Basin. In many regions of the world, a positive correlation between TRF and NPP was reported (Li *et al.,* 2020b; Sun and Du, 2017). Similarly, the negatively correlated areas are in highland areas of the Basin, where NPP drastically decreases as the TRF reaches the threshold. Thus, the increase in TRF in the growing season (Kiremt) does not significantly boost vegetation growth but weakens photosynthesis by cutting down energy sources from solar radiation (Guan et al., 2017). Spatially, the negative correlation between NPP and Kiremt TRF was mainly observed in the southwestern part of the Basin (Figure 10). In arid and semi-arid areas of the basin, precipitation is the major limiting factor of vegetation growth (Peng *et al*., 2021; Sun *et al.,* 2021).

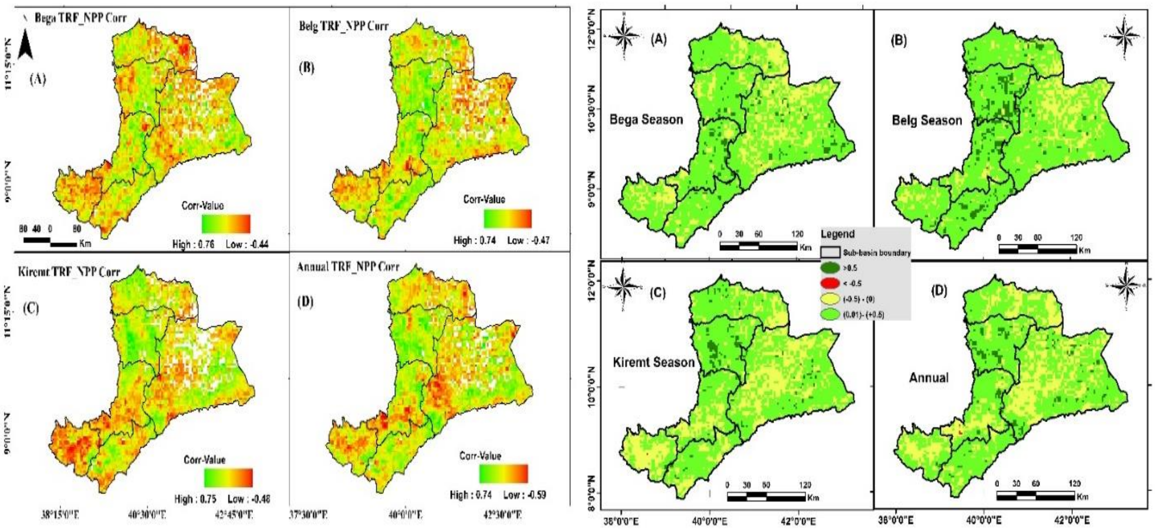

Figure 4.11 Spatiotemporal distribution of correlation between TRF and NPP in the Basin

Table 4.2. Annual and seasonal percentage of the area where correlation is positive or negative.

	Percentage of area		
Variable	**Positive**	**Negative**	**Total**
NPP_TRF_Annual	67.64	32.36	100.00
NPP_TRF_Kiremt	67.67	32.33	100.00
NPP_TRF_Bega	74.00	26.00	100.00
NPP_TRF_Belg	82.19	17.81	100.00

The significant positive correlations suggest that NPP was sensitive to the variation in precipitation and confirmed that precipitation could be the major climatic factor affecting NPP changes in the Awash Basin. The growth season total rainfall and NPP may represent an oversimplification of a more complex relationship between water availability and primary production in areas with low correlation values since the timing and effectiveness of precipitation have a large influence on vegetation production. This finding is in line with previous studies conducted in different parts of the world (Huang and Kong, 2016; Feng *et al*., 2019), where the Spatio-temporal relationships between NPP and rainfall vary with the year's season and positively correlate with it. Furthermore, the relationship between NPP and TRF was generally strong in arid and semi-arid regions, where rainfall determines vegetation growth. Decreased precipitation can reduce photosynthetic efficiency, suppression of plant activity, and reduction in organic matter production (Gourdji *et al*., 2013), thereby inhibiting vegetation growth. The study found a negative correlation between TRF and NPP in mountainous areas. Awash Upper Stream Koka basin and agricultural areas of eastern catchments where irrigation was widely practiced, and perennial crops dominated the area.

This practice could decrease the dependence of vegetation on rainfall in this area (Qu *et al*., 2020).

4.3.5. Human activities and climate change contributed to NPP dynamics.

The relative roles of climate change and human activities in driving the NPP dynamics were assessed by comparing the trends in NPP and the correlation between TRF and NPP. The variations in observed NPP in the study may be due to the balance between human activities and climate change. Our study result indicated that the river basin experienced climate and NPP change. The Spatiotemporal distribution and relative contribution of climatic and human factors to the change in NPP in the Basin are presented in Figure 4.11 and Table 4.6. During the study period, climate change contributed to the decrease in NPP in about 37.0%, 63.7%, and 38.8% of the area during the Bega, Belg, and Kiremt seasons, respectively. These areas are concentrated in the lowlands of Awash Adaitu, Awash Haldebi, Awash Awash, and Eastern Catchment. In arid and semi-arid lowlands of the Basin, a change in rainfall can regulate the growth of plants and thus overall ecosystem productivity. A decrease in the mean and trends of TRF over the years highly contributed to the decrease in NPP. Especially during the belg season, the decreasing trend in belg rainfall contributed to climate induced NPP being the largest area coverage in the basin. This result possibly implies that climate change is influencing the NPP dynamics in a different season of the Basin. A study by Senior *et al.* (2017) affirmed that climate change-induced precipitation differences affect NPP. Lai *et al.* (2018) also reported that climate change plays a vital role in the variation of NPP in arid and semi-arid regions of China.

Furthermore, the significant increase in the mean and trend of TRF in spot areas Eastern catchment, Awash-Adaitu, and Awash terminal of the Basin also promoted vegetation restoration (Figures 4.5 and 4.7). However, the positive effect of precipitation on the NPP increase is not obvious in most sub-basins. Extreme climate events such as drought can be an important factor in controlling vegetation variation in most of the arid and semi-arid areas of the Basin. The finding was consistent with many previous studies that showed that vegetation production in arid or semi-arid regions was very sensitive to rainfall changes (Berdimbetov *et al*., 2021; Peng *et al.*, 2021; Ahmed *et al.*, 2022).

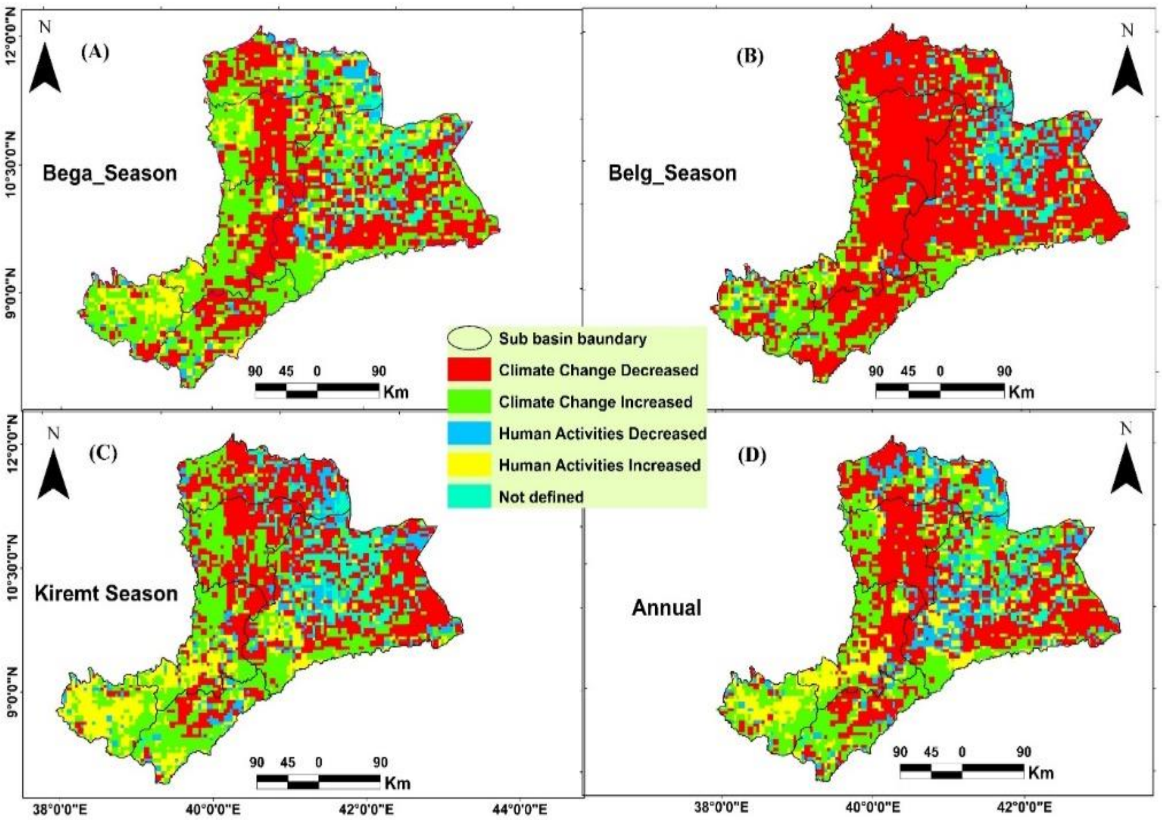

Figure 4.12 Spatial distribution of relative effects of climate change and human activities on NPP during the periods of 1982–2018

Table 4.3 Spatiotemporal distribution of relative effects of human activities and climate change on NPP in the Awash basin for the Bega

	Percentage of area			
Dominant factors	**Bega**	**Belg**	**Kiremt**	**Annual**
Climate-Induced Decreased	37.04	63.69	38.81	39.93
Climate-Induced Increased	36.96	5.76	13.89	27.72
Human-induced Decreased	5.42	5.58	28.97	11.77
Human-induced Increased	14.6	18.5	9.18	14.98
NA	5.97	6.46	9.15	5.59
Total	100.00	100.00	100.00	100.00

Human activities in arid and semi-arid areas of the awash river basin were also the main factors behind the vegetation degradation and improvements. Human activities led to an increase in NPP in about 14.9 % of the area. The increase in NPP-area caused by human activities is mainly found in areas where dominant human activities occur. These areas are found in Awash Upper Stream Koka and Awash Awash, where large-scale and small-scale irrigation activities are practiced throughout the year, and Awash Haldebi and highlands of the eastern catchment, where the sub-basin is covered with agricultural lands, grasslands, woodlands, and shrub and bushlands (Figure 4.11 and Table 4.6). In our context, the rehabilitation of degraded land in the highlands of the Basin, expansion of irrigated agriculture, and planting of perennial crops in Awash upstream Koka, Awash Awash, and Awash Adaitu sub-basin are the reason behind an increment in NPP in some spotted areas (Figure 4.11). Studies show that population pressure causes land use and cover changes, supported by earlier research in various parts of the basin (Tola and Shetty, 2021). Furthermore, overgrazing (Tessema et al., 2020), deforestation (Srigiri *et al*., 2021), and urban expansion (Tadese *et al*., 2020b; Daba and You, 2022) are also the main factors behind a decrease in NPP in Awash River. In general, variations in NPP in the Basin had permanently been linked with changes in rainfall and anthropogenic causes.

4.3.6. Response of NPP to LULC transition and its implication for agriculture

Our study result shows that the spatiotemporal heterogeneity of NPP across the Basin is controlled by climate and anthropogenic factors. The spatial distribution of land use and land cover change can determine the NPP variations (Eisfelder *et al.*, 2014; Wei *et al.*, 2022). A previous study (Damtew *et al.,* 2022a) in the Awash-Awash sub-basin indicated they had undergone land use and land cover transition.

Table 4.4 Changes in LULC and NPP in the Awash-Awash sub-basin from 1986 to 2018

LULC_Type	Area (km^2)			Mean NPP (gC/m^2)		
	1986	**2018**	**Change**	**1986**	**2018**	**Change**
Bare land	108.27	232.7	124.43	63.36	52.67	-10.69
Cultivated land	3750.9	8093.3	4342.4	83.25	76.56	-6.69
Irrigated land	229.7	268.9	39.2	103.45	118.67	15.22
Forest land	943.52	680.6	-262.92	133.21	121.29	-11.92
Grassland	1144.32	342.9	-801.42	109.38	86.80	-22.58
Shrub land	4549.52	2317.8	-2231.72	54.81	46.08	-8.73
Water	205.13	245.5	40.37	1.78	5.82	4.04
Woodland	393.14	199.7	-193.44	76.61	45.54	-31.07

Human activities in land use and land cover change, including expansion of bareland areas, irrigated lands, and vegetation losses, possibly resulted in NPP reduction. Figure 4.12 (Supplementary material) and Table 4.4 revealed considerable gains/losses for major LULC categories during the study period. Expansion in cultivated land, bareland, and water body are among the changes attributed to gain. In contrast, the decline in shrubland, woodlands, forestland, and grasslands are the major changes attributed to loss. Since 1986, cultivated land has experienced a significant transition from shrubland **(Table 4.5, Supplementary).**

The LULC transition from shrubland, woodland, forest land, and grassland to cultivated land affects the NPP in the sub-basin (Table 4.4). The decrease in vegetation NPP in the sub-basin due to LULC transition is consistent with recent findings in different parts of the world (Ji *et al*., 2020; Pan *et al.*, 2020; Zhang *et al*., 2021), where land use transition from vegetation to other land cover decreased the NPP. From our case study conducted in the Awash-Awash sub-basin, most of the sub-basin is susceptible to LULC transition (Table 4.4 and Figure 4.13). The change in LULC transition, especially the conversion of vegetation to agricultural land, is increasingly burdening the amount of NPP in the sub-basin.

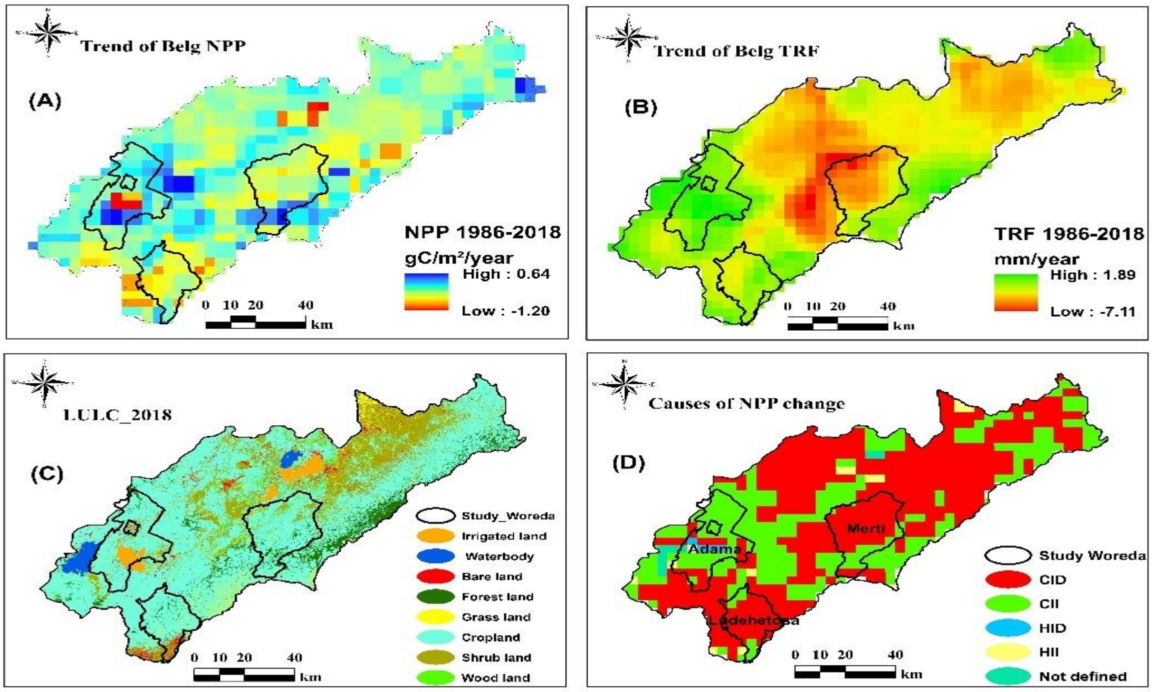

Figure 4.13 Spatial distribution of trends of belg NPP (A), Belg TRF (B), LULC (C) and relative effects of climate change and human activities on NPP during the periods of 1982–2018 in Awash-Awash sub-basin

The gains from converting vegetated lands can elucidate the decline of NPP (-6.69 gC/m$^{2)}$ due to agricultural land expansion. Previous studies affirmed that agricultural land expansion in areas with similar or more fertile land covers tends to decrease the NPP of converted land (Franco-Solís *et al*.,2021; Raihan *et al.*, 2022). This trend is not always true in areas where human management, such as afforestation, irrigation, and fertilization, increased agricultural land's total NPP (Pan *et al.*, 2021; Patapov *et al.*, 2022). Consistently, 39.2 km^2 irrigated land in the sub-basin increased the NPP by 15.22 gC/m^2. The increase in NPP can be explained by the expansion of irrigated land, availability of soil moisture, and fertilizing effect in irrigated areas. The decreasing area of grassland (-801.42 km^2), shrubland (-2231.72 km^2), and woodland (-193.44 km^2) between 1986 and 2018 in the sub-basin have a negative effect on livestock productivity through decreasing total area of grazing land. The NPP reduction in grassland (-22.58 gC/m^2), shrubland (-8.73 gC/m^2) and woodland (-31.07 gC/m$^{2)}$ has an implication for the pastoral and agro-pastoral community in the sub-basin. The total livestock unit in the sub-basin is estimated at 6.5 million tropical livestock units (TLU) (CSA, 2019). The decrease in grassland, shrubland, and woodland possibly hamper livestock productivity by creating pressure on available grazing land.

Cropland expansion, braced by the destruction of vegetation in arid and semi-arid parts of the sub-basin, can result in the loss of ecosystem services (Fenta *et al*., 2020). Equally, the decreasing trend of belg season total rainfall in the sub-basin seriously threatens farmers producing crops during this specific period of the year (Figure 4.13). The study investigated that Merti woreda (district) is one of the Belg-producing areas in the sub-basin, significantly affected by decreasing and delaying rainfall during this season. According to Woreda agriculture office data (2013-2021), crop production produced during the belg season is declining from 18.5 to 10.2 quintals per hectare for cereal crops and 5.2 to 4.1 quintals per hectare for pulses **(Annex K, Table 4.5).** This figure shows total rainfall expected during the belg season is declining, indicating a serious crop production failure in the woreda. Belg season rainfall is more vital than Kiremt rainfall in the woreda. The rainfall during the belg season is essential for seedbed preparation for short and long-cycle Kiremt (main season) crops such as maize and sorghum. Recent studies in the Awash Awash sub-basin support the finding that extreme events such as consecutive dry days (CDD) and drought events are increasing in the sub-basin (Damtew *et al*.,2022b). The decreasing trend of NPP coupled with decreasing seasonal rainfall possibly threatens farmers whose livelihood mainly depends on rainfed agriculture. Moreover, the increase of NPP due to the transition of vegetation LULC to irrigated agricultural land can increase the risk of soil degradation and possibly hamper ecosystem service.

4.4. Conclusion

Exploring NPP responses to climate change and its feedback is crucial for understanding the terrestrial ecosystem dynamics and sustainable development. The Spatio-temporal distribution of seasonal average NPP and TRF from 1983 to 2018 in the Awash River basin revealed significant spatial heterogeneity. The estimated mean annual NPP in the Basin was 36.5 gC/m2, with a trend revealing a significant decrease over 56.6% of the area of the Basin. The observed average TRF distribution pattern in the Basin indicated a significant variation across seasons influenced the NPP, RUE, and RESTREND results. Because of the vegetation correlation's intense rainfall, RUE showed seasonal variations. The spatial Spatio-temporal correlation between TRF and NPP revealed apparent variation across seasons. This relationship revealed that the spatiotemporal pattern of TRF and NPP correlation are spatially heterogenous, and the high correlation values are in lowland areas of the Basin. The significant positive correlations suggest that NPP was sensitive to the variation in precipitation and confirmed that precipitation could be the major climatic factor affecting NPP changes in the Awash Basin.

In arid and semi-arid lowlands of the Basin, a change in rainfall can regulate the growth of plants and thus overall ecosystem productivity. Human activities in arid and semi-arid areas of the awash river basin are the main factors behind vegetation degradation and improvements. Human activities led to an increase in NPP in about 14.9 % of the area. The increase in NPP - area caused by human activities is mainly found in areas where irrigation agriculture occurs. These areas are found in Awash Upper Stream Koka and Awash Awash, where large-scale and small-scale irrigation activities are practiced throughout the year, and Awash Haldebi and highlands of the eastern catchment, where the sub-basin is covered with agricultural lands, grasslands, woodlands, and shrub and bushlands. Case studies conducted in the Awash Awash sub-basin revealed that human activities in the form of LULCC and transition, including expansion of bareland areas, agricultural lands, and vegetation losses, possibly resulted in NPP reduction. The statistically significant decreasing trend of belg season total rainfall and NPP in Awash Awash-sub-basin threatens rainfed farmers' crop and livestock production and productivity.

In conclusion, the declining rate of NPP in the Basin suggests that land degradation is increasing, resulting in reduced ecosystem service. Therefore, agricultural land expansion at the expense of vegetation loss in the Basin needs attention from the local government to rehabilitate the degraded land and implement sustainable land use policy in the arid and semi-arid ecosystem. As a result, the Basin's overall management of vegetation production should be done following the conditions and factors unique to the local area. In areas where climate and human-induced change is the major determinant factor, climate-induced risk management techniques such as planting suitable agro-ecological vegetations, rehabilitation of degraded land through water and soil conservation measures, adoption of irrigated agriculture, promotion of crop insurance and adaptive to changing climate conditions is encouraged. The development of monitoring systems and response mechanisms is very important at the regional and national levels. In this study, we only considered precipitation as the major determinant of NPP in the Basin. However, drought, temperature, soil moisture, solar radiation, and evapotranspiration can be considered in future research.

CHAPTER FIVE

5. General Discussions, Conclusions and Recommendations

5.1. Introduction

Humans have been altering land resources to meet their increasing basic needs for centuries by expanding agricultural land and settlement (Zhong *et al*. 2020; Rahaman *et al*. 2020). With population growth and industrialization, human-induced land use and land cover change, climate change and ecosystem degradation have become one of the most important anthropogenic factors threatening human livelihoods (Garedew, 2010; Gedefaw *et al* .2021). LUCC change results from complex processes caused by biophysical and human-related driving factors and the interaction between these forces. Although affected by biophysical conditions, LUCC processes are influenced most by humans, and their use of the land has various biophysical and socio-economic consequences. Similarly, IPCC (2021) reported that the evolution of climate change and extreme events and its main physical effects on land and ocean temperature change, sea level rise, and ocean acidification is growing evidence. A changing climate leads to changes in climate extremes and can result in unprecedented extreme harm to people, property, and nature (Ahsan *et al*. 2022; Diffenbaugh 2020). Land degradation in the form of loss of natural vegetation due to human activities affects ecosystem functioning (Eisfelder *et al.* 2014; Xiao *et al*. 2021). Human-induced land use and land cover change from vegetated areas to non-vegetated areas have become one of the utmost important human activities affecting Net Primary Productivity (Chen *et al.* 2017; P. Zhang *et al*. 2020).

Various studies conducted in A wash Basin have shown that land use land cover change is attributed to improper agricultural practices, climate variability and change, over-exploitation, demographic changes, economic activities, poverty, and policy and institutional changes (Degife *et al.* 2018; Woldesenbet *et al*. 2020; Yesuph and Dagnew 2019). Because of climate change and extreme events, the change was blamed for widespread land degradation and biodiversity loss, affecting smallholder farmers' livelihoods (Berihun *et al.* 2021; Degife *et al.* 2018). This necessitates assessing and separating the contributions of climate change and human activities to ecological changes that can be used for ecological regulation and management (Bi *et al*. 2020; Xiao *et al*. 2019). The study employed a mixed research method that combines data from different sources. Climate, land use land cover, net primary productivity, and household survey data were sourced and used. Depending on the objectives of the study, qualitative data from Key Informant Interview (KII), Focus Group Discussion

(FGD), and Field Observation (FO) were also used to assess local level perception in the sub-basin.

Land use land cover dynamics of the sub-basin were quantified and evaluated using geospatial techniques from multi-date land sat imageries of 1986, 1996, 2006 and 2018. Landsat data from 1986 and 2018 were analyzed to better understand the magnitudes of LULC transitions through computational losses, gains, swaps, shifts, persistence, vulnerability, and the identification with major LULC transition clues. To identify the possible determinants of land use land cover transitioning the study area, a combination of Landsat images from 1986 to 2018, local understanding of possible drivers and proximity and topographic indicators were used. To give priority to land use management in the sub-basin, a major signal of land use and land cover transitions were identified.

The spatiotemporal mean and extreme climate indices were computed using daily time series (1983-2016) maximum and minimum temperature and rainfall. The analysis was made based on the major agroecological setting in the basin. Daily climate data were used to analyze 23 extreme climate indices. The Mann–Kendall test was used to assess the magnitude and significance of the changes. Some important extreme climatic indicators were used to interpret their possible agricultural impacts. Furthermore, household perception data were analyzed to compare with climatic records.

Using net primary productivity (NPP) as a healthy ecosystem indicator and biomass dynamics, the study analyzed the trends and relationships between NPP and climate. For accurate assessment and a separate contribution climate and human-induced NPP change in the basin, the study used long-term NPP estimated from Multisource Data Synergized Quantitative-Net Primary Productivity (MuSyQ-NPP) algorithm climatic datasets (Total Rainfall) classified by seasons of the year were used. To identify the separate impacts of human activities and climate change, trends of NPP and TRF, their relationships were computed through the Mann Kendall trend test and Pearson correlation coefficients, respectively. Furthermore, residual trend analysis and rain use efficiency were computed to strengthen the study result.

5.2. Major finding of the study

The sub-basins land use and land cover (LULC) have recorded significant pattern, structure, and extent changes. Between 1986 and 2018, bareland, cultivated land and water body increased, while grassland, woodland, shrub, bushland, and forestland declined. Expansion in bareland, water body and cultivated land are among the changes attributed to gains, whereas a decline in shrub and bushland, woodlands, forestland, and grasslands are the major changes attributed to losses **(Chapter 2 and 4,** (Damtew, Teferi, and Ongoma 2022)

The simultaneous occurrence of systematic gains and losses in land use can tell the most dominant change signals (Ouedraogo et al. 2011). During the study periods (1986–2018), the vulnerability and major signals of land use and land cover change were observed. The study identified the difference between observed and expected gains under the random change process for shrub and bushland to cultivated land. Compared to other LULC categories, cultivated land shares the highest area and experienced the topmost persistence 31.9%. This indicated that cultivated land systematically gained the highest area from shrubs and bushland. On the other hand, shrubs and bushland were systematically gained from cultivated land **(Chapter 2)**.

Regarding the drivers of LULC change in the study area, our informants argued the range of LULC change drivers and their effects. The most mentioned drivers of LULC change in the basin informants were population growth, agricultural land expansion, deforestation and overgrazing, and urbanization. Furthermore, the information from focus group discussants and community elders supported the argument from the literature that population growth, agricultural land expansion, deforestation and overgrazing are also major contributors to LULC change **(Chapter 2)**. Similarly, experts stated that the household contribution to vegetation loss is immense as they clear the vegetation resource for their livelihoods, such as the source of income for farmers through selling firewood and charcoal, the forest, and its product for their day-to-day livelihoods.

The study identified the LULC transition from shrub and bushland to cultivated land as the dominant transition in the sub-basin. The binary logistic regression result shows that elevation, cosine of aspect, and distance to the major river are positively associated with the transition from shrubs and bushland to cultivated land. This directly implies that deforestation increases with decreasing distance from rivers and roads. The study also confirmed that vegetation resources of the sub-basin are incessantly declining **(Chapter 2 and 4)**.

A significant decrease in annual total precipitation (TRF) and an increase in minimum (Tmin) and maximum temperature (Tmax) have been detected between 1983 and 2016. The Observed annual trend in extreme temperature over the last 34 years revealed a significant increase and decrease in extreme temperature indices across the agro-ecologies. Warm extreme temperature indicators like TXx, TNx, TN90p, TX90p, and WSDI significantly increase in most agro-ecology zones. However, WSDI, TX90p, and TXx indicate a non-significant decreasing trend **(Chapter 3, Damtew et al., 2022b)**. Though the magnitudes vary, unlike the case in TX90p, all AEZs show increasing trends in the frequency of TN90p. Because of the seasonal nature of crop production in the basin, an increase in trends of TX90p and TN90p is usually associated with decreased crop yields.

Cold extreme temperature indicators such as TNn, TN10p, TX10p, and CSDI significantly decrease in many studied agro-ecology zones. The significant decrease in Coldest night (TNn) and increase in Warmest night (TNx) in most agro-ecologies are clear indicators of a warming pattern in the sub-basin. The study also revealed that the frequency of cool nights (TN10p) is significantly decreasing, and the frequency of cool days (TX10p) in most studied agro-ecology. Overall, the magnitude and direction of change differ across studied agro-ecologies, the growing trend of warm extreme temperature events in the cold to very cold humid, tepid to cool humid, and tepid to cool sub moist agro-ecology possibly threaten the livelihoods of farmers who depend on rain feed agricultural **(Chapter 3, Damtew et al., 2022)**.

Diurnal temperature range (DTR), number of summer days (SU), the cold spell duration (CSDI), and warm spell duration indices (WSDI) in most of the studied agro-ecology showed a significant increasing trend. Overall, the increase in trends of extreme warm and cold temperature events coupled with a lack of preparedness for increasing trends affects agricultural productivity and farmers whose livelihood depends on it.

Unlike consecutive wet days (CWD), the maximum number of consecutive dry days (CDD) shows an increasing trend across agroecological zones. When the trends in CDD are higher during the cropping season, the consequence for rain-fed agriculture is adverse. Compared with other agro-ecologies, the highest significant change of 0.032°C/year ($p < 0.05$) magnitude for CWD was recorded in the cold to very cold humid AEZ. This is an alert for the study area where the basin's highland areas face dry conditions. In line with this, the trends in several heavy precipitation days (R10mm) and several very heavy precipitation days (R20mm) show a significant decreasing trend in some agro-ecology. A decreasing trend in the number of heavy and very heavy precipitation suggests potential risks related to drought in most agro-ecologies (**Chapter 3).**

For the annual drought (SPEI 12) index, there is a sign of change across agro-ecologies between the years 1983 to 2016. The study revealed that all studies of agro-ecology experienced negative and significant trends in annual SPEI. A significant and negative annual SPEI trend indicates an increase in drought across agro-ecology. Compared with other agro-ecologies, the biggest significant magnitude changes of (SPEI-12) were recorded at -0.088°C/year ($p < 0.001$) in the tepid to cool sub-moist agro-ecology. The increasing frequency of drought events across agro-ecology can affect agricultural production by limiting soil water availability for different crops and reducing crop yields **(Chapter 3).**

Most interviewed key informants, focus group discussants, and surveyed sample farmers in different agro-ecology (89.3%) perceived changes in climate. Farmers from different agro-ecology zones perceived climate change, variability, and extreme events over the last two decades. Furthermore, they elaborated on the changes in climate through changes in rainfall pattern, amount, and length of the rainy and dry seasons. Similarities between meteorological data (increase in drought frequency) and farmers’ perceptions were reported. Similarly, farmers indicated that food and product inflation, crop productivity decline, increased crop pests and diseases, increased livestock disease, the emergence of new pests and weeds, and a shortage of water for irrigation are brought from climate change **(Chapter 3).**

The Awash Basin's mean seasonal and annual Net Primary Productivity (NPP) showed significant spatial heterogeneity. Though the amount of mean NPP across seasons varies, the high NPP areas are found in the basin's highland forest, grassland, and croplands areas. The lowest NPP values are detected in lowland areas of the basin where the land is covered with bareland and very low vegetation cover. During the study period and seasons, the different areas of the basin show variations in the NPP trend. The annual NPP trend analysis shows a significant decrease over 56.6% of the basin. A significant and negative trend in NPP has been observed in the majority areas of eastern catchment Awash Adaitu sub-basins. This is due to the expansion of urban areas and land degradation in the sub-basins. Areas with a positive trend appeared to be associated with increased vegetation coverage due to the invasion of Prosopis Juliflora, an expansion of irrigated land **(Chapter 4).**

The study found that the variation in TRF can influence the land degradation assessment indicators, including NPP, rain use efficiency (RUE) and residual trend (RESTREND) results. The mean RUE varies with the season in most parts of the basin, like RESTREND. Most of the basin area showed positive trends of residuals with time and, therefore, an apparent increase in vegetation productivity per unit of rainfall. There were similarities in the geographic patterns of the residual and the NPP trends. However, the magnitude of annual and seasonal residual trends shows variation across the basin. About 76.3% and 54.5% of the basin area had negative residual trends during the Belg season and Annual, respectively, suggesting the vegetation productivity indicators in the basin during this time is declining **(Chapter 3, 4).**

The long-term status of land degradation varied across the river basin. In some spot areas eastern catchment, Awash Halidebi, and Awash Adaitu sub-basin, positive RESTREND value was spotted. This could be due to the vegetation restoration efforts of national parks and reserves in the basin. Conversely, a significant decreasing RESTREND was detected in the same sub-basins. This could be due to overgrazing, frequency of drought, and expansion of irrigated land along the river course in the lower part of Awash River. This result is like our study, where the spatial homogeneity in this relationship at the basin level was tremendous **(Chapter 3, 4).**

This revealed that the spatio-temporal pattern of TRF and NPP correlation are spatially heterogenous, and the high correlation values are located in lowland areas of the basin. This shows that precipitation is the major limiting factor of vegetation growth in the basin in arid and semi-arid areas. Decreased precipitation can lead to a reduction in photosynthetic efficiency, suppression of plant activity and reduction in organic matter production, thereby inhibiting vegetation growth **(Chapter 3, 4)**.

The relative roles of climate change and human activities in driving the NPP dynamics were assessed by comparing the trends in NPP and the correlation between TRF and NPP. The variations in observed NPP in the study may be due to the balance between human activities and climate change. During the study period (1982-2018), climate change contributed to the decrease in NPP in about 37.0%,63.7%, and 38.8% of the area during Bega, Belg and Kiremt season, respectively. These areas are concentrated in the lowlands of Awash Adaitu, Awash Haldebi, Awash Awash and Eastern Catchment. In arid and semi-arid lowlands of the basin, a change in rainfall can regulate the growth of plants and thus, overall ecosystem productivity **(Chapter 3, 4)**.

Human activities in arid and semi-arid areas of the awash river basin were also the main factors behind the vegetation degradation and improvements **(Chapter 3, 4)**. Human activities led to an increase in NPP in about 14.9 % of the area. The increase in the NPP area caused by human activities is mainly found in areas where dominant human activities occur. These areas are found in Awash Upper Stream Koka and Awash Awash, where large-scale and small-scale irrigation activities are practiced throughout the year, and Awash Haldebi and highlands of the eastern catchment, where the sub-basin is covered with agricultural lands, grasslands, woodlands and shrub and bushlands. In our context, the rehabilitation of degraded land in the highlands of the basin, expansion of irrigated agriculture and planting of perennial crops in Awash upstream Koka, Awash Awash and Awash Adaitu sub-basin are the reason behind an increment in NPP in some spotted areas.

Results show that the spatiotemporal heterogeneity of NPP across the Basin is controlled by climate and anthropogenic factors. Undeniably, the spatial distribution of land use land cover change can determine the NPP variations **(Chapter 2, 3, and 4)**.

Human activities in land use land cover change, including expansion of bareland areas, irrigated lands, and vegetation losses, possibly resulted in NPP reduction. Since 1986, cultivated land has experienced a significant transition from shrubland (**Chapter 3, 4)**. From our case study conducted in the Awash-Awash sub-basin, the majority area of the sub-basin is susceptible to LULC transition. The change in LULC transition, especially the conversion of vegetation to agricultural land, is increasingly burdening the amount of NPP in the sub-basin **(Chapter 3, 4)**.

The gains from converting vegetated lands can elucidate the decline of NPP due to rainfed agricultural land expansion. The increase in NPP can be explained by the expansion of irrigated land, availability of soil moisture, and fertilizing effect in irrigated areas. The decreasing area of grassland, shrubland, and woodland between 1986 and 2018 in the sub-basin harm livestock productivity by decreasing the total area of grazing land **(Chapter 3, 4)**. The NPP reduction in vegetation land implies the pastoral and agro-pastoral community by creating pressure on available grazing land.

Cropland expansion braced by the destruction of vegetation in arid and semi-arid parts of the sub-basin can result in loss of ecosystem services. Equally, the decreasing trend of belg season total rainfall in the sub-basin seriously threatens farmers producing crops during this specific period of the year. The study investigated that the Belg-producing areas in the sub-basin are significantly affected by decreasing and delaying rainfall during this season. This shows that the total rainfall expected during the belg season is declining, indicating a serious crop production failure in the woreda. The study in the Awash Awash sub-basin **(Damtew et al., 2022b)** supports the finding that extreme events such as consecutive dry days (CDD) and drought events are increasing in the sub-basin. The decreasing trend of NPP coupled with decreasing seasonal rainfall possibly threatens farmers whose livelihood mainly depends on rainfed agriculture. Moreover, the increase of NPP due to the transition of vegetation LULC to irrigated agricultural land can increase the risk of soil degradation and possibly hamper ecosystem service.

5.3. Conclusions

One of the major environmental problems facing our world today are a change in land use land cover, human-induced climate change and problems related with these changes. Because of this, assessing the historical records of land use land cover and climate change has significantly increased due to its wide range of livelihood impacts. This study examined changes in land use and land cover transition, climate extremes, and vegetation productivity and their possible agricultural risks in the Awash River Basin, Ethiopia. Based on the study results the following conclusions were drawn.

Over the last three decades, the study area has been experiencing land use and cover change. Land use and land cover classes like bareland, cultivated land and water bodies showed the highest rate of change, while grassland, woodland, shrub and bushland, and forestland declined. The net change in gains and losses for each LULC class during the study period depicts a major change in the basin. Gains in bareland, cultivated land and the water body of the sub-basin is likely because of the substantial loose in shrub and bushland, woodland, and forestland. In addition, about 48% of the area has shown persistence, and the rest 52% not. Cultivated land experienced the topmost persistence of 31.9% and the highest gain compared to other LULC categories. However, shrubs and bushland experienced a significant loss in size, with about 25.9%.

The loss-to-persistence ratio (Lp) for water body and cultivated land is less than 1; this indicates all land classes except cultivated land and water body showed a higher tendency to lose than to persist. On the other hand, bareland, woodland, and cultivated land categories experienced the highest gain-to-persistence ratio (G_p) than others, indicating that these land classes experienced more persistence and less gain. The net change to persistence (Np) is negative for vegetation resources of the sub-basin. More particularly, the vegetated LULC class shows a negative net change to persistence, indicating the LULC class has higher probability of losing area to other LULC classes.

The study area experienced random and systematic land cover transitions between the years 1986 to 2018. The study identified the largest difference in the random change process between the observed and expected gains for shrub and bushland to cultivated land. Systematically, cultivated land gains the highest from shrubs and bushlands. This indicated that cultivated land systematically gained additional lands from shrubs and bushland.

The study result indicated topographic and proximate shrub and bushland drivers to cultivated land transition. The qualitative data analysis strengthened the result where population growth, agricultural land expansion, deforestation, and other socio-economic development factors contribute to land use and land cover change in the basin.

The study investigated notable trends in maximum and minimum temperature and decreasing total rainfall. These generally indicated that the mean and extreme climate in the study area is experiencing warming.

In general, warm extreme temperature indicators like TXx, TNx, TN90p, TX90p, and WSDI in study area shows a significant increasing trend in most of the studied agro-ecologies. However, indicators such as WSDI, TX90p, and TXx show a non-significant decreasing trend. Cold extreme temperature indicators such as TNn, TN10p, TX10p, and CSDI, show a significant decreasing trend in most of the studied agroecological zones. Overall, the magnitude and direction of change differ across studied agro-ecologies, the growing trend of warm extreme temperature events in the most of agro-ecology possibly affect agricultural production and productivity.

Extreme precipitation indicators such as RX1day, RX5day, R10mm, R95p, R99p, and PRCPTOT show a decreasing trend over most studied agro-ecology zones. The decreasing trend of extreme precipitation events in the highland agro-ecology may indicate the increase in the number of consecutive dry days (CDD), an indicator of drought occurrences in most agro-ecologies never experienced in prior years.

The ever-increasing price of food and other product, the decline in crop productivity, the spread of crop pests and disease, increase of livestock disease, emergence of new pests and weeds, shortage of water for irrigation and initiating conflict over decreasing resources as the major impacts come because of climate change and extreme events. The study compared farmers' perceptions of trends of climate change and some selected extreme indicators. Similarities in farmers' perceptions of meteorological results were found.

The Spatio-temporal distribution of seasonal average NPP and TRF from 1983 to 2018 in the Awash River basin revealed significant spatial heterogeneity. The estimated mean annual NPP in the Basin revealed that about 56.6% basin area is experiencing a decrease in NPP. The observed average TRF distribution pattern in the Basin influenced the NPP, RUE, and RESTREND results. This relationship revealed that the spatiotemporal pattern of TRF and NPP correlation are spatially heterogenous, and the high correlation values are in lowland areas of the Basin. The significant positive correlations suggest that NPP was sensitive to the variation in precipitation and confirmed that precipitation could be the major climatic factor affecting NPP changes in the Awash Basin.

In arid and semi-arid lowlands of the Basin, a change in rainfall can regulate the growth of plants and thus overall ecosystem productivity. Human activities in arid and semi-arid areas of the awash river basin are the main factors behind vegetation degradation and improvements. The increase in NPP area caused by human activities is mainly found in areas where irrigation agriculture occurs. Case studies conducted in the Awash-Awash sub-basin revealed that human activities in the form of LULCC and transition, including expansion of bareland areas, agricultural lands, and vegetation losses, possibly resulted in NPP reduction. The decreasing trend of belg season total rainfall and NPP in Awash Awash-sub-basin threatens rainfed farmers' crop and livestock production and productivity.

5.4. Contribution of the study

In countries like Ethiopia, environmental change in land use, land cover, climate change and land degradation are one of the major environmental issues affecting the livelihood of millions living in the country. To properly address the existing challenges, local and context-specific studies like this have a substantial role. Specifically, the study has the following contribution.

Methodological contributions: Micro and agro-ecological analysis of climate extreme through standard mean and extreme climate indicators in the study area can be considered as new insight and support for those who deal with agro-ecology-based adaptation practices. Similarly, the use of newly blended ENACT climate datasets (0.0375 * 0.0375 degree) as an alternative to station-based data is encouraging due to the poor availability and scarcity of climatic data. To this end, it is a unique contribution of this study to the growing and least studied theme of the study at the local scale and specific agro-ecological zone. Additionally, the combined way of studying extreme and mean climate with farmers' perception in the study area can help get the complete picture of the climate in the studied agro-ecology. Furthermore, the study presented the combined use of land degradation indicators to assess and disentangle human-induced net primary productivity from climate-induced indicators. The outputs from this analysis can be used to detect possible risks coming to the area by considering and combining the real data on the ground. The application of different data analysis methods and the application of various datasets from field observation to satellite data examination, from primary to secondary and the use of different models (climatic, econometrics, spatial models) at various scales make the study multidimensional in terms of methodologies used.

Conceptual contributions: the study has contributed to clarifying and contextualizing the concepts of application of net primary production to disentangle climate-induced from human-induced land degradation/productivity at various scales of the basin. The combined use of trends and correlation between NPP and TRF and spatial models is a very simple and easily reproducible method that can be used at different spatial scales. Moreover, the study tried to affirm that the local-level agricultural datasets support the outputs we produced from the method.

Empirical contributions: Combining the LULC transition, mean and extreme climate and seasonal NPP data to identify their implication on agriculture to the study area is the empirical contribution of the study.

Theoretical contributions: The analysis of land use and land change is essentially the analysis of the association between people and land. GIS and remote sensing approaches are tested to provide practical answers to land use and land cover analysis including the where, what, when how and who questions.

5.5. Recommendations

The study found that different factors contribute to random and systematic land use land cover transition. Agricultural land (including large-scale irrigation land) in the sub-basin is expanding at the expense of natural vegetation resources. This possibly impacts the multifaceted and interlinked ecosystem services, including the decline rate of net primary productivity in the basin. Therefore, to go between the expansion of agricultural land and vegetation loss in the sub-basin, it is important to consider this prominent signal of LULC change. Hence, implementing integrated and sustainable land use planning could significantly contribute to regulating and provisioning ecosystem services, leading to overall economic development. Though the restorations in vegetation resources require follow-up studies investigating wide ranges of drivers and impacts, priority should be given to vegetation conservation and restoration.

Further, optimal land use requires a land use policy that can regulate various competing land uses and mitigate potential conflicts that may arise from these competing demands on finite land resources. A national land use policy that provides a framework within which planning takes place for existing limited resources is a vital tool to balance the trade-offs between economic growth and long-term sustainability through environmental conservation. Proper land use planning, legal backing, and institutional integration are also a key recommendations to sustain vegetation resources degradation of the area.

The overall management of vegetation productivity in the Basin should be accomplished to the local condition and determinants behind the change. In areas where climate and human-induced change is the major determinant factor, climate-induced risk management techniques such as planting suitable agro-ecological vegetations, rehabilitation of degraded land through water and soil conservation measures, adoption of irrigated agriculture, promotion of crop insurance and adaptive to changing climate conditions is encouraged. Developing monitoring systems and response mechanisms is vital at the regional and national levels.

Ethiopia is one of the first countries to have developed a climate-resilient green economy strategy. In doing so, the country hopes to capitalize on its current economic growth by becoming more resilient to the impacts of climate change while developing its economy in a carbon-neutral way. The adopted and implemented Climate Resilient Green Economy Strategy

(CRGE) can help in this regard to achieve the overall objective of tackling the possible impacts of climate change through its development objectives.

Climate change and extreme events cause wide-ranging effects on the environment and socioeconomic and related sectors. The study has generated agro ecology-based empirical evidence on the area's mean and extreme climate events. Thus, it is suggested to use the evidence in designing, planning, and implementing agroecology-specific mean and climate extreme-related adaptation strategies.

Combined seasonal and annual rapidly warming temperatures with high rainfall irregularities affected the agricultural productivity of smallholder farmers in all LZs of the study area. Rather than taking precautions during a crisis, integrated measures should be designed based on a projected and ongoing active risk management response. Climate variability research at the livelihood zone level has been updated and has good implications for climate-resilient agriculture development and long-term ecosystem services. Up-to-date and scientific climate data assists communities in adapting to low-risk agricultural operations and crop productivity through technological advances.

Hence, there could be visible threats to the existing vegetation resource of the country in general and the sub-basin. Therefore, it is important to prioritize the restoration and conservation of vegetation to go between the expansion of agricultural land and the loss of vegetation in the sub-basin. It could contribute significantly to their regulating and providing ecosystem services, leading to broad economic development in rural areas. Additionally, providing fertile and productive land for crop production is one of the most important roles that vegetation resources play. Hence, it is essential to implement integrated and sustainable land use planning that could significantly contribute to the regulating and provisioning of ecosystem services, which lead to the broad economic development of the region.

The sub-basin is endowed with various livestock due to diversity in the agroecological zone. Even though livestock productivity is low, most smallholder farmers in the sub-basin still practice free grazing on very limited communal land. Coupled with the low level of local breed productivity, the low adoption rate of livestock feed and forage varieties, the low level of agricultural extension works, and the perception of smallholder farmers to continually see the number of livestock as an indicator of wealth contributed to overgrazing in their district. Thus, the government and related development partners should work on this to study the causes of the low adoption rate of improved feed as means to feed their livestock, and they are continually in clash with park administrators.

5.6. Future research

The agro-ecology-specific study result shows crucial information to the policy developers, decision-makers, and farmers about the possible impacts of climate change and extreme events that lead to developing agro-ecology-based adaptation measures. Furthermore, agro-ecology-based vulnerability assessment to extreme climate events in the sub-basin can provide the opportunity to minimize the high cost of crisis management, thereby increasing the adaptive capacity of farmers for sustainable production. Understanding the effects of climate extremes on agricultural yields in the past and present climate is essential for securing and optimizing harvests in a changing environment. As the effect of change in mean and extreme climate on agriculture is complex, future research must explore in detail the impacts of seasonal variations of extreme climate events on crop and livestock resources. In this study, we only considered precipitation as the major determinant of NPP in the Basin. However, drought, temperature, soil moisture, solar radiation, and evapotranspiration can be considered in future research.

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APPENDICES

Annex A

Table 2.6 List of variables for logistic regression computation

List of Independent variables	Abbreviations	Units	Proxy for
Topographic Variable			
Elevation	ELEV	m	Diffuse solar radiation
Slope	SLP	Degree	Mean annual air temperature
Cosine of Aspect	COS-ASP	-1 to 1	Northness
Sine of Aspect	SIN-ASP	-1 to 1	Eastness
Proximity Variable			
Proximity to River	DIS_RIV	m	likelihood for cultivated land use
Proximity to Town Centers	DIS_TC	m	Accessibility
Proximity to Major Roads	DIS_RD	m	Accessibility

Annex B

Table 2.7 Distribution of sample respondents

Name of Sub_basin	Woreda (District)	Kebeles (Villages)	Agro-ecology	Qualitative	Quantitative

				FGD	KII	Survey
Awash-Awash	Lude Hitosa	Gebbe	Highland	1	6	101
		Tulu Jebi		1		88
	Merti	Gado Arba	Midland	1	6	78
		Watro Dino		1		54
	Adama	Sekekelo	Lowland	1	6	23
		Gedemsa Kurfa		1		39
Total	3	6	3	6	18	384

Annex C

(Eq. 15)

$$\boldsymbol{Kappa\ Coefficient(K)}\ = \frac{\mathrm{N}\sum_{\mathrm{i=1}}^{\mathrm{r}}\mathrm{x_{ii}}-\sum_{\mathrm{i=1}}^{\mathrm{r}}(\mathrm{x_i}-\mathrm{X_{x+i}})}{\mathrm{N^2}-\sum_{\mathrm{i=1}}^{\mathrm{r}}(\mathrm{x_{ii}}-\mathrm{X_{x+i}})} \qquad \textbf{(1)}$$

where; $\boldsymbol{r}$ is number of rows and columns in error matrix, **N**, $\boldsymbol{N}$ is total number of observations (pixels) $\mathbf{X_{ii}}$ is observation in raw i and column i $\boldsymbol{x_i} +$ is marginal total of raw i and $\boldsymbol{x + i}$ is marginal total of column i. A coefficient of Kappa equal to 1 indicates perfect agreement while if it is close to zero it means the agreement is no better than expected.

Annex D

Table 2.8 Confusion matrix (error matrix) for the 2018 classification map

Reference data 2018									
Classified Data	**CL**	**WL**	**WB**	**SBL**	**GL**	**FL**	**BL**	**Row Total**	**User Accuracy**
CL	69	1	0	1	4	0	0	75	92.00%
WL	1	70	1	0	1	2	0	75	93.33%
WB	0	3	72	0	0	0	0	75	96.00%
SBL	2	2	0	67	0	1	3	75	89.33%
GL	3	0	0	3	67	0	0	73	89.33%
FL	2	6	0	0	0	67	0	75	89.33%
BL	0	1	0	0	4	0	70	75	93.33%
Column Total	77	83	73	71	76	70	73	523	
Producer Accuracy	89.61%	84.34%	98.63%	94.37%	88.16%	95.71%	95.89%		
Overall Accuracy = 92.16%					**Kappa Coefficient = 0.908**				

Note that: BL: Bareland, CL: Cultivated land, FL: Forestland, GL: Grassland, SBL: Shrub and Bushland, WL: Woodland, WB: Water body.

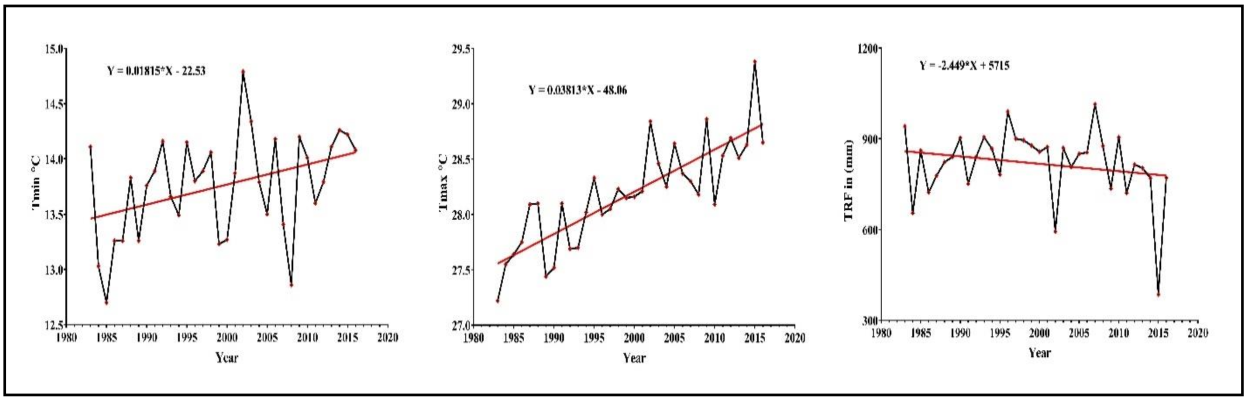
Annex E

Table 2.10 Transitions in percentage of total landscape under random process of gain (G_{ij}), and random process of loss (L_{ij}) for the period (1986-2018)

LULC type	Variable	BL	CL	FL	GL	SBL	WB	WL	(1986) (P_{i+})	Loss (L_i)
BL	Obs	0.2	0.4	0.0	0.0	0.3	0.1	0.0	1.0	0.8
	G_{ij}	0.2	0.3	0.0	0.0	0.1	0.0	0.0	0.7	0.5
	L_{ij}	0.2	0.6	0.0	0.0	0.2	0.0	0.0	1.0	0.8
CL	Obs	0.4	31.9	1.1	1.1	5.0	0.2	0.6	40.3	8.4
	G_{ij}	0.7	31.9	1.2	1.0	3.5	0.2	0.7	39.3	7.3
	L_{ij}	0.3	31.9	0.8	0.4	2.7	0.3	0.2	36.5	4.6
FL	Obs	0.1	3.8	2.8	0.1	0.7	0.0	0.1	7.7	4.8
	G_{ij}	0.0	2.8	2.8	0.2	0.6	0.0	0.1	6.7	3.8
	L_{ij}	0.1	3.5	2.8	0.1	1.0	0.1	0.1	7.8	4.9
GL	Obs	0.3	6.6	0.5	0.4	1.3	0.0	0.1	9.3	9.0
	G_{ij}	0.0	3.6	0.3	0.4	0.8	0.1	0.2	5.4	4.9
	L_{ij}	0.2	6.6	0.5	0.4	1.9	0.2	0.2	10.0	9.6
SBL	Obs	0.7	22.6	0.5	1.0	11.0	0.3	0.8	37.0	25.9
	G_{ij}	0.0	17.6	1.3	1.2	11.0	0.3	0.8	32.2	21.2
	L_{ij}	0.7	27.7	2.3	1.1	11.0	0.8	0.7	44.4	33.3
WB	Obs	0.0	0.0	0.0	0.0	0.0	1.5	0.0	1.6	0.1
	G_{ij}	0.0	0.6	0.0	0.0	0.1	1.5	0.0	2.3	0.8
	L_{ij}	0.0	0.0	0.0	0.0	0.0	1.5	0.0	1.5	0.0
WL	Obs	0.0	1.9	0.6	0.1	0.5	0.0	0.1	3.2	3.1
	G_{ij}	0.0	1.2	0.1	0.1	0.3	0.0	0.1	1.7	1.6
	L_{ij}	0.1	2.2	0.2	0.1	0.6	0.1	0.1	3.2	3.2
(2018) (P_{+j})	Obs	1.8	67.2	5.5	2.8	19.0	2.0	1.6	100.0	52.1
	G_{ij}	1	58	6	3	16	2	2	88.2	40.2
	L_{ij}	1	73	7	2	17	3	1	104.5	56.5
Gain (G_i)	Obs	1.6	35.3	2.7	2.3	7.9	0.5	1.6	52.0	
	G_{ij}	0.7	26.1	3.0	2.5	5.4	0.6	1.8	40.2	
	L_{ij}	1.3	40.6	3.8	1.8	6.3	1.5	1.2	56.5	

Annex F

Figure 2.7 Trends of minimum, maximum temperature, and total rainfall of the basin (1983-2016)



Annex G

Table 2.11

Predicted probability	**Slope Coefficient**	**Constant**	**t-statistics**	**P-value**
ELEV	0.00093920	-0.643	1275.95	***
SLP	-0.00469240	0.6	-52.09	***
COS-ASP	0.01305120	0.578	17.39	***
SIN-ASP	-0.01511810	0.579	-20.07	***
DIS-TC	0.00004210	0.5	121.92	***
DIS-RIV	0.00000316	0.548	33.17	***
DIS-RD	-0.00000008	0.579	0.646	NS

****** p<.01, ** p<.05, * p<.1, NS Not Significant***

Annex H

Table 3.3 Annual drought frequency over agro-ecologies for the period 1983-2016

SPEI-12 index value and description	Agro-ecological zones					
	[AEZ_1]	[AEZ_2]	[AEZ_3]	[AEZ_4]	[AEZ_5]	[AEZ_6]
+ 2.0 and above (Extremely wet)	1	2	0	0	1	1
+ 1.5 to + 1.99 (Very wet)	3	1	3	3	1	1
+ 1.0 to + 1.49 (Moderately wet)	0	1	2	2	2	4
+ 0.5 to + 0.99 (Mild wet)	3	4	7	4	9	2
− 0.49 to + 0.49 (Normal condition)	17	17	11	14	10	18
− 0.5 to − 0.99 (Mild drought)	5	2	6	6	5	3
− 1.0 to − 1.49 (Moderate drought)	2	5	3	1	3	3
− 1.5 to − 1.99 (Severe drought)	2	1	2	4	3	2
− 2.0 and below (Extreme drought)	1	1	0	0	0	0
Drought frequency	29.4%	26.5%	32.4%	32.4%	32.4%	23.5%

Cold to very cold humid [AEZ_1], Tepid to cool humid [AEZ_2], Hot to warm moist [AEZ_3], Hot to warm arid [AEZ_4], Tepid to cool sub moist [AEZ_5], and Hot to warm semi-arid [AEZ_6]

Annex I

Table 3.4 Agro-ecology-based farmers' perception of trends of selected climate indices

Perception		Major Agro-Ecology Zone						Total
		AEZ_1	AEZ_2	AEZ_3	AEZ_4	AEZ_5	AEZ_6	
Perceived about Climate Change	No	9.3	14.0	13.8	9.8	12.5	2.4	10.7
	Yes	90.7	86.0	86.2	90.2	87.5	97.6	89.3
Temperature over the years has increased	Disagree	18.7	12.9	37.9	26.2	0	0	18.2
	Agree	81.3	87.1	62.1	73.8	100	100	81.8
Physical data (Tmin and Tmax)	Decreased	0	0	100	0	0	100	33.3
	Increased	100	100	0	100	100	0	66.7
The number of Warm days (TX90P) over the years increased	Disagree	23.4	25.8	24.1	32.8	0	17.1	23.4
	Agree	76.6	74.2	75.9	67.2	100	82.9	76.6
Physical data (TX90P)	Decreased	0	0	0	0	0	0	0
	Increased	100	100	100	100	100	100	100
The number of cold nights (TN10p) over the years increased	Disagree	70.1	68.8	46.6	70.5	91.7	29.3	36.7
	Agree	29.9	31.2	53.4	29.5	8.3	70.7	63.3
Physical data (TN10P)	Decreased	100	100	100	100	0	0	66.7
	Increased	0	0	0	0	100	100	33.3
The amount of rainfall (TRF) over a year has increased	Disagree	63.6	50.5	60.3	70.5	100	61	55.5
	Agree	36.4	49.5	39.7	29.5	0	39	44.5
Physical data (TRF)	Decreased	100	100	100	100	100	0	80.3
	Increased	0	0	0	0	0	100	16.7
Drought occurrence frequency increases	Disagree	39.3	37.6	45.8	39.0	24.1	34.4	36.2
	Agree	60.7	62.4	54.2	61.0	75.9	65.6	63.8
Physical data (SPEI and SPI 12)	Decreased	0	0	0	0	0	0	0
	Increased	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Cold to very cold humid [AEZ_1], Tepid to cool humid [AEZ_2], Hot to warm moist [AEZ_3], Hot to warm arid [AEZ_4], Tepid to cool sub moist [AEZ_5], and Hot to warm semi-arid [AEZ_6]. Responses are in percentage.

Annex J

Table 4.5 Annual and seasonal NPP and TRF percentage of area where trends are significant or not and Positive or negative.

Variables	**Percentage of area**				
	Significant (%)	Not significant (%)	Positive	Negative	Total
NPP_Annual_Sig	39.41	60.59	43.33	56.67	100.00
NPP_Kiremt_Sig	24.45	75.55	59.99	40.01	100.00
NPP_Bega_Sig	35.38	64.62	60.17	39.83	100.00
NPP_Belg_Sig	38.40	61.60	14.60	85.40	100.00
TRF_Annual	37.44	62.56	16.49	83.51	100.00
TRF_Kiremt	23.83	76.17	83.25	16.75	100.00
TRF_Bega	13.61	86.39	2.16	97.84	100.00
TRF_Belg	55.33	44.67	-	100.00	100.00

Table 1. Annual and seasonal trends of mean TRF (mm/year) and NPP (gC/m^2/year) in Awash River Basin during 1982-2018

Variables	**Slope**	**Tau**	**P-Value**
NPP_Annual	0.047	0.114	0.327
NPP_Kiremt	0.041	0.219	0.058
NPP_Bega	0.035	0.213	0.065
NPP_Belg	-0.039	-0.144	0.214
TRF_Annual	**-3.335**	-0.329	**0.004**
TRF_Kiremt	0.601	0.062	0.601
TRF_Bega	-0.583	-0.131	0.261
TRF_Belg	**-2.821**	-0.314	**0.007**

Table 2. Annual and seasonal RESTREND percentage of area where trends are positive or negative.

Variables	**Percentage of area**				
	Significant (%)	Not significant (%)	Positive	Negative	Total
RESTREND_Annual	35.51	64.49	45.45	54.55	100.00
RESTREND_Kiremt	24.37	75.63	54.95	45.05	100.00
RESTREND_Bega	34.78	65.22	65.03	34.97	100.00
RESTREND_Belg	26.61	73.39	23.71	76.29	100.00

Table 3 Land use and land cover change flow matrices from (1986_2018) (percentage).

1986/2018	BL	CL	FL	GL	SBL	WB	WL	Total	Loss	(P_{jj})	(C_j)	(D_j)	(S_j)	(L_p)	(G_p)	(N_p)
BL	**0.2**	0.4	0.0	0.0	0.3	0.1	0.0	**1.0**	**0.8**	0.2	2.5	0.8	1.6	5.3	10.5	5.2
CL	0.4	**31.9**	1.1	1.1	5.0	0.2	0.6	**40.3**	**8.4**	31.9	43.6	26.9	16.7	0.3	1.1	0.8
FL	0.1	3.8	**2.8**	0.1	0.7	0.0	0.1	**7.7**	**4.8**	2.8	7.5	2.1	5.4	1.7	1.0	-0.8
GL	0.3	6.6	0.5	**0.4**	1.3	0.0	0.1	**9.3**	**9.0**	0.4	11.3	6.6	4.7	19.9	0.3	-19.7
SBL	0.7	**22.6**	0.5	1.0	**11.0**	0.3	0.8	**37.0**	**25.9**	11.0	33.9	18.0	15.9	2.3	0.7	-1.6
WB	0.0	0.0	0.0	0.0	0.0	**1.5**	0.0	**1.6**	**0.1**	1.5	0.6	0.5	0.1	0.0	0.4	0.3
WL	0.0	1.9	0.6	0.1	0.5	0.0	**0.1**	**3.2**	**3.1**	0.1	4.7	1.6	3.1	52.1	26.0	-26.1
Total	**1.8**	**67.2**	**5.5**	**2.8**	**19.0**	**2.0**	**1.6**	**100.0**	**52.0**	**48**	104.1	56.6	47.5			
Gain	**1.6**	**35.3**	**2.7**	**2.3**	**7.9**	**0.5**	**1.6**	**52.0**								

P_{jj}: Persistence, C_j: Total change, D_j: Net change, S_j: Swap, Gain-to-persistence (Gp), Loss-to persistence (Lp), and net change-to-persistence (Np) ratio of the land cover classes in the Awash Awash Sub-Basin, Ethiopia Obs: Observed Gain-to-persistence (G_p), Loss-to-persistence (L_p), and net change-to-persistence (N_p) ratio of the land cover classes in the Awash Awash Sub-Basin, Ethiopia

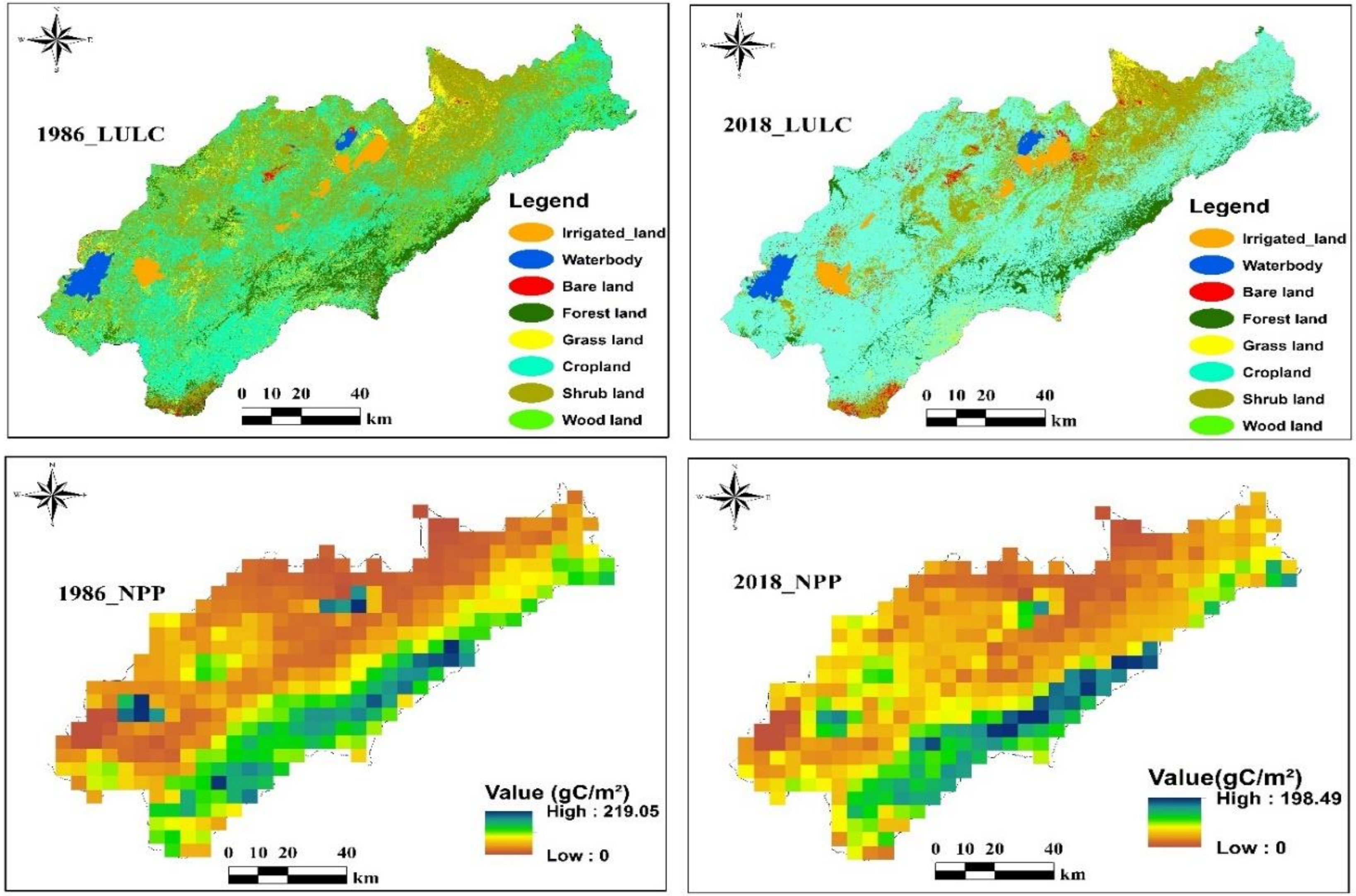


Figure 1. Spatiotemporal pattern of LULC and NPP in Awash-Awash sub-basin

Merti Woreda Belg Season Production											
	Kebeles	G/Silingoo		Ferekesa jewi		M/Qarsaa		M/Arja'oo		Merti Woreda	
Year		Cereal	Pulses	Cereal	Pulses	Cereal	Pulses	Cereal	Pulses	Cereal	Pulses
2005	Total hectare	410	12	534	12	632	21	1200	30	2994	82
	Production Quintal	1700.0	67.0	2567.0	54.0	2450.0	75.0	3750.0	110.0	10467	306
2006	Total hectare	508	34	534	8	876	31	1234	47	3152	120
	Production Quintal	3001	190	2890	54	4123	129	6675	176	16689	549
2007	Total hectare	577	0	601	0	870	0	1,345	0	3,413	0
	Production Quintal	2312.0	0	432	0	4534.0	0	3,650	0	10,928	0
2008	Total hectare	96	15	98	15	216	20	315	30	725	80
	Production Quintal	991.8	132	1012.4	132	2231.5	176	3254.3	264	7490	704
2009	Total hectare	353	8	660	35	850	45	1450	54	3313	142
	Production Quintal	6209.5	43.2	11609.9	188.8	14952.1	242.7	25506.5	291.3	58278	766
2010	Total hectare	600	187	800	70	1100	90	1750	108	4250	285
	Production Quintal	9024	635.8	12032	238	16544	306	26320	367.2	63920	969
2011	Total hectare	450	16	674	15	670	21	1200	30	2994	82
	Production Quintal	1832.5	70.8	2744.6	66.4	2728.3	93.0	4886.6	132.8	12192	363
2012	Total hectare	513	46	550	15	830	35	1340	55	3233	131
	Production Quintal	2996.6	205.4	3212.7	67.0	4848.3	156.3	7827.4	245.6	18885	585
2013	Total hectare	514	0	546	0	756	0	1,220	0	3,036	0
	Production Quintal	1158.9	0	1231	0	1704.5	0	2,751	0	6,845	0

Annex K

DATA COLLECTION TOOLS

School of Graduate Studies

College of Development Studies

Center for Environment and Development

Household survey questionnaire (HSQ)

Introduction and consent

Dear respondents,

The purpose of this HSQ is to **"Analysis of changes in land use and land cover transition, climate extremes, and vegetation productivity: Drivers and agricultural risks in the Awash River Basin, Ethiopia.** This is therefore to collect detailed information on households' vulnerability situations and explore the existing adaptation response in the face of the changing climate. You are selected randomly for this survey and your participation is based on your willingness to take part. Therefore, your kind cooperation with honest responses to the HSQ will be vital for the overall success of the study.

Dear, you should be confident that the data/information you give us works only for academic purposes. To this end, the anonymity and confidentiality of our respondents are highly guaranteed unless and otherwise under mutual agreement between the concerned parties.

General instruction for the interviewer/enumerator

- ⇒ Please put the code chosen by the respondent in the space provided for some of the close-ended questions and encircle the chosen reposes for those which do not have space to put the codes.
- ⇒ The respondent can choose more than one response for some questions (multiple response items).
- ⇒ Skip the code to which it does not require the response.
- ⇒ Write down the response for open-ended questions whenever the respondent provides and necessary.
- ⇒ Respondent agrees to be interviewed Respondent does not agree to be interviewed.

...1 **... 2 → END**

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MODULE 1: HOUSEHOLD IDENTIFICATION

N	Date of the enumeration:	Time: Start: Finish: _
1.1	HH identification number:	
1.2	Woreda:	
1.3	Kebele:	
1.4	Village:	
1.5	Agro-ecology type:	
Enumerator name: ______________		**Signature: _____________**

MODULE 2: BASIC DEMOGRAPHIC INFORMATION

2.1 Relation to the head [**code 1**]	**2.2** Age in years (**write years**)	**2.3** Sex [**code 2**]	**2.4** Marital status ***(****If age above 18*) *[***code 3***]*	**2.5** Occupation **[See code 5]**		***2.6*** Highest level of education (completed) [for education level different from 1- 12. *[***code 6***]*	***2.7*** Length of years in the current residence [**write *years]***	***2.8*** Responsibility in the community *[***code 7***]*
				Main	Secondary			

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

Codes for 2: 1=Male 2=Female

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

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

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

Codes for 6: 1= None; 2=Religious leader; 3= Coordinator of community development work; 4=*Kebele* Administrator; 5= other (specify) ______________

2.9 Is this your village of origin? 1=Yes 2=No

2.10 If your birthplace differs from the current one, what is the reason for coming here? (**Multiple response is possible)**

1=Marriage; 2=Join relative; 3=Displacement by drought; 4=Displacement by flooding; 5=Divorce 6=Search for agricultural land; 7=War/conflict; 8=others specify_____________________

2.11 Number of permanent household members: Male__________female______________

2.12 If agriculture is your major livelihood activity, for how long did you work in agriculture? (Write in years) ___________________________

2.13 Which farming system are you following currently? 1=Only crop production; 2= Livestock raring; 3=Mixed farming (Crop production and livestock raring)

2.14 Have you changed your farming system in the past 5-10 years? 1=Yes 2=No

2.15 If yes for QN # 2.17, why did you change the farming system you were following? (Multiple response is possible)

1=Decrease in rainfall amount; 2= Drought; 3=Decrease in productivity of livestock; 4=Decrease in productivity of land; 5=Decrease in grazing land; 6=increase in pest and disease; 7=Others specify__________________

MODULE 3: PERCEPTION OF CAUSES OF LAND USE LAND COVER CHANGE

3.1. Have you observed any land use land cover change in your locality? 1= Yes; 2=No

3.2. If question **No 3.1.** is Yes What major shift in land use occurred in your locality in the last 20 years? (Provide qualitative description

3.3. What causes land use/land cover change in your area? (Multi-response)

Possible causes	**Yes [1]**	**No [2]**
1. Population growth		
2. Expansion of town		
3. Deforestation		
4. Overgrazing		
5. Agricultural land expansion		
6. If other, please specify ______________________________		

3.2.Following the land use/land cover change, which environmental problems are very. common in your area?

Environmental problems	**Yes [1]**	**No [2]**
1. Soil erosion		
2. Deforestation		
3. Degradation of watersheds		
4. If other, specify -----		

3.3.If your choice for question number **3.3.** is soil erosion, what are the major causes?

Cause of soil erosion	**Yes [1]**	**No [2]**
1. Land fragmentation		
2. Absence of fallowing		
3. Overgrazing		
4. Intensive use of land		
5. Expansion of agriculture onto marginal areas		
6. Absence of soil and water conservation techniques		

3.4.If your choice for question number 3**.3.** is deforestation, what are the major causes?

Cause of deforestation	**Yes [1]**	**No [2]**
1. Expansion of agricultural land		
2. An increase demand for firewood		
3. Cutting of forest for residence construction		
4. Cutting of forest to generate income		
5. Wildfire		
6. If other, please specify		

3.5.If your choice for question number **3.3.** is degradation of watersheds, what are the major causes?

Cause of degradation of watersheds	**Yes [1]**	**No [2]**
1. Change in cropping pattern from annual to perennial crops		
2. An increasing demand for local consumption		
3. Water withdrawal for irrigating chat and other annual crops		
4. Change in the local climate (decline in annual rainfall and an increase in temperature)		
5. Water withdrawal for the nearby urban areas		
6. If other, please specify		

MODULE 4: FARMERS' PERCEPTION TO CLIMATE VARIABILITY OR CHANGE

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

No.	Perception indicators	Level of agreement or disagreement (five-point scale)				
Change in temperature		Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
1.	Temperature has increased					
2.	No change in temperature					
3.	Temperature has decreased					
4.	Rainy season temperature has decreased					

5.	Dry season temperature has increased					
6.	Number of hot days in a year increased					
7.	Number of warm nights increased					
8.	The degree of coldness of cold seasons increased					
Change in rainfall						
9.	Amount of rainfall has increased					
10.	No change in rainfall					
11.	Amount rainfall has decreased					
12.	The onset of rainfall become more unpredictable					
13.	The cessation of rainfall become more unpredictable					
14.	Belg rain has decreased					
15.	Rain fall during main rainy season has decreased					
16.	Drought occurrence frequency increases					

MODULE 5: CLIMATE-INDUCED SHOCKS INDICATORS

5.1.Have you ever faced crop failure during the last five to ten years?

1=Yes 2=No

5.2.If yes for QN# 9.1, what are the main reasons for the crop failure? [Multiple response is possible]

1=Erratic rainfall; 2=Lack of Improved seeds; 3=Unaffordable price of inputs; 4=Low level of soil fertility; 5=Pest and disease; 6=Shortage of farm oxen; 7=Other (specify)_________________

5.3.Have you ever experienced flooding due to excessive rainfall over the last 10-20 years?

1=Yes 2=No

5.4.If yes for QN# 9.3, how do you rate the frequency of flooding in your locality over the last 10-20 years?

5= Highly increased; 4= Increased; 3= No change; 2= Decreased; 1= Highly decreased

5.5.Have you ever experienced drought due to climate variability/change over the last 10-20 years?

1=Yes 2=No

5.6.If yes for QN # 9.5, how do you rate drought frequency in your locality over the last 10-20 years?

5= Highly increased; 4= Increased; 3= No change; 2= Decreased; 1= Highly decreased

5.7.Have you ever experienced disease (crop, livestock, and human) disease outbreak due to climate variability/change over the last 10-20 years?

1=Yes 2=No

5.8.If yes for QN# 9.7, how do you rate the frequency of disease outbreak in your locality over the last 10-20 years?

5= Highly increased; 4= Increased; 3= No change; 2= Decreased; 1= Highly decreased

MODULE 6: Self-Reported Climate Related Shock Indicators

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

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

6.2.Who has been affected most by the shocks mentioned above?

1=Men; 2=Women; 3=Children; 4=Elders; 5=All segment of the society

MODULE 7: PERCEIVED CLIMATE IMPACTS OF CLIMATE CHANGE AND EXTREME EVENTS

7.1.Would you please indicate the type of impacts that climate change has brought to you or your household?

No.	**Indicators questions**	**Dummy**	**Response**
1.	Crop productivity decline	1= Yes 2= No	
2.	Shortage of water for irrigation	1= Yes 2= No	
3.	Shortage of water for home/animal consumption	1= Yes 2= No	
4.	Emergence/resurgence of new pests (weeds and	1= Yes 2= No	
5.	Increased level of temperature	1= Yes 2= No	
6.	Increased frequency of drought	1= Yes 2= No	
7.	Increased frequency of flooding	1= Yes 2= No	
8.	Geographic isolation/inaccessibility	1= Yes 2= No	
9.	Livestock disease	1= Yes 2= No	
10.	Crop pests and diseases	1= Yes 2= No	
11.	Local conflict over diminishing resources	1= Yes 2= No	
12.	Food price inflation	1= Yes 2= No	

Guiding question for Key Informants in the Study Kebeles

Name: ___________________________________

Responsibility: _____________________________

Name of study Kebele: ______________________

1. Is there land use and land cover change in the village/Kebele? Would you explain the cause and extent of the change? What were the major land use and cover types 30 years ago?

2. Which resources are more affected due to land use and land cover change? In your opinion what are the factors /reasons for these significant changes?

3. What visible changes have you observed as related to rain fall, temperature, soil fertility, forest vegetation, wildlife, crop productivity, livestock productivity, flow of streams, occurrence of big floods, incidence of drought, forest vegetation cover, river/stream flow etc., during your lifetime in the village?

4. How often is the occurrence of drought in the locality? And what are the probable causes? How is the trend of the rainfall during the past 20 to 30 years? Is it increasing, decreasing, coming on time, and stopping at the right time?

5. What effect has climate change inflicted on the livelihood of the local people?

6. What development interventions are carried out in the village to avert the impact of climate change? (Afforestation, water harvesting, irrigation, soil, and water conservation, off farm employment, etc.

7. Do you agree that development interventions in the village are well planned, well discussed and undertaken by consensus or do you lack these attributes?

8. Do you feel that farmers are happy to participate in development activities such as soil and water conservation, forestry development without payment? How do you evaluate the agricultural extension agents' role in motivating and mobilizing the community to strengthen their adaptive strategies to climatic changes?

9. Based on your experience, have you observed any changes in climate? What are the causes of climate change?

10. Do you think you and your family / men and Women are most vulnerable to climate change? Why?

11. How do you evaluate government policies and strategies in relation to their effectiveness to address climate related problems as well as in maximizing livestock/crop production?

12. How does climate change impact on farming, your crops/ Livestocks and on your livelihood?

13. Are there any adaptation strategies you /Community have made for the change in climate (precipitation and temperature)? What is the adaptation strategy?

14. If you don't have the possibility in dealing with climate change issues, what would you do?

15. What agricultural technology and meteorology information system do you access regularly and during climatic extremes?

16. Do you receive early warning information on short term variations and/or long-term climate change from any sources?

17. Do you believe that it is possible to reduce or totally stop the negative impacts of climate change? If yes how?

18. What are the success stories you observed in relation to coping and adaptation strategies adopted by yourself (if) to withstand climatic shocks?

19. What should the government and the community do to avert the impact of climate change in the Kebele?

Focus group Discussion checklist

Place: ___________________________

Date: ____________________________

Time: ____________________________

	Name the discussant	Sex	Age	Family Size	Any Position in community	Educational Background	Years of residence

1. What were the major land use and cover types 30 years ago?
2. Is there land use and land cover change in the village/Kebele? Would you explain the cause and extent of the change? What is the present status of different land uses / land cover in your area (Grass land, forest land, shrub and bush land, water body, wood land agricultural/Cultivated land)
3. Which resources are more affected due to land use and land cover change? In your opinion what are the factors /reasons for these significant changes?
4. Based on your experience, have you observed any changes in climate? What are the causes of climate change?
5. What visible changes have you observed as related to rain fall, temperature, soil fertility, forest vegetation, wildlife, crop productivity, livestock productivity, flow of streams, occurrence of big floods, incidence of drought, forest vegetation cover, river/stream flow etc., during your lifetime in the village?
6. What effect has climate change had on your livelihood?
7. How often is the occurrence of drought in the locality? And what are the probable causes? How is the trend of the rainfall during the past 20 to 30 years? Is it increasing, decreasing, coming on time, and stopping at the right time?
8. What development interventions are carried out in the village to avert the impact of climate change? (Afforestation, water harvesting, irrigation, soil, and water conservation, off farm employment, etc.
9. Do you feel that farmers are happy to participate in development activities such as soil and water conservation, forestry development without payment? How do you evaluate the agricultural extension agents’ role in motivating and mobilizing the community to strengthen their adaptive strategies to climatic changes?
10. Do you think you and your family / men and Women are most vulnerable to climate change and land use change? Why?
11. How does climate change impact on farming, your crops/ Livestocks and on your livelihood?

12. Are there any adaptation strategies you as a farmer used in plot of land made for the change in climate (precipitation and temperature)? What is the adaptation strategy? What agricultural technology and meteorology information system do you access regularly and during climatic extremes?
13. Do you receive early warning information on short term variations and/or long-term climate change from any sources? What are the success stories you observed in relation to coping and adaptation strategies adopted by yourself (if) to withstand climatic shocks?
14. Do you agree that development interventions in the village are well planned, well discussed and undertaken by consensus or lack these attributes? What should the government and the community do to avert the impact of climate change in the Kebele?

Key informant interview (KII) Guides (Woreda level)

Guiding questions for government institution staff (Agricultural Development Offices, Land Administration Offices, Meteorological Agency, Disaster Prevention and Preparedness office)

Name of the office	
Interviewee	
Interviewer	
Time of Interview	
Place of interview	
Mobile Number	
Responsibility	

1. Is there land use and land cover change in Woreda/Zone? What were the major land use and land cover types some 30 years ago? Would you explain the extent of the change?
2. Which resources are more affected due to land use and land cover change? In your opinion what are the factors /reasons for these significant changes?
3. What are the major changes in land use (area) and management you noted in communal properties over the last 30 years and the institutional changes that go along with these?
4. What do you understand by the term climate change and climate variability? What are the indicators of the occurrence of climate change? How do you evaluate the climate situation in the district over the years?

5. What are the damages imposed by climate change to society?
6. Does climate change an important agenda for Agricultural Development Offices? If yes, what are the development interventions introduced in the woreda (District or study kebeles)?
7. Are the development interventions appreciated and owned by the community? Are they sustainable?
8. Do you think farmers are aware of climate change and local variability? If yes, how did they acquire the awareness?
9. What coping mechanisms do farmers use in times of drought in the woreda? Also what adaptation strategies do rural households use to withstand the ill effects climate change?
10. What challenges do farmers face to effectively implement coping and adaptation mechanisms?
11. What social capital has rural households to avert the dangers that arise because of climate change and variability?
12. How do you evaluate government policies and strategies in relation to their effectiveness to address climate related problems as well as in maximizing a livestock/crop production?
13. How does climate change impact on farming and farming livelihood?
14. How do you evaluate the impacts of climate change on rural household’s livelihoods (Crop/ Livestock production), water resources, grazing lands, woodlands, farmlands?
15. Which segment of the local community is more affected by climate variability/climate change?
16. Is there any local level organizational arrangement made that helps farmers to overcome the damages caused by climate change/climate variability?
17. How integrated are government institutions working on activities that are deemed helpful to avert climate shocks?
18. Do you believe that it is possible to reduce or totally stop the negative impacts of climate change? If yes how?
19. Of the development interventions which ones are more important to reduce damages that could be caused by climate change/climate variability?
20. How does agricultural research in the region attempt to address the need for crop varieties tolerant to moisture stress and other supporting technologies to tackle climate change.
21. How do you evaluate the role of the Disaster prevention and preparedness office contribution to coping against climate change?

22. How does the Meteorology Agency contribute to efforts to withstand climate change and variability? Does the agency have a strong institutional set up to provide adequate weather information?

23. What are the success stories you observed in relation to coping and adaptation strategies adopted by farmers to withstand climatic shocks?

Addis Ababa University

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Center for Environment and Development Studies

Field Survey Checklist (GPS data collection)

Field Code	**GPS Reading**			**Land Use Type**	**Description**
	Altitude	**X-Coordinate**	**Y-Coordinate**		
GCP 1					
GCP 2					
GCP 3					
GCP 4					
GCP 5					
GCP 6					
GCP 7					
GCP 8					
GCP 9					
GCP 10					
GCP 11					
GCP 12					
GCP 13					
GCP 14					
GCP 15					
GCP 16					
GCP 17					
GCP 18					
GCP 19					
GCP 20					
GCP 21					
GCP 22					
GCP 23					
GCP 24					
GCP 25					
GCP 26					
GCP 27					
GCP 28					
GCP 29					
GCP 30					