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Spatio-Temporal Dynamics of Climate
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Perceptions and Adaptation:
Implications for Cereal Crop Production
in the Ayehu Watershed, Awi Zone,
Northwest Ethiopia

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BAHIR DAR UNIVERSITY

FACULTY OF SOCIAL SCIENCES

DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

Spatio-Temporal Dynamics of Climate Variability and Smallholder Farmers' Perceptions and Adaptation: Implications for Cereal Crop Production in the Ayehu Watershed, Awi Zone, Northwest Ethiopia

BY

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Spatio-Temporal Dynamics of Climate Variability and Smallholder Farmers' Perceptions and Adaptation: Implications for Cereal Crop Production in the Ayehu Watershed, Awi Zone, Northwest Ethiopia

By

Abebe Biresaw Bitew

A Dissertation Submitted to

The Department of Geography and Environmental Studies, Faculty of Social Science, Bahir Dar University in Partial Fulfilment of the Requirement for the Degree of Philosophy in Geography and Environmental Studies (Specialization in Environment and Natural Resource Management)

Principal Advisor

Prof. Amare Sewnet Minale (PhD)

June, 2026

Bahir Dar, Ethiopia

Declaration

I hereby declare that this Ph.D. dissertation, entitled “spatio-temporal dynamics of climate variability and smallholder farmers’ perceptions and adaptation: implications for cereal crop production in the Ayehu watershed, Awi zone, northwest Ethiopia,” is my original work and has not been submitted to any other university for the award of any degree. All sources of information used in this study have been duly acknowledged and properly cited.

Abebe Biresaw Bitew ___________________________25/06/2026

Bahir Dar University

Faculty of Social Sciences

Department of Geography and Environmental Studies

Approval of Dissertation Defence

I hereby certify that I have supervised, read, and evaluated this dissertation titled spatio-temporal dynamics of climate variability and smallholder farmers' perceptions and adaptation: implications for cereal crop production in the Ayehu watershed, Awi zone, northwest Ethiopia, prepared under my guidance. I recommend the thesis/dissertation be submitted for oral defense.

Prof. Amare Sewnet Minale		24/06/2026
Advisor's name	Signature	Date
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Bahir Dar University

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Approval of Dissertation Defence

We hereby certify that the dissertation prepared by Abebe Biresaw Bitew, entitled " spatio-temporal dynamics of climate variability and smallholder farmers' perceptions and adaptation: implications for cereal crop production in the Ayehu watershed, Awi zone, northwest Ethiopia," and submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Geography and Environmental Studies (Environment and Natural Resource Management), complies with the regulations of the University and meets the accepted standards of originality and academic quality.

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LIST OF ABBREVIATIONS

AEZs	Agroecological Zones
ADF	Augmented Dickey-Fuller
APF	Adaptation Policy Framework
ARDL	Auto Regressive Distributed Lag
CBA	Community-Based Adaptation
CC	Contingency Coefficient
CHIRPS	Climate Hazards Group InfraRed Precipitation with Stations
CMIP	Coupled Model Intercomparison Project
CRGE	Climate Resilient Green Economy
CRRPI	Climate Related Risk Perception Index
CSA	Central Statistical Agency
CV	Coefficient of Variation
DM	Distributional Mapping
EBA	Ecosystem-Based Adaptation
EMI	Ethiopian Meteorological Institute
ESGF	Earth System Grid Federation
FGD	Focus Group Discussion
GCM	General Circulation Model
GEF	Global Environmental Facility
GDP	Gross Domestic Product
FAO	Food and Agriculture Organization
IDW	Inverse Distance Weighted
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
KNMI	Royal Netherlands Meteorological Institute
MK	Mann-Kendall
NASA	National Aeronautics and Space Administration

NSE	Nash-Sutcliffe Efficiency
PCI	Problem Confrontation Index
PCI	Precipitation Concentration Index
PT	Power Transformation
RAI	Rainfall Anomaly Index
RCM	Regional Climate Model
RCPs	Representative Concentration Pathways
RMSE	Root Mean Square Error
SD	Standard Deviation
SDGs	Sustainable Development Goals
SI	Severity Index
SSE	Sen's Slope Estimator
SSPs	Shared Socio-Economic Pathways
UNDP	United Nations Development Programme
WAI	Weighted Average Index
WCRP	World Climate Research Programme
VIF	Variance Inflation Factor

ABSTRACT

Climate variability poses a major challenge to smallholder farmers who depend on rain-fed agriculture, with significant implications for cereal crop production and rural livelihoods. Although numerous studies have examined climate trends and agricultural impacts, limited research has integrated climate variability, crop yield responses, farmers' perceptions, and adaptation strategies within a single watershed-scale framework across different agroecological zones. This study aimed to evaluate historical and future climate trends, assess the impacts of climate variability on cereal crop yields, examine farmers' perceptions of climate-related risks, and identify the factors influencing adaptation strategies in the Ayehu watershed, Upper Blue Nile Basin, Ethiopia. A mixed-methods approach was employed, combining climate data analysis, crop yield assessment, household surveys, key informant interviews, focus group discussions, and econometric modeling. Historical climate analysis revealed a slight but statistically insignificant decline in annual rainfall, accompanied by declining Belg rainfall, increasing Kiremit rainfall, and significant warming trends in both minimum and maximum temperatures. Future climate projections indicated continued increases in temperature under all emission scenarios, while rainfall projections showed mixed patterns, with some scenarios suggesting increases in rainfall amounts and variability. The results further showed that climate variability significantly influences cereal crop production. While rising minimum temperatures were associated with improved crop yields, rainfall variability and irregular rainfall distribution negatively affected production, highlighting the sensitivity of cereal crops to changing rainfall patterns. Farmers' perceptions generally corresponded with observed climatic trends, although significant differences were evident across agroecological zones. Drought, water scarcity, pest outbreaks, and declining crop yields were identified as the major climate-related risks. Farmers employed a combination of indigenous and introduced adaptation strategies, including crop diversification, local crop varieties, adjusted planting dates, and improved agricultural inputs. Adaptation decisions were significantly influenced by education, access to credit, extension services, climate information, agroecological conditions, and household income, whereas small landholdings, soil degradation, limited irrigation access, and high input costs constrained adaptation efforts. The study makes a novel contribution by integrating climate science, crop yield analysis, farmers' perceptions, and adaptation behavior within a single watershed-scale framework. It further advances understanding through agroecological comparisons and the incorporation of CMIP6-based future climate projections, enabling a comprehensive assessment of both current and future climate risks. By linking observed climatic changes with farmers' perceptions and adaptation decisions, the study provides context-specific evidence on how climate variability influences agricultural production and livelihood resilience. Overall, the findings highlight increasing climate risks in the Ayehu watershed and underscore the need for targeted, climate-smart interventions that strengthen adaptive capacity, enhance cereal production, and support sustainable rural livelihoods.

Keywords: Adaptation strategies, Ayehu watershed, Climate variability; Perception, Projection

CHAPTER ONE
INTRODUCTION

1.1. Background of the Study

Climate variability and climate change have emerged as major global challenges with profound environmental and socioeconomic consequences in the 21st century. Climate change refers to long-term alterations in average climatic conditions primarily driven by anthropogenic greenhouse gas emissions and land-use change, whereas climate variability refers to short- to medium-term fluctuations in temperature and rainfall around their long-term means at seasonal, annual, or decadal scales (Gries et al., 2019; IPCC, 2021; Kumar et al., 2022). Increasing greenhouse gas concentrations have intensified both the magnitude and frequency of climate variability, resulting in more unstable weather patterns and heightened exposure to climate-related risks. Global mean surface temperature has already increased by approximately 1.1°C above pre-industrial levels, with the most rapid warming observed in recent decades (IPCC, 2023; Sagar et al., 2025). At the same time, precipitation patterns have become increasingly erratic, while the frequency and intensity of extreme events such as droughts, floods, and heatwaves have increased, with widespread consequences for ecosystems, water resources, agriculture, and human well-being (Ali & Kamraju, 2025; Singh et al., 2023). Climate projections further indicate that global temperatures may rise by 1.8°C to 4.0°C by the end of the century, amplifying risks for both natural and human systems, particularly in vulnerable regions (Farooq et al., 2022; Nautiyal et al., 2024; Rahman et al., 2024).

Within this global context, agriculture is one of the most climate-sensitive sectors because crop production is directly dependent on temperature, rainfall, and seasonal climate conditions. At the same time, agriculture plays a central role in livelihoods, food security, and sustainable development, and is directly linked to the achievement of Sustainable Development Goal 2, which aims to eliminate hunger and improve food security (Arora & Mishra, 2023). However, the sector faces increasing pressure from population growth, which is projected to reach approximately 9.8 billion by 2050, thereby intensifying global food demand and the need for resilient agricultural systems (Oluwole et al., 2023). Empirical evidence consistently shows that rising temperatures, shifting rainfall patterns, and increasing climate extremes negatively affect agricultural productivity, although the magnitude of impacts varies across regions, farming systems, and crop types (Davis et al., 2023; Kumar et al., 2024; Radwan et al., 2025;

Sida et al., 2025). These variations highlight the importance of location-specific studies that capture the spatial heterogeneity of climate impacts on agriculture.

The impacts of climate variability are particularly severe in sub-Saharan Africa (SSA), where agriculture is largely rain-fed and characterized by limited technological and institutional support. In this region, the interaction between climatic exposure, livelihood sensitivity, and limited adaptive capacity increases the vulnerability of rural households to climate-related shocks (Ahmad et al., 2024; Meressa & Bantie, 2024). Climate projections also indicate that Africa will experience substantial warming, with temperature increases ranging between 2°C and 6°C by the end of the century, alongside increasing rainfall uncertainty (Ayugi et al., 2023; Spinoni et al., 2021). However, these impacts are spatially uneven. Some areas are increasingly affected by drought, while others experience floods and land degradation (Osman et al., 2021; Raza et al., 2019). These climatic stresses have already contributed to declining yields of major staple crops such as maize, millet, and sorghum, leading to repeated crop failures and food insecurity (Mutengwa et al., 2023; Mulla et al., 2023; Omokpariola et al., 2025; Simane et al., 2025). This evidence demonstrates that climate impacts are not only determined by exposure to hazards but also by the socioeconomic and institutional capacity to respond effectively.

Ethiopia represents a highly relevant case for examining these dynamics because agriculture forms the backbone of the national economy and supports the majority of the population. The sector contributes more than one-third of GDP and provides livelihoods for approximately 85% of the population (Belay et al., 2021). Climate records showed that mean temperature has increased by about 0.3°C to 0.66°C in recent decades, with projections suggesting further increases of 1.8°C to 3.7°C under high-emission scenarios by 2100 (Getachew et al., 2021). Ethiopia has also experienced recurrent climatic shocks, including the 1983–1984 drought and the 2015–2016 El Niño event, both of which caused severe agricultural and economic losses (Kasie et al., 2020; Mera, 2018). Despite these national-level trends, climate impacts in Ethiopia are highly heterogeneous due to variations in altitude, rainfall patterns, temperature regimes, and farming systems. As a result, agroecological differences strongly influence agricultural productivity and climate sensitivity. Lowland areas are often affected by heat stress and moisture deficits, while midland and highland areas experience increasing rainfall variability and changing growing conditions. Consequently, the productivity of major cereal crops such as maize, wheat, and barley varies significantly across agroecological zones (Asfaw et al., 2021; Marshal et al., 2024; Mazengiya, 2024; Sinore & Wang, 2024).

In addition to biophysical variability, farmers' perceptions of climate variability play a critical role in shaping agricultural responses. Perception acts as an intermediary between climatic conditions and adaptation decisions, influencing how farmers interpret risks and choose response strategies. Evidence suggests that farmers who perceive changes in temperature, rainfall variability, and extreme events are more likely to adopt adaptation measures than those with limited awareness (Sertse et al., 2021). Empirical studies show that perceived climate risks influence decisions such as crop diversification, soil and water conservation, adjustment of planting dates, and adoption of improved crop varieties (Ayanlade et al., 2017; Gashure & Wana, 2023; Teshome et al., 2021). These practices contribute to improved resilience by reducing production risks and enhancing the capacity of households to cope with climatic stress (Damtew et al., 2022). However, limited access to information, resource constraints, and institutional barriers continue to limit effective adaptation and may reduce agricultural productivity (Grossi & Dinku, 2022; Mramba & Mapunda, 2025).

From a conceptual perspective, climate variability, farmers' perceptions, adaptation, and crop productivity are closely interconnected within a dynamic agricultural system. Climate variability directly affects agricultural production through changes in temperature and rainfall, and indirectly through farmers' perceptions and subsequent adaptation decisions. The effectiveness of adaptation strategies determines the extent to which agricultural systems can sustain productivity under changing climatic conditions. Therefore, crop productivity reflects the combined effects of climate conditions, perception-driven responses, and socioeconomic and institutional contexts (Ricart et al., 2025; Usmail et al., 2023). Understanding these linkages is essential for developing effective, context-specific adaptation strategies and improving the sustainability of smallholder farming systems.

Against this background, this study adopts an integrated analytical framework that links historical and future climate variability, crop production, farmers' perceptions, and adaptation strategies across agroecological zones of the Ayehu watershed. Specifically, the study analyzes historical climate trends and future projections using CMIP6 scenarios, evaluates spatial and temporal variability of temperature and rainfall, and assesses their impacts on major cereal crop productivity. It further examines the consistency between observed climatic trends and farmers' perceptions, identifies the socioeconomic, institutional, and environmental determinants of adaptation decisions, and evaluates how adaptation strategies influence agricultural outcomes across different agroecological settings. By integrating climate data, crop production analysis, and household-level evidence within a unified framework, the study provides robust empirical insights that can inform targeted adaptation policies, strengthen climate-resilient agricultural development, and support sustainable rural livelihoods in climate-sensitive environments.

1.2. Statement of the Problem

Climate variability, particularly changes in temperature and rainfall, is a major constraint on Ethiopia’s agriculture-dependent economy (Tesema et al., 2025). Increasing temperatures, erratic rainfall, and more frequent extreme events such as droughts and floods disrupt agricultural production, reduce crop yields, and threaten food security (Alemu & Mengistu, 2019b). Ethiopia has experienced severe climatic shocks, including the 1983–84 drought, which reduced crop production by 21% and GDP by 7–9%, and the 2015–16 El Niño event, which affected about 10 million people (Kasie et al., 2020; Mera, 2018). Mean temperatures increased by about 1.3°C between 1960 and 2006 and could rise by up to 3.7°C by the end of the century under RCP8.5 scenarios (Getachew et al., 2021). Meanwhile, rainfall remains highly variable and uncertain across space and time (Gummadi et al., 2018). Without effective adaptation, these trends could reduce Ethiopia’s GDP by up to 10% by 2045 (Feleke et al., 2025).

At the local level, smallholder farmers in the study watershed are increasingly exposed to rising temperatures, erratic rainfall, droughts, and floods, which adversely affect crop production and household livelihoods (Ahmad et al., 2022; Berhanu et al., 2024). Although the watershed possesses considerable agricultural potential, dependence on rain-fed farming and limited access to irrigation, improved technologies, and climate information increase farmers' susceptibility to climatic shocks (Amare & Simane, 2017). Observational evidence indicates persistent warming and increasing rainfall variability within the watershed (Tesema et al., 2025). However, adaptation efforts remain constrained by socioeconomic, institutional, and biophysical barriers that limit the adoption of both indigenous and introduced adaptation practices (Belay et al., 2017; Manono et al., 2025).

Several studies have examined temperature and rainfall variability in Ethiopia using different datasets and analytical approaches (Abeje & Alemayehu, 2019; Alemayehu et al., 2020; Ketema & Siddaramaiah, 2020). Most studies consistently report warming trends characterized by increasing minimum and maximum temperatures, although the magnitude and rate of change vary across locations and time periods (Alemayehu et al., 2022b; Asfaw et al., 2018; Geleta et al., 2022; Mengistu et al., 2014). In contrast, findings regarding rainfall trends remain inconsistent, with some studies reporting declining precipitation while others identify strong interannual variability or statistically insignificant trends (Feke et al., 2021; Jury & Funk, 2013; Shawul & Chakma, 2020; Wagesho et al., 2013). These inconsistencies reflect differences in data quality, station density and coverage, analytical approaches, spatial resolution, and local environmental conditions (Belay & Mengistu, 2019; Mekonen & Berlie, 2020). Moreover, ongoing scientific debate persists regarding whether observed rainfall fluctuations represent long-term climatic change or short-term natural variability, particularly in data-scarce regions. Despite these advances, much of the existing literature remains descriptive and provides limited insight into how climate variability translates into crop-specific agricultural impacts across different agroecological zones.

Although climate variability has been widely investigated, the integration of historical climate analysis with future climate projections and agricultural impact assessment remains limited, particularly at local and watershed scales (Alemayehu & Bewket, 2017a; Esayas et al., 2018; Etana et al., 2020). Recent developments in climate modeling, particularly through the Coupled Model Intercomparison Project Phase 6 (CMIP6), provide improved opportunities for localized climate assessment through enhanced spatial resolution and a better representation of regional climate processes (Alaminie et al., 2021; Du et al., 2022; Teshome et al., 2021b). Nevertheless, these advances have not been sufficiently integrated with analyses of crop productivity and household adaptation behavior. As a result, empirical evidence remains limited regarding how historical climate variability and future climate change projections jointly influence crop production trajectories, including yield variability, changes in growing seasons, shifts in cropping calendars, and future crop suitability at the watershed level. This limitation constrains the development of forward-looking and evidence-based adaptation strategies.

Climate variability in Ethiopia is further complicated by substantial agroecological heterogeneity; however, this diversity is often inadequately represented in existing studies (Cheru, 2024; Gashaw et al., 2023). Ethiopia's agricultural systems are shaped by marked differences in altitude, rainfall regimes, temperature conditions, soil characteristics, and farming practices, all of which influence crop performance under changing climatic conditions (Sinore & Wang, 2024). Despite this complexity, many studies rely on aggregated analysis that obscure important local variations in crop responses, yield stability, and production risks (Alemayehu et al., 2023; Ginbo, 2022). The magnitude and nature of these impacts vary considerably across highland, midland, and lowland agroecological zones due to differences in temperature conditions, moisture availability, and soil–water interactions (Belay & Mengistu, 2024; Engda et al., 2024; Zeleke et al., 2023). Consequently, there is a need for more spatially explicit and crop-specific analysis that adequately capture agroecological differences and their implications for agricultural production.

Farmers' perceptions of climate variability constitute another critical but insufficiently understood dimension of climate adaptation. Perceptions influence how farmers interpret climatic risks, evaluate response options, and implement adaptation measures (Mairura et al., 2021; Muneer et al., 2024). Although several studies report that farmers' perceptions generally correspond with observed climatic trends, others reveal important discrepancies associated with differences in education, access to climate information, and experiential knowledge (Abid et al., 2019; Hein et al., 2019). In Ethiopia, comparative assessments of farmers' perceptions across agroecological zones remain limited (Dendir & Simane, 2019; Jawo et al., 2023). This represents an important gap because agroecological conditions influence both exposure to climate-related stressors and the ways in which climatic changes are perceived and interpreted by farming communities (Etana et al., 2020; Owusu et al., 2021). Furthermore, insufficient attention has been given to understand the extent to which farmers' perceptions correspond with observed climate records and how these perceptions shape adaptation behavior and agricultural outcomes.

Climate change adaptation is widely recognized as a key strategy for reducing climate-related risks and sustaining agricultural production (Bennett et al., 2016; IPCC, 2023; Bryan et al., 2009; Deressa et al., 2009). In Ethiopia, smallholder farmers employ a wide range of indigenous and introduced adaptation strategies (Alemayehu & Bewket, 2017b; Bekuma et al., 2023). However, adaptation responses are highly context-specific and influenced by agroecological, socioeconomic, and institutional conditions (Marie et al., 2020; Simane et al., 2016). Despite growing research on adaptation, comparative evidence regarding the adoption patterns and determinants of adaptation strategies across agroecological zones remains limited. Moreover, existing studies often examine adaptation independently from climate trends, farmer perceptions, and crop productivity outcomes (Gebre et al., 2023; Megabia et al., 2022). Consequently, understanding remains limited regarding how farmers' perceptions influence adaptation decisions and how adaptation strategies contribute to sustaining crop production under changing climatic conditions.

Consequently, there remains limited integrated understanding of how historical and projected climate variability influences crop production directly and indirectly through farmers' perceptions and adaptation responses across diverse agroecological settings.

Overall, four interrelated research gaps are evident. First, empirical studies inadequately capture crop-specific and agroecologically differentiated impacts of climate variability on agricultural production. Second, methodological fragmentation persists because climate trends, future climate projections, crop productivity, farmers' perceptions, and adaptation responses are frequently analyzed separately rather than within an integrated analytical framework. Third, limited evidence exists regarding the consistency between observed climate records and farmers' perceptions across different agroecological zones. Fourth, insufficient attention has been given to understanding how farmers' perceptions influence adaptation decisions and how adaptation strategies affect agricultural production under changing climatic conditions. These limitations restrict the ability of policymakers and development practitioners to design effective, evidence-based, and location-specific adaptation interventions.

In response to these gaps, this study systematically examines historical and projected climate variability and its spatiotemporal dynamics within the study watershed. It further assesses the impacts of climate variability on crop production, evaluates farmers' perceptions across different agroecological zones, and investigates the determinants of adaptation strategies, including both indigenous and introduced practices. By integrating historical climate observations, CMIP6 climate projections, crop productivity data, and household-level evidence within a unified agroecological framework, the study provides a comprehensive understanding of the relationships among climate variability, crop production, farmer perception, and adaptation. The findings are expected to generate robust and context-specific evidence that can support climate adaptation planning, strengthen agricultural decision-making, and contribute to the development of sustainable and climate-resilient farming systems.

1.3 The objective of the study

To analyze the spatio-temporal dynamics of climate variability and their impacts on cereal crop productivity, smallholder farmers' perceptions, and adaptation strategies in the Ayehu Watershed, Awi Zone, Northwest Ethiopia.

Based on the above general objective, the following specific objectives were formulated:

- ✓ To examine the spatio-temporal past trends, future projections, and variability of temperature and rainfall in the study area.
- ✓ To determine the impacts of climate variability on major cereal crop productivity across agro-ecological zones in the study area.

- ✓ To explore smallholder farmers' perceptions of climate variability and its impacts on cereal crop productivity across agro-ecological zones in the study area.
- ✓ To identify factors affecting smallholder farmers' choice of adaptation strategies to climate variability in the study area.

1.4 Research Questions

To achieve the objectives of the study, the following research questions were proposed:

- ➢ What have been the historical trends of the past temperature and rainfall status in the watershed over the past three decades?
- ➢ How do CMIP6 climate models project future prospects of temperature and rainfall under different emission scenarios?
- ➢ How does climate variability vary spatially and temporally between agroecological zones?
- ➢ What are the impacts of climate variability on cereals crop production across different agroecological zones?
- ➢ How do smallholder farmers perceive changes in rainfall and temperature patterns across different agroecological zones?
- ➢ What adaptation strategies are commonly used by smallholder farmers to adapt to climate variability across agroecological zones?
- ➢ What socioeconomic, institutional, and environmental factors influence farmers' choices of adaptation strategies?

1.5. Research Methods

1.5.1. Study area description and context of the study

The Ayehu watershed, located in the Upper Blue Nile Basin of northwestern Ethiopia, lies approximately 450 km west of Addis Ababa and 137 km southwest of Bahir Dar, between 10°30′–11°06′ N latitude and 36°40′–37°00′ E longitude, covering an area of about 456.53 km² (Fig. 1.1). The watershed is characterized by a highly dissected topography comprising steep slopes, rugged hills, valleys, and undulating plains, which create diverse microclimatic and ecological conditions that strongly influence agricultural production systems and settlement patterns (Assaye et al., 2020).

Hydrologically, the watershed is drained by the Ayehu River and its tributary stream networks, which form part of the Upper Blue Nile Basin drainage system. The river and its tributaries are essential for sustaining surface water availability, supporting dry-season water access, livestock watering, and small-scale irrigation activities. However, irrigation development remains limited and largely traditional, making agricultural production highly dependent on rainfall variability and seasonal streamflow fluctuations. This strong dependence on rain-fed systems makes the watershed particularly sensitive to climate variability, especially in terms of water availability for cereal crop production.

Climatically, the watershed experiences a bimodal rainfall pattern that governs agricultural activities. The main rainy season (*Kiremit*, June to September) contributes the bulk of annual rainfall, while the short rainy season (*Belg*, March to May) supports early-season crops, pasture regeneration, and soil moisture replenishment. The dry season (*Bega*, October to February) is typically associated with moisture deficits that constrain agricultural activities. Annual rainfall varies considerably, reflecting the spatial heterogeneity of the landscape, while temperature conditions also vary with altitude, influencing crop suitability and growing seasons. These climatic conditions are central to cereal crop production systems in the watershed, particularly under increasing climate variability.

The Ayehu watershed exhibits marked altitudinal and ecological variation that shapes agricultural land use and crop distribution. Although previous classifications broadly categorize the area into lowland, midland, and highland agroecological zones, these zones should be interpreted in relation to local topographic variability rather than strict national agroecological boundaries. The highland and midland areas dominate the landscape and are generally characterized by cooler temperatures and higher rainfall, supporting cereals such as barley, wheat, and pulses. The midland zones are more suitable for mixed crop-livestock production, while lower elevation areas are relatively warmer and drier, favoring drought-tolerant crops such as maize and sorghum. This agroecological diversity plays a critical role in shaping spatial differences in crop performance under climate variability.

Agriculture is the dominant livelihood system in the watershed, with the majority of households engaged in mixed crop-livestock farming. Cereal crops, including teff, wheat, barley, maize, and sorghum, constitute the backbone of production, complemented by pulses, oilseeds, and vegetables. Livestock production is integrated with cropping systems, contributing to income diversification, soil fertility management, and risk mitigation under climate stress conditions (Deressa et al., 2025; Hagos et al., 2023). Farming practices remain largely traditional, with limited mechanization and dependence on rainfall, which increases vulnerability to climate variability and extremes. Household livelihoods are further supported by petty trade, seasonal labor, and remittances, reflecting the diversification strategies adopted in response to environmental and economic pressures.

Population pressure is relatively high, with the watershed supporting a substantial rural population engaged primarily in agriculture (CSA, 2016). However, access to improved agricultural technologies, irrigation infrastructure, extension services, and market facilities remains limited and unevenly distributed. These constraints are particularly pronounced in midland and lowland areas, where transportation challenges restrict market integration and income opportunities. Social services such as education and health infrastructure exist but remain insufficient to meet growing demands, further influencing adaptive capacity to climate variability.

Vegetation distribution closely reflects the agroecological variation of the watershed. The highland and midland areas are characterized by species such as bamboo, eucalyptus, Acacia decurrens, and other mixed vegetation, while the lower elevation areas support drought-tolerant species including Acacia, Cordia africana, Carissa edulis, Olea africana, and Dodonaea angustifolia (Meshesha et al., 2024; Shifaw et al., 2024). Both natural and planted vegetation, particularly eucalyptus and Acacia decurrens, play important roles in household livelihoods through fuelwood, construction materials, soil improvement, and income generation (Afework et al., 2023). In addition, culturally protected forest patches, particularly around Orthodox Christian churches, contribute to biodiversity conservation and ecological stability within the watershed.

The selection of the Ayehu watershed as the study area is justified by its high sensitivity to climate variability, strong dependence on rain-fed cereal-based agriculture, and pronounced agroecological heterogeneity within a relatively small spatial extent. These characteristics make it an ideal representative case for examining how climate variability interacts with crop production systems, farmers' perceptions, and adaptation responses. Furthermore, the presence of diverse agroecological conditions, combined with observable climate impacts on agriculture, provides a suitable context for analyzing crop-specific responses to climate variability and developing location-specific adaptation insights.

Overall, the Ayehu watershed provides a highly relevant natural laboratory for studying the interactions between climate variability, agroecological diversity, water availability, and cereal crop production systems under changing climatic conditions.

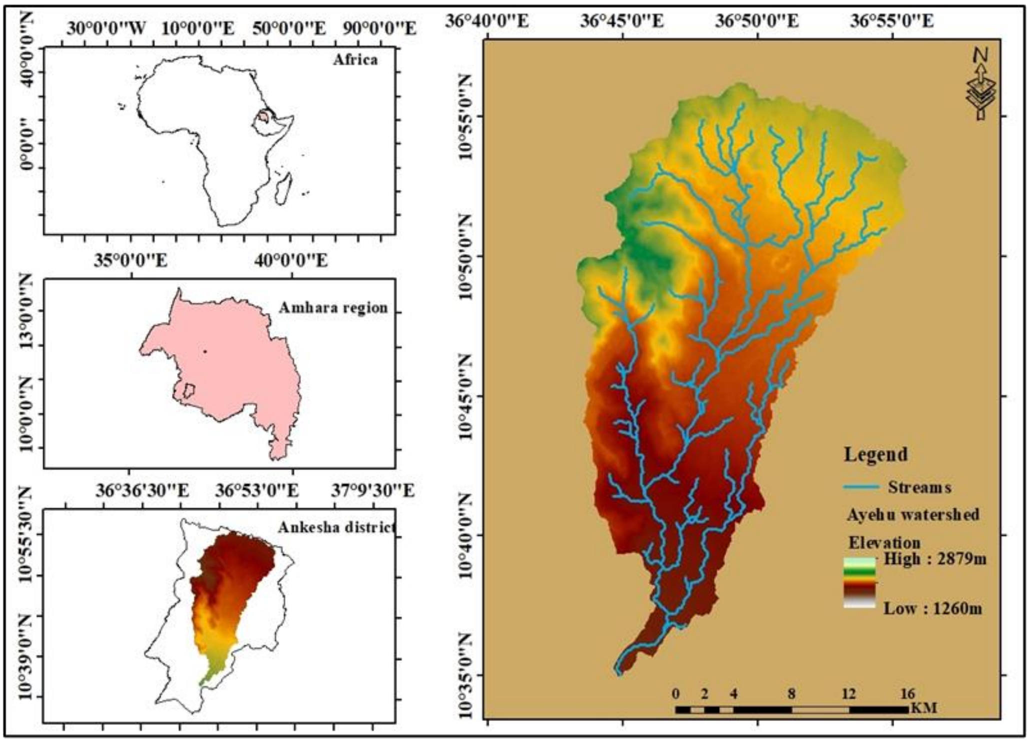

Figure 1.1 Map of the study area

1.5.2. Research philosophy / paradigm

A research philosophy or paradigm encompasses a comprehensive set of beliefs and assumptions that guide a researcher's approach to inquiry. It also influences the selection of methods, strategies, and the overall design of the study (Creswell, 2021).The statement offers an epistemological and ontological foundation that shapes the conceptualisation, generation, and interpretation of knowledge. Depending on the disciplinary orientation, the nature of the research problem, prior research experience, and methodological guidance, scholars may adopt different philosophical perspectives such as post positivism, constructivism, transformative, or pragmatism (Panya & Nyarwath, 2022; Paudel, 2024).

Among these perspectives, pragmatism has been widely recognized as a suitable philosophical foundation for mixed-method research. Pragmatism recognizes that there are various ways to understand reality. It highlights the practical outcomes of research and the importance of knowledge in solving real-world problems. This perspective encourages the integration of both quantitative and qualitative approaches within a single research framework to provide a more comprehensive understanding of complex phenomena (Creswell, 2009; Tashakkori & Teddlie, 2021). A key feature of pragmatism is its emphasis on the connection and combination of methods, enabling researchers to develop a coherent and context-sensitive methodological strategy that best addresses the research problem (Creswell, 2009). Within this perspective, researchers are not restricted to a single method but can employ multiple techniques and analytical tools simultaneously or sequentially to generate meaningful and actionable evidence (Masrizal, 2012).

Consistent with these considerations, the study adopted pragmatism as its guiding philosophical stance, since the research problem inherently demands the integration of diverse data types and analytical approaches. It investigates the spatiotemporal dynamics of climate variability and its impacts on major cereal crops, along with the perceptions of smallholder farmers and adaptation strategies within the Ayehu watershed. Addressing such a complex and multidimensional issue requires the use of both quantitative and qualitative evidence. Quantitative data, including long-term climate records and crop yield statistics, were analyzed using statistical and econometric techniques to identify climate trends and examine crop–climate relationships. Simultaneously, qualitative data obtained from household surveys, focus group discussions, and key informant interviews were used to elucidate farmers' perceptions, lived experiences, and context-specific adaptation practices. Integration of these datasets and methodological approaches generates complementary insights that would not be attainable through a single methodological paradigm alone.

Therefore, the pragmatic paradigm was considered to be the most appropriate because it allows methodological flexibility and prioritizes the research problem rather than adherence to a single philosophical tradition. By integrating multiple data sources and analytical methods, this study generates practically orientated and contextually grounded evidence that improves understanding of climate variability, crop yield dynamics, and farmers’ adaptation strategies. In doing so, the pragmatic perspective enables the study to bridge empirical climate analysis with farmers’ lived experiences, producing findings that are both scientifically robust and relevant for informing climate-resilient agricultural policies and practices.

1.5.3 Research approach and research design

This study adopted a mixed-methods research approach, which integrates quantitative and qualitative research paradigms within a single study. Mixed-methods research is widely recognized for its ability to provide a more comprehensive understanding of complex socioenvironmental phenomena by combining numerical analysis with contextual interpretation. In the context of climate variability studies, this approach is particularly appropriate as it enables the identification of statistical relationships while simultaneously capturing farmers' perceptions, experiences, and contextual realities that shape adaptation behavior (Creswell, 2009). By integrating quantitative and qualitative evidence, mixed-methods research enhances the depth, validity, and interpretive richness of findings (Almalki, 2016; Dawadi et al., 2021).

In terms of research design, this study adopted a convergent parallel mixed-methods design (Bhattacherjee, 2012; Creswell, 2021). This design was considered appropriate because it allows quantitative and qualitative data to be collected during the same fieldwork period, analyzed independently, and then integrated during interpretation to generate a more comprehensive understanding of the research problem. The design enhances methodological complementarity by enabling comparison and convergence of statistical findings with qualitative explanations, thereby improving the validity and explanatory depth of the study.

Accordingly, quantitative and qualitative data were collected concurrently in the Ayehu watershed during the same survey period. The quantitative component involved a structured household survey administered to smallholder farmers. This was used to examine patterns and determinants of farmers' perceptions of climate variability and to assess adaptation practices across agroecological zones. It also enabled statistical analysis of relationships among socio-economic, institutional, and environmental variables influencing perception and adaptation behavior.

The qualitative component consisted of focus group discussions (FGDs) and key informant interviews (KIIs) conducted alongside the survey. A total of six FGDs were held, with 8–10 participants in each discussion, selected to represent different agroecological zones and farming experiences. In addition, twelve key informant interviews (KIIs) were conducted with individuals including agricultural experts, development agents, and community leaders. These qualitative tools were used to capture farmers' lived experiences, indigenous knowledge, and contextual explanations of climate variability and adaptation practices.

Qualitative data were analyzed using thematic content analysis. All FGDs and KIIs were transcribed, coded, and systematically organized into key themes such as perceived climate variability, adaptation strategies, decision-making processes, and barriers to adaptation. The quantitative data were analyzed using appropriate statistical techniques to identify patterns and determinants.

Integration of the two datasets was carried out at the interpretation stage using a side-by-side comparison approach. Specifically, quantitative results were first presented, followed by qualitative findings that were used to explain, contextualize, and elaborate on statistical patterns. Areas of convergence and divergence between the two datasets were identified and discussed to strengthen interpretation and ensure consistency across findings. This integration process enhanced the coherence of results and provided a more complete understanding of climate perceptions and adaptation across agroecological zones.

1.5.4. Sampling strategies and sample size

This study employed a multistage sampling technique to ensure that the selected *kebeles* and household heads reasonably represent the agroecological diversity of the Ayehu watershed. In the first stage, the watershed was purposively selected due to its dominance of subsistence-oriented mixed crop–livestock farming systems, which are highly sensitive to climate variability and related agricultural risks. In addition, the watershed contains clearly differentiated agroecological zones ranging from lowland to highland areas, making it suitable for examining spatial differences in climate exposure and farmers' perceptions and responses.

In the second stage, all *kebeles* were stratified into three agroecological zones: highland (*Dega*), midland (*Woina Dega*), and lowland (*Kolla*). This stratification was based on the understanding that agroecological variation strongly influences climate conditions, farming systems, and livelihood experiences, which in turn shape farmers' perceptions and adaptation behavior (Tofu et al., 2022; Zeleke et al., 2023). It is also widely recognized that such agroecological differences contribute to heterogeneous adaptation strategies among smallholder farmers (Belay et al., 2017; Likinaw et al., 2023). From each agroecological zone, one *kebele* was randomly selected. However, it should be noted that selecting only one *kebele* per zone may not fully capture intra-zone variability, and therefore findings should be interpreted with appropriate caution regarding generalization to the entire watershed.

In the third stage, sample households were selected from the chosen *kebeles* using proportional allocation to ensure representation based on the size of each *kebele* population. A complete list of household heads was obtained from official local administrative records to construct the sampling frame. From this list, the initial household was randomly selected, and thereafter a systematic sampling technique was applied using a fixed sampling interval (n^{th} household) determined by the ratio of the total household population to the required sample size. This approach helped ensure an unbiased selection process and maintained proportional representation across the sampled kebeles while reducing selection bias.

The total sample size was determined using the formula proposed by Kothari (2004), assuming a 95% confidence level and a 5% margin of error:

$$n = \frac{Z^2 P.Q.N}{e^2(N-1) + Z^2.P.Q} \tag{1}$$

where n is the sample size; N is the total number of households (2821); p is the sample proportion (0.5); q =1-p; e is the error margin / acceptable error considered (5%); and Z = 1.96 is the critical value at the 95% confidence interval.

Table 1. 1 Samples taken from each agroecological area in the study watershed

Agro-ecology	Sample *Kebeles*	Total household size	Sample size
Dega (High land)	Bekafta	1002	120
Woina Dega (Mid-land)	Sostu Segno	986	118
Kolla (Lowland)	Dikuna Dereb	833	100
Total		2821	338

1.5.5. Data sources and collection methods

This study employed both primary and secondary data sources and integrated quantitative and qualitative data collection methods to provide a comprehensive understanding of farmers' perceptions of climate variability and their adaptation strategies across agroecological zones. Primary data were collected through structured household surveys, focus group discussions (FGDs), and key informant interviews (KIIs), while secondary data were obtained from peer-reviewed journal articles, institutional reports, and long-term meteorological records.

The household survey was conducted using a structured questionnaire developed through an extensive review of the literature on climate variability, risk perception, and adaptation strategies among smallholder farmers. The questionnaire incorporated both closed- and open-ended questions to capture farmers' perceptions of changes in rainfall patterns, rainfall reliability, temperature conditions, and the occurrence of extreme climatic events, as well as their perceived impacts on agricultural production and livelihoods. In addition, socioeconomic and demographic information, including farm size, crop production, income sources, educational status, access to extension services, and climate information, was collected to identify factors influencing farmers' perceptions and adaptation decisions. To ensure clarity, validity, and contextual relevance, the questionnaire was pretested with a small group of farmers, and feedback from the pilot survey was used to refine its content and structure. Initially prepared in English, the questionnaire was translated into local languages and administered through face-to-face interviews by six trained enumerators under the close supervision of the principal investigator to ensure data quality and consistency.

To complement the survey findings, qualitative data were collected through FGDs and KIIs, which provided in-depth and context-specific insights that could not be adequately captured through structured questionnaires alone. Participants in the FGDs were purposively selected based on their long-term residence in the area (more than 20 years), familiarity with local climatic conditions, educational background, and willingness to participate. Key informants included agricultural development agents, extension personnel, and local experts with extensive knowledge of climate-related agricultural challenges and adaptation practices. These qualitative approaches generated valuable information on local interpretations of climate variability, historical climate experiences, perceived risks, adaptation responses, barriers to adaptation, and factors influencing farmers' decision-making processes.

The field survey was conducted over a three-month period, covering different agroecological zones to capture spatial variations in climate perceptions and adaptation practices. Prior to data collection, ethical approval was obtained from Bahir Dar University, and informed verbal consent was secured from all participants. Respondents' anonymity and confidentiality were maintained throughout the study.

To enhance the reliability of perception data and minimize potential recall bias, information obtained from household surveys, FGDs, and KIIs was triangulated with long-term meteorological records. Monthly rainfall and temperature data for the period 1992–2022 were obtained from the National Meteorological Agency of Ethiopia. These records provided an objective basis for assessing the extent to which farmers' perceptions corresponded with observed climatic trends and helped distinguish perceptions grounded in long-term climatic changes from those influenced by recent weather events. The integration and triangulation of quantitative survey data, qualitative evidence, and meteorological observations strengthened the robustness, reliability, and depth of the study's findings regarding farmers' perceptions of climate variability, associated risks, and adaptation strategies.

1.5.6. Validity and reliability

The validity was verified by carefully aligning its methodologies with the stated objectives. Climate trend analysis in CMIP6 used high-quality datasets and reliable statistical methods. The spatiotemporal variability and crop yields were validated by comparing long-term climate and yield data. Farmers' climate perceptions were gathered with pretested questionnaires customized to the local environment, assuring clarity and cultural relevance. The determinants of adaptation techniques were analyzed with robust econometric models. Explanatory variables were selected based on the basis of theory and previous research.

Reliability was maintained through standardised data collection, the use of trained enumerators, and a consistent application of analytical procedures. Diagnostic checks, such as multicollinearity and model specification tests, further strengthened the consistency of the results. By integrating quantitative climate and yield data with qualitative insights from farmers, the study achieved both credibility and dependability, ensuring that the findings are robust, replicable, and useful for policy, practice, and future research.

1.6. Significance of the Study

Ethiopia is currently prioritizing the implementation of its Climate-Resilient Green Economy (CRGE) policy, which seeks to develop a robust and sustainable economy capable of withstanding the adverse impacts of climate change while minimizing greenhouse gas emissions (Paul & Weinthal, 2019; Tombe, 2016). Achieving the objectives of this ambitious policy requires a multifaceted approach, including the advancement of targeted adaptation measures informed by up-to-date, site-specific research. In this context, empirical studies that generate localized evidence on climate trends, impacts on crop production, and adaptation strategies are critical for guiding effective policy and practical interventions. Therefore, this research is particularly significant, as it provides the scientific basis necessary to inform national and local planning, strengthen resilience strategies, and support the successful implementation of Ethiopia's CRGE objectives.

Building on the context above, this study aims to characterize climate trends over past and future time horizons by focusing on key climatic variables, particularly rainfall and temperature, within the study area for the selected period. Understanding these climate trends is crucial, as it provides evidence-based insights that can guide policymakers, planners, and practitioners in various sectors, especially agriculture and natural resource management, in making informed decisions and implementing effective strategies. By identifying patterns and potential changes in temperature and rainfall, the study offers a scientific foundation for anticipating climate-related risks, enhancing adaptive planning, and promoting sustainable use in the region.

This study would also be significant by providing a localized understanding of how farmers perceive and respond to changes in rainfall and temperature impacts on cereal crop production, offering essential for designing context-specific adaptation strategies that align with farmers' experiences and knowledge. By examining variations in perception across agroecological zones, the study highlights spatial differences in vulnerability and adaptive capacity. This information can help policymakers, extension services, and development agencies target interventions to the most at-risk areas and communities. Furthermore, the study bridges the gap between empirical climate data and farmer lived experiences. It shows how observed trends in rainfall and temperature translate into perceived household-level risks, thus improving climate risk communication and promoting informed adaptive behaviors. In general, the findings provide evidence-based insights that can inform national and regional development planning, the design of climate-smart policies and risk reduction strategies, ultimately contributing to improved food security, livelihood resilience, and sustainable development in the study area.

This study identifies the most common adaptation strategies used by smallholder farmers across different agroecological zones. It also helps to understand the key factors that influence their decisions. By examining these factors, the study uncovers the decision-making processes that shape farmers' adaptive responses to climate variability. It provides a detailed understanding of how local conditions, available resources, and perceptions interact to determine adaptation. Understanding local climate patterns and adaptation practices is essential for prioritizing interventions, designing tailored support measures, and effectively addressing vulnerabilities caused by climate variability. Furthermore, the study serves as a valuable resource for researchers, policymakers, and development practitioners by providing empirical evidence on climate drivers, potential impacts, adaptation options, and the socioeconomic and environmental factors that influence local adaptation choices. Finally, its findings will support the development of context-specific evidence-based policies to improve resilience and promote sustainable livelihoods in the face of ongoing climate change.

1.7. Scope of the Study

Climate variability and change are among the most pressing environmental challenges in Ethiopia, as fluctuations in rainfall and temperature strongly affect agriculture and the livelihoods of farmers who depend largely on rainfed systems. This study examines the spatiotemporal dynamics of climate variability, its impacts on crop production, and the adaptation strategies of smallholder farmers in the Ayehu watershed, Awi Zone, Northwest Ethiopia. Specifically, it analyzes historical and projected rainfall and temperature under CMIP6 scenarios, respectively; evaluates the effects of climate variability on crop yields in agroecological zones; assesses the perceptions of climate variability and associated risks; and identifies the key factors shaping their adaptation strategies. By integrating climatic data with farmer experiences and responses, the study seeks to generate a comprehensive understanding of the challenges posed by climate variability and inform the development of context-specific adaptation measures.

The study was carried out over the period 2022 to 2025, encompassing the systematic collection and analysis of primary and secondary data. Primary data were collected directly from the study area and focused on capturing socio-economic and demographic characteristics of local farming communities, which are essential for understanding climate variability and adaptation strategies. Secondary data, drawn from multiple sources, included historical and contemporary records of temperature, rainfall, and crop production. These datasets allowed the researcher to analyze past trends, assess the impacts of climate variability on crop productivity, assess farmer perceptions of climatic risks, and examine the adaptation strategies used to mitigate adverse effects. The sequential integration of primary and secondary data provided a comprehensive temporal framework to investigate both the human and environmental dimensions of climate variability in the Ayehu watershed.

1.8. Limitations of the Study

Despite providing valuable insights into farmers' perceptions of climate variability and adaptation strategies, this study has some methodological limitations. First, the selection of only one *kebele* from each agroecological zone may not fully capture the socioeconomic, environmental, and climatic heterogeneity within the watershed, thereby limiting the broader generalizability of the findings. Second, the cross-sectional nature of the study reflects farmers' perceptions and adaptation practices at a single point in time and may not adequately capture their temporal dynamics. Third, although farmers' perceptions were triangulated with focus group discussions, key informant interviews, and long-term meteorological records, perception-based data remain susceptible to recall bias and subjective interpretation. Finally, the climate projection analysis relied on a single CMIP6 model, which may not fully represent the uncertainty associated with future climate scenarios; therefore, future studies could enhance the robustness of projections by employing multi-model ensemble approaches.

1.9. Organization of the Dissertation

This dissertation is structured into six chapters, complemented by a list of references and appendices. To provide a clear and comprehensive overview of the study, a concise description of each chapter and its contents is given below.

The first chapter provides a comprehensive overview of the dissertation, covering the background of the study, theoretical and empirical foundations, the problem statement, objectives, research questions, significance, and the scope and context of the study area. The following chapters are presented as four articles, each aligned with the specific objectives of the research. Although grounded in the overall objective of the study, each article is framed by its own objectives, theoretical framework, methodology, findings, conclusions, and recommendations. Consequently, the dissertation is structured and organized as follows.

Chapter Two (Article I) investigates historical and predicted temperature and rainfall trends in the Ayehu watershed, Upper Blue Nile Basin, Northwest Ethiopia, using CMIP6 models. It examines historical and future climate patterns under various emission paths over two projection periods. The chapter also discusses the level of climate variability and trends in important climatic factors, particularly rainfall and temperature, in the study area, placing them in both global and national settings. Furthermore, data on past and future climate patterns are interpreted in terms of their consequences for water resources, as well as adaptation and mitigation plans for climate change.

Chapter Three (Article II) addresses the spatio-temporal dynamics of climate variability and its effects on major crop yields across the agroecological zones of the Ayehu watershed, Upper Blue Nile Basin, Northwest Ethiopia. First, it examines the variability of temperature and rainfall across the three agroecological zones and then investigates how these climatic fluctuations influence major crop yields, employing the Auto-Regressive Distributed Lag (ARDL) model for analysis.

Chapter Four (Article III) examines smallholder farmers' perceptions of small farmers about climate variability and its associated risks in the agroecological zones of the Ayehu watershed, Upper Blue Nile Basin, Northwest Ethiopia. It evaluates farmers' awareness of climate variability and identifies the most perceived climate-related risks using the Climate-Related

Risk Perception Index (CRRPI). The chapter also compares farmers' perceptions with meteorological records to assess their consistency and concludes by identifying the key factors that influence farmers' perceptions of climate variability.

Chapter Five (Article IV) examines the determinants of smallholder farmers' adaptation strategies to climate variability in the Ayehu watershed, Upper Blue Nile Basin, Northwest Ethiopia. It identifies the indigenous and introduced measures prevalent in the agroecological zones and analyzes the socio-economic, institutional, and environmental factors that shape their adoption. The chapter also highlights key barriers, such as limited farm size, high input costs, and inadequate access to information and technologies that constrain effective implementation, thus underscoring the complexity of adaptation decision-making and the need for context-specific interventions.

Chapter Six brings the dissertation to a close by synthesizing the principal findings, drawing general conclusions, offering policy and practical recommendations, and highlighting avenues for future research.

NB: This dissertation repeated specific elements of the research, such as the research methods and the analysis part within each article, to adhere to journal formatting requirements and PhD guidelines (article-based format).

1.10. Theoretical and Conceptual Frameworks of the Study

1.10.1 Conceptualization of climate variability, climate perception, and adaptation strategies

Understanding climate variability has evolved from a narrow statistical interpretation of short-term deviations in temperature and rainfall to a more integrated and dynamic systems-based perspective. Earlier studies conceptualized climate variability as random fluctuations around long-term climatic means, often treated as "noise" within a relatively stable system (Bradley & Diaz, 2021). However, advances in atmospheric science, improved observational datasets, and climate modeling have significantly reshaped this understanding (Ghil & Lucarini, 2020). Climate variability is now recognized as an inherent feature of the Earth's climate system, emerging from complex interactions among the atmosphere, oceans, land surfaces, and biosphere (Loeb et al., 2016), and operating across multiple spatial and temporal scales through nonlinear feedback processes (Forster et al., 2021).

Large-scale climate phenomena, including interannual oscillations and decadal variability, play a major role in shaping regional climate dynamics (Shamim et al., 2018). These processes generate structured but spatially heterogeneous variability, meaning that climate impacts differ across locations depending on altitude, geography, and local agroecological conditions (Perlwitz et al., 2017). In sub-Saharan Africa, where agriculture is predominantly rainfed, even small changes in rainfall timing or temperature variability can significantly affect production and rural livelihoods (Farah & Muhumed, 2024). In this study, this spatial heterogeneity is explicitly addressed through the use of agroecological zones as a key stratification variable in the empirical analysis.

Contemporary literature further emphasizes that climate variability and climate change are deeply interconnected rather than separate phenomena. Variability influences the manifestation of long-term climate change by shaping the frequency and intensity of extremes such as droughts, floods, and heatwaves (Alves et al., 2021), and it can either amplify or mask long-term climatic trends (Hansen et al., 2011). To capture this relationship empirically, this study operationalizes climate variability using rainfall and temperature anomalies, the Rainfall Anomaly Index (RAI), and long-term trends in minimum and maximum temperature. These variables are incorporated into the econometric models as measurable indicators of climatic variability rather than treating variability as a purely conceptual construct (Lehner & Deser, 2023).

Within this climate context, farmers' perception plays a central mediating role between climatic signals and adaptation responses. Perception is understood not as a direct reflection of climate conditions but as a socially and cognitively constructed interpretation shaped by experience, indigenous knowledge, and socio-cultural context (Arora & Feng, 2024). In this study, farmers' perception is operationalized through structured survey-based indicators capturing perceived changes in rainfall onset and cessation, perceived temperature increases, frequency of droughts, and perceived crop failure risks. These indicators are transformed into composite perception indices that are used as explanatory variables in the econometric analysis (Mossie & Chanie, 2024).

Empirical evidence shows that climate perception is influenced not only by environmental exposure but also by socioeconomic and institutional factors such as access to climate information, education, extension services, and social networks (Manono et al., 2025). Accordingly, these variables are explicitly included in the empirical model as determinants of perception and adaptation behavior. Farmers who have access to reliable seasonal forecasts are expected to develop more accurate risk perceptions, whereas those relying solely on experiential knowledge tend to interpret climate signals through localized and context-specific lenses (Aniye et al., 2024; Kaske et al., 2022).

Adaptation strategies are conceptualized as deliberate behavioral responses to perceived climatic risks aimed at reducing vulnerability or enhancing productivity under changing climatic conditions. In this study, adaptation is operationalized as a categorical dependent variable within a multinomial logit (MNL) model, where farmers select among indigenous strategies such as crop diversification, use of local varieties, and adjustment of planting dates, as well as introduced practices such as improved seed varieties, fertilizer application, and soil and water conservation measures (Erekalo & Yadda, 2023; Gashure, 2024). The selection of these strategies is modeled as a function of perception indices, livelihood assets, institutional access, and socioeconomic characteristics (Anzum et al., 2023).

Overall, climate variability, perception, and adaptation are conceptualized as an interconnected and sequential system in which climatic variability influences perception, perception shapes adaptation decisions, and adaptation outcomes subsequently feedback into future perception and resilience formation (Ricart et al., 2025). This study empirically captures this system through integrated climate indicators, perception indices, and econometric modeling approaches applied across agroecological zones.

1.10.2 Theoretical framing of farmers' climate perceptions and adaptation decisions

Farmers' perceptions of climate variability are socially constructed and shaped through shared knowledge systems, cultural norms, and community-level interactions (Etana et al., 2021; Jovchelovich, 2012). In this study, an integrated socio-cognitive framework is adopted to operationalize perception as a measurable construct derived from farmers' responses regarding observed climatic changes, risk awareness, and access to climate-related information (Mugi-Ngenga et al., 2021).

The Theory of Planned Behavior provides a structured explanation of how perception translates into action by emphasizing attitudes, subjective norms, and perceived behavioral control. In this research, these constructs are operationalized using survey-based variables where attitudes are reflected in perceived effectiveness of adaptation strategies, subjective norms are captured through community influence and peer practices, and perceived behavioral control is measured through access to resources, extension services, and institutional support (Dey et al., 2025). These variables are incorporated into the multinomial logit model as key predictors of adaptation choice.

Self-efficacy theory complements this framework by focusing on farmers' confidence in their ability to implement adaptation practices. This is measured using Likert-scale indicators capturing perceived capability to adopt technologies such as improved seeds, soil conservation structures, and diversified cropping systems (Li & Wang, 2026). Protection Motivation Theory further explains adaptation behavior through perceived severity and perceived vulnerability, which are operationalized as indices derived from farmers' assessments of expected crop losses and exposure to climatic shocks (Niles et al., 2016; Ouertani et al., 2025).

At the structural level, the Sustainable Livelihoods Framework is used to operationalize resource constraints through measurable household asset indices. Human capital is represented by education level, financial capital by income and credit access, natural capital by landholding size, physical capital by access to irrigation and farm inputs, and social capital by participation in community networks and organizations (Pandey et al., 2017). These variables are included directly in the econometric model to explain variation in adaptation capacity across households (King et al., 2018; Yaméogo et al., 2018).

Diffusion of Innovation theory is operationalized through variables capturing farmers' exposure to new agricultural technologies, including extension contact frequency, participation in demonstration plots, and peer-to-peer information exchange. Adoption decisions are influenced by perceived relative advantage, compatibility, and complexity of innovations, which are measured through structured survey responses (Rizzo et al., 2024; Vasudevan et al., 2025). This allows the study to empirically capture how introduced technologies spread within rural communities through social learning mechanisms (Qange et al., 2025).

Importantly, rather than treating these theories independently, this study integrates them into a unified socio-cognitive–livelihood–diffusion framework. Behavioral theories explain perception and decision-making processes, livelihood frameworks explain structural constraints, and diffusion theory explains exposure and adoption dynamics. This integrated framework is empirically operationalized through measurable constructs incorporated into the multinomial logit model, thereby explicitly linking theoretical concepts to statistical estimation.

A key theoretical contribution of this study is therefore its explicit translation of multi-theoretical constructs into measurable empirical variables and their integration into a unified econometric framework, enabling a coherent analysis of climate perception and adaptation behavior.

1.10.3 Nexus of climate variability and crop production

The relationship between climate variability and crop production is fundamentally biophysical but mediated through ecological systems and farm management practices. Crop yield formation is determined by the interaction between climatic variables and physiological crop processes (IPCC, 2022; Lobell et al., 2020). In this study, this relationship is empirically examined using an autoregressive distributed lag (ARDL) model, where crop yields of teff, maize, and wheat are regressed against rainfall, temperature, and variability indicators.

Temperature regulates key physiological processes such as photosynthesis, respiration, and phenological development, while rainfall determines soil moisture availability and water balance in crops (Ray et al., 2019; Zhao et al., 2017). To capture both short-run fluctuations and long-run climate effects, the study incorporates rainfall anomalies, temperature trends, and the Rainfall Anomaly Index into the ARDL framework. These variables allow the model to distinguish between transient shocks and persistent climatic changes (Lesk et al., 2016).

The vulnerability and resilience framework is operationalized through agroecological zoning, which captures spatial heterogeneity in exposure and sensitivity. Lowland areas are typically more exposed to drought stress, while highland areas experience risks related to excessive rainfall and frost (Swami & Parthasarathy, 2021; Seo, 2014). Resilience is reflected in diversification practices and adaptive capacity indicators incorporated into the model (Folke et al., 2016).

The agricultural production function approach is used to conceptualize climate variables as stochastic inputs alongside traditional factors of production such as land and labor (Just & Pope, 1978; Schlenker & Roberts, 2009). Risk and uncertainty are incorporated through variability measures that capture unpredictable climate conditions affecting production decisions (Rosenzweig & Udry, 2020; Karlan et al., 2014). Systems thinking further explains feedback effects between land use, adaptation practices, and local microclimates, which may either intensify or mitigate climate impacts over time (Vermeulen et al., 2012).

1.10.4 Theoretical framing of adaptation strategies

Adaptation in smallholder agriculture is conceptualized as a constrained decision-making process influenced by perceived climate risks, resource availability, and institutional conditions (Dang et al., 2019; Eshetu et al., 2021). In this study, adaptation strategies are empirically modeled as a categorical dependent variable using a multinomial logit model, where farmers choose among multiple adaptation options based on their individual and contextual conditions.

Behavioral theories such as the Theory of Planned Behavior and Protection Motivation Theory explain how perceived risk, behavioral control, and coping appraisal influence adaptation decisions (Hagger et al., 2022; Niles et al., 2016). Utility maximization theory provides the economic foundation for understanding adaptation as a rational choice under uncertainty, where farmers select strategies that maximize expected benefits given constraints (Atube et al., 2021).

Diffusion of Innovation theory explains how awareness and adoption of introduced technologies spread through extension systems, social learning, and peer interactions, influenced by perceived advantages and compatibility with existing practices (Anibaldi et al., 2021; Qange et al., 2025; Vasudevan et al., 2025). These theoretical perspectives are integrated into a unified analytical framework that explains adaptation as the outcome of interacting cognitive, structural, and informational processes.

The theoretical contribution of this study is explicitly articulated in its transformation of multiple theoretical perspectives into a single empirically testable framework. Climate variability is operationalized through statistical indicators, perception through constructed indices, and adaptation through multinomial logit modeling, while crop responses are analyzed using ARDL models. This integrated approach provides a coherent and operationally grounded framework for analyzing climate–perception–adaptation linkages across agroecological zones.

1.10.5 Conceptual framework

The conceptual framework of this study focuses on the interwoven links between climate variability, farmers' perceptions, crop productivity consequences, and adaptation techniques in the Ayehu watershed, Awi Zone, Northwest Ethiopia. Climate variability manifests itself as rising temperatures, irregular rainfall, seasonal and interannual changes, and an increase in the frequency of extreme events such as droughts, floods, and heatwaves. These shifts bring enormous uncertainty to small-holder farmers who rely on rainfed agriculture. As a result, farmers are more likely to experience crop failure, food insecurity, soil degradation, and proliferation of pests and diseases. Rising temperatures can cause heat stress in crops, accelerate growth cycles, and reduce grain filling periods, resulting in lower yields. At the same time, erratic rainfall disrupts planting schedules, decreases soil moisture, and increases the probability of prolonged dry spells and sudden flooding. These dynamics degrade arable land, accelerate soil erosion, and reduce soil fertility, undermining agricultural sustainability. Furthermore, altered climatic conditions create favorable environments for pests, invasive weeds, and crop diseases, increasing the labor and financial inputs required for their management. Together, these interrelated impacts compromise smallholder farmers' capacity to secure stable harvests, intensifying food insecurity, and heightening rural livelihoods' vulnerability to climate shocks.

Farmers' climate perceptions constitute a critical intermediary between climatic variability and adaptive responses. Farmers' perceptions of climate are shaped by personal observations, traditional knowledge, and farming experience, along with external influences such as extension services, peer networks, and the media (Chemeda et al., 2023; Murthy & Sri, 2023). Farmers often report declining rainfall, rising temperatures, and shifts in the onset and cessation of rainy seasons, and these lived experiences frequently carry more weight in decision making than formal meteorological data. Consequently, perceptions strongly influence adaptation practices, including adjustments in planting dates, crop diversification, and adoption of drought-tolerant varieties (Kwakye, 2023). However, awareness alone does not always translate into action. Resource limitations, institutional barriers, and cognitive biases can hinder adaptive behavior, sometimes resulting in decisions that diverge from scientific evidence (Ekstrom & Moser, 2014; Korteling et al., 2023). Furthermore, sociodemographic factors such as age, education and access to extension services further shape how climate information is interpreted and applied (Mehta, 2024; Mustafa et al., 2023).

In response to climate variability, smallholder farmers employ a variety of adaptation strategies, encompassing crop diversification, adjusting planting dates, improved crop varieties, irrigation, agroforestry, and soil and water conservation measures. While these strategies improve agricultural resilience, their adoption is influenced by a multifaceted interaction of sociodemographic, economic, institutional, and biophysical factors (Cherinet et al., 2025). Evidence from Africa and Asia underscores the roles of age, gender, education, household and farm size, landholding, farming experience, income, and access to credit, extension services, markets, training, and climate information in shaping adaptation decisions (Ankrah et al., 2023; Myeni & Moeletsi, 2020). Farmers' decisions are shaped by the cost-effectiveness, accessibility, and suitability of available adaptation options. Despite their efforts, their implementation is often limited by limited budgets, inadequate institutional support, restricted market access, and environmental challenges, which can hinder the effectiveness of adaptation strategies and ultimately affect agricultural productivity. As a result, adaptation practices typically combine traditional measures, such as crop diversification and soil conservation, with scientific innovations, including improved crop varieties, resilient livestock breeds, and conservation agriculture. This combination highlights the diversity and context-specific nature of adaptation strategies. Consequently, this study examines the approaches used by smallholder farmers and the key factors that facilitate or hinder their adoption, offering insights to inform future research, policy and resilience-building interventions.

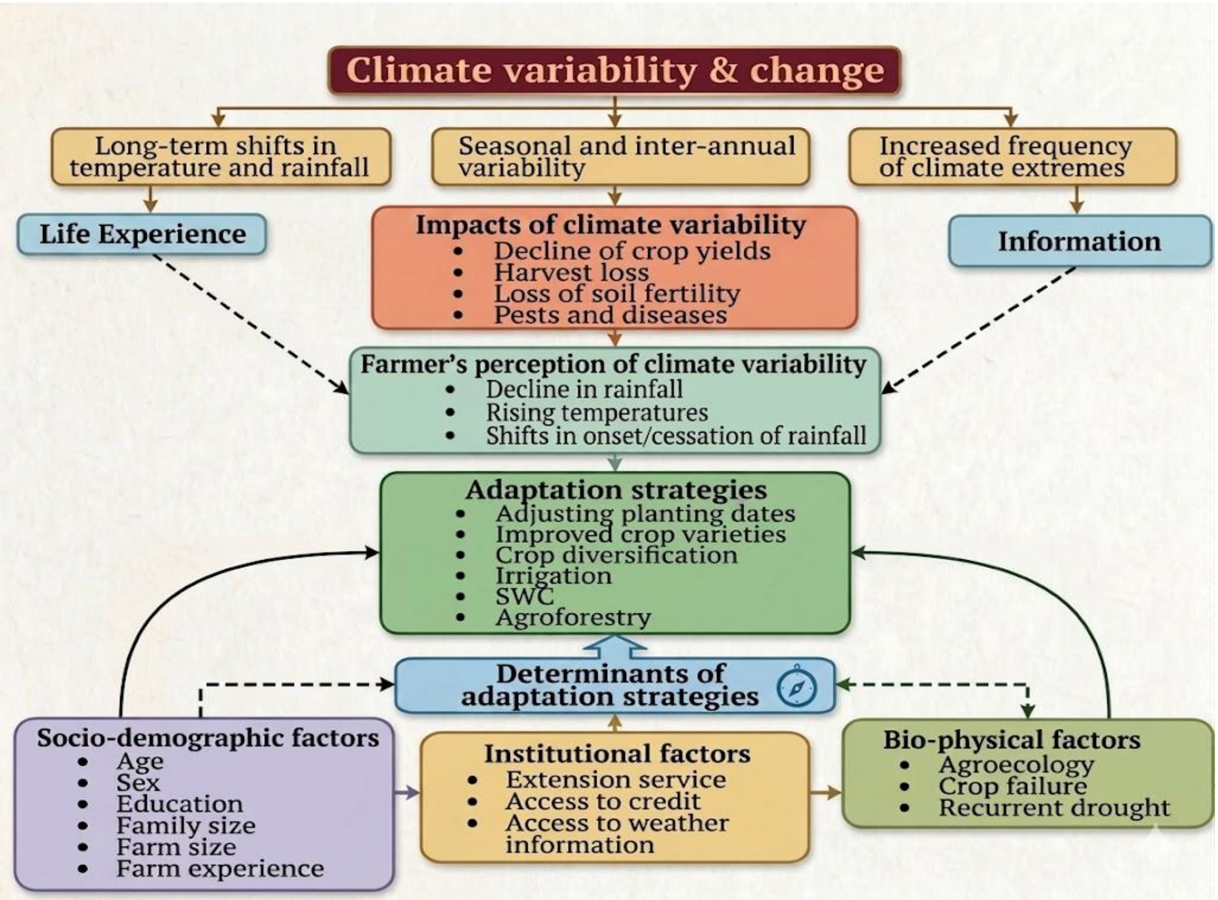

Figure 1.2 A conceptual framework of the study (Modified from Jha & Gupta, 2021)

CHAPTER TWO

2. EVALUATION OF PAST AND FUTURE TRENDS OF TEMPERATURE AND RAINFALL IN THE AYEHU WATERSHED, UPPER BLUE NILE BASIN, ETHIOPIA

Based on publication:

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Abstract

Understanding historical and future climate variability is essential for effective adaptation planning in vulnerable agroecological systems. This study analyzes observed climate trends and future climate projections in the Ayehu watershed, northwestern Ethiopia, using a clear distinction between historical observations (1992–2022) and CMIP6-based scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) for the near-term (2030–2060) and long-term (2070–2100) periods. Historical climate analysis was conducted using quality-controlled rainfall and temperature data from three meteorological stations. Trends were assessed using the Mann–Kendall test, while Sen's slope estimator quantified the magnitude of change. CMIP6 model outputs were evaluated, with IPSL-CM6A-LR selected for temperature and MPI-ESM1-2-LR for rainfall, followed by bias correction to improve simulation reliability. Results indicate a non-significant decline in annual rainfall (1.53 mm year^{-1}), driven mainly by a significant reduction in Belg rainfall (2.78 mm year^{-1}). In contrast, Kiremit rainfall shows a significant increase (7.84 mm year^{-1}), indicating a clear intra-annual redistribution of rainfall. This seasonal imbalance explains the apparent contradiction between declining annual totals and increasing Kiremit rainfall. Temperature analysis reveals statistically significant warming in both minimum and maximum temperatures over the study period. Future projections consistently indicate continued warming across all scenarios, with higher increases under SSP5-8.5. Temperature is projected to rise by approximately +1.2°C to +2.1°C in the near term and +2.5°C to +4.3°C in the long term relative to the baseline period. Rainfall projections show greater uncertainty, with slight declines under SSP1-2.6, SSP2-4.5, and SSP3-7.0, while SSP5-8.5 indicates a potential increase but with strong inter-model variability. Overall, the watershed is expected to experience persistent warming and increasing rainfall variability characterized by strong seasonal redistribution rather than uniform change. These shifts are likely to intensify hydrological instability, increasing risks of crop establishment failure, mid-season moisture stress, and water scarcity for agriculture. The findings highlight the need for targeted adaptation strategies, including adjustment of cropping calendars, expansion of small-scale irrigation and water harvesting, improved climate information services, and promotion of agroecology-specific climate-resilient farming practices.

Key words: Ayehu watershed; CMIP6; Projections; Rainfall; Temperature

2.1. Introduction

Climate variability and change are among the most pressing environmental challenges of the 21st century, with far-reaching consequences for ecosystems, water resources, agricultural production, and human livelihoods (Ahmed et al., 2019; IPCC, 2021; Kamruzzaman et al., 2021). These changes are primarily driven by increasing greenhouse gas concentrations, particularly atmospheric CO_2, which have altered the Earth's energy balance and intensified global warming (Asfaw et al., 2018; IPCC, 2014c). The IPCC confirms that human activities are the dominant cause of observed warming in the atmosphere, oceans, and land systems (Dantas et al., 2022; Hassan & Knight, 2023; IPCC, 2022), resulting in rising temperatures, shifting precipitation regimes, and increasing frequency of extreme events such as droughts, floods, and heatwaves (IPCC, 2012, 2014b). Global mean temperature has already increased by about 1.1°C above pre-industrial levels and is projected to rise by 1.8°C to 4.0°C by the end of the century, posing severe risks to food security and ecosystem stability (Bendell, 2018; Berg & Lidskog, 2018; Farooq et al., 2022; Hayhoe et al., 2017).

Africa is among the most climate-vulnerable regions despite its low contribution to global emissions. Projected warming ranges from 2°C to 6°C under high-emission scenarios (Ayugi et al., 2023; Ongoma et al., 2018), with pronounced spatial variability in precipitation. While parts of Northern and Southern Africa are expected to experience declining rainfall and intensified drought risk, Eastern Africa is likely to face increased rainfall variability and flood hazards (Osman et al., 2021; Raza et al., 2024). In Sub-Saharan Africa, where agriculture is predominantly rainfed, climate variability has already contributed to declining productivity, land degradation, and increasing food insecurity (Déqué et al., 2017; IPCC, 2014a; Tofu & Wolka, 2023). Smallholder farmers remain particularly vulnerable due to their high dependence on climate-sensitive livelihoods and limited adaptive capacity (El Kenawy, 2024; Jain et al., 2024).

Within this context, Ethiopia represents a highly relevant case study because its economy and livelihoods are strongly dependent on rainfed agriculture. Agriculture contributes more than one-third of GDP and supports the majority of the population (Belay et al., 2021). Observational evidence indicates a warming trend of approximately 1.3°C between 1960 and 2006 (Jury & Funk, 2013; Kobe, 2023), with further increases projected under future climate scenarios (Getachew et al., 2021). However, rainfall trends remain highly uncertain and spatially heterogeneous, with frequent interannual variability and recurrent drought events

(Gummadi et al., 2018; Zegeye, 2018; Mekonen & Berlie, 2020). These climatic stresses continue to undermine agricultural production and rural livelihoods, highlighting the need for context-specific climate evidence to support adaptation planning.

At the local scale, the Ayehu watershed in the Upper Blue Nile Basin is a highly climate-sensitive agricultural system characterized by strong dependence on rainfed farming and natural resource-based livelihoods. Recent evidence indicates increasing exposure to warming temperatures, rainfall variability, droughts, and floods, all of which threaten agricultural productivity and water availability (Berhanu et al., 2024). Although previous studies have reported general warming and rainfall variability in the watershed and surrounding areas (Alemayehu et al., 2022b; Mengistu et al., 2014; Mohamed et al., 2022), the results for precipitation trends remain inconsistent. More importantly, existing studies are largely restricted to historical climate analysis and provide limited insight into future climate trajectories at the watershed scale.

This limitation is critical because robust climate adaptation planning requires not only understanding past climate behavior but also anticipating future climate conditions under different emission pathways. Yet, localized climate projections for the Ayehu watershed remain scarce, particularly those based on the latest CMIP6 models, which offer improved representation of climate processes and scenario-based pathways. Furthermore, very few studies have systematically integrated observed historical trends with downscaled CMIP6 projections to assess both climate variability and future change within a unified analytical framework. This represents a key scientific gap that limits the development of forward-looking, evidence-based adaptation strategies.

Addressing this gap is essential because agricultural planning, water resource management, and climate-resilient development depend on reliable, spatially explicit climate information. Without integrating historical climate dynamics with future projections, adaptation responses risk being reactive rather than anticipatory. In addition, understanding seasonal and long-term variability in temperature and rainfall is particularly important in agroecological systems where small climatic shifts can significantly influence crop performance and farming decisions.

The main objective of this study was to evaluate historical and future trends in temperature and rainfall under CMIP6 scenarios in the Ayehu watershed of the Upper Blue Nile Basin, Ethiopia. Specifically, the study aimed to: (i) analyze historical trends in rainfall and temperature during

1992–2022; and (ii) assess projected changes in temperature and rainfall for the near-future (2030–2060) and far-future (2070–2100) periods.

2.2. Research Methods

2.2.1. Data types and sources

2.2.1.1. Ground measured stationed data

This study utilized monthly rainfall and temperature data for the period 1992–2022 obtained from the National Meteorological Agency of Ethiopia for three meteorological stations: Injibara, Gimjabet, and Ayehu Farm Development Station. These observations served as the primary reference dataset for historical climate characterization, trend analysis, and validation of gridded and climate model outputs. The study period was selected because it represents the most complete and quality-controlled observational record available for the region, with relatively minimal missing data compared to earlier decades. In addition, the 31-year period satisfies the World Meteorological Organization (WMO) climatological standard, ensuring statistical robustness for climate variability and trend analysis. Prior to analysis, the dataset was subjected to rigorous quality control procedures, including screening for missing values, outlier detection, and consistency checks to ensure reliability for subsequent comparative and modeling applications.

2.2.1.2 Gridded Satellite Data

Gridded climate datasets were used as a complementary source to station observations in order to improve spatial representation of climate variability across the watershed. This approach addresses limitations associated with sparse station density, data gaps, and spatial discontinuities in ground-based observations (Alaminie et al., 2021). Monthly rainfall and temperature data were obtained from the KNMI Climate Explorer (https://climexp.knmi.nl/start.cgi) and NASA POWER (https://power.larc.nasa.gov/data-access-viewer/), both of which provide spatially continuous climate information at approximately $0.5° \times 0.5°$ resolution.

For consistency, gridded data were extracted at coordinates corresponding to the selected meteorological stations and evaluated against observed records. Importantly, gridded datasets were not merged directly with station data; instead, they were used for validation, bias assessment, and spatial consistency analysis. The best-performing dataset, determined through statistical agreement with station observations, was retained for supplementary spatial characterization of climate variability across the watershed.

2.2.1.3 CMIP6 Global Climate Model Data

Future climate projections were obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) through the Earth System Grid Federation (ESGF). A structured multi-stage model selection approach was employed to ensure robustness and transparency. Initially, ten Global Climate Models (GCMs) were selected based on the availability of required variables (precipitation and temperature), completeness of historical and future simulations under relevant Shared Socioeconomic Pathways (SSPs), spatial resolution suitability for watershed-scale analysis, accessibility through ESGF, and prior application in East African climate studies (Belay et al., 2024; Enyew et al., 2024).

Model performance was then evaluated against observed station data for the historical period using Pearson's correlation coefficient (r), Nash–Sutcliffe Efficiency (NSE), root mean square error (RMSE), and percent bias (PBIAS). Based on this multi-criteria evaluation, the MPI-ESM1-2-LR and IPSL-CM6A-LR models were selected due to their superior performance and relatively low bias in representing observed climate conditions. To reduce structural uncertainty, a two-model ensemble mean was used for subsequent analyses.

Future climate projections were analyzed for two standard climatological periods: the near future (2030–2060) and the far future (2070–2100), consistent with the World Meteorological Organization (WMO) 30-year climatological norm, ensuring comparability across temporal horizons and robustness of climate change assessment.

Table 2. 1 List of CMIP6 climate models for projection of climate data

No	CMIP6 model name	Country	Horizontal resolution (long. by lat. in degrees)	Variant label	Key references
1	ACCESS-CM2	Australia	1.87° × 1.25°	r1i1p1f1	Bi et al. (2020)
2	BCC-CSM2MR	China	1.1° × 1.1°	r1i1p1f1	Enyew et al. (2024)
3	CanESM5	Canada	2.8° × 2.8°	r1i1p1f1	Swart et al. (2019)
4	CMCC-ESM2	Italy	0.94° × 1.25°	r1i1p1f1	Feyissa et al. (2023)
5	CNRM-CM6	Germany	0.9° × 0.9°	r1i1p1f1	Arfasa et al. (2024)
6	GFDL-ESM4	USA	1.00° × 1.25°	r1i1p1f1	Dunne et al. (2020)
7	IPSL-CM6A-LR	France	2.50° × 1.27°	r1i1p1f1	Boucher et al. (2020)
8	MIROC 6	Japan	1.4° × 1.4°	r1i1p1f1	Tatebe et al. (2019)
9	MPI-ESM1-2-LR	Germany	1.9° × 1.9°	r1i1p1f1	Mauritsen et al. (2019)
10	MRI-ESM2-0	Japan	1.1° × 1.1°	r1i1p1f1	Kawai et al. (2019)

2.2.1.4. Description of Shared Socio-Economic Pathways (SSPs)

This study employed four CMIP6 Shared Socioeconomic Pathways (SSPs): SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 (Estoque et al., 2020). These scenarios represent alternative future trajectories of socioeconomic development and associated greenhouse gas emissions. SSP1-2.6 describes a sustainability-oriented pathway characterized by low emissions, strong climate policies, and global cooperation, resulting in strong mitigation outcomes. SSP2-4.5 represents a "middle-of-the-road" development pathway with moderate mitigation efforts and intermediate radiative forcing. SSP3-7.0 describes a fragmented world with limited climate cooperation and high vulnerability, leading to elevated emissions. SSP5-8.5 represents a fossil-fuel–intensive development pathway with very high emissions and severe climate change impacts (Gidden et al., 2019; O'Neill et al., 2016; Magang et al., 2024). Unlike baseline climatology, SSPs are scenario-based projections and are not treated as reference or historical baselines. Instead, SSP2-4.5 is commonly used as a central comparison scenario due to its intermediate pathway characteristics.

2.2.1.5. Climate model bias correction

Global Climate Models (GCMs) simulations frequently exhibit consistent biases in precipitation and temperature (Gudmundsson et al., 2012; Mbienda et al., 2023). To create valid estimates of local-scale climate, GCM must be post-processed. This work used power transformation (PT) to correct precipitation data biases and distribution mapping (DM) for temperature adjustments, both methods performed using the CMhyd programme (Enyew et al., 2024; Londhe et al., 2023). PT and DM are useful methods to increase precipitation and temperature output from global climate models (Feyissa et al., 2023). The CMhyd tool corrects bias by assessing disparities between raw GCM simulations and historical reference data and then making suitable changes (Alaminie et al., 2021). Designed for precise climate data refinement, it ensures that the corrected datasets accurately represent conditions at each monitoring station within the study area (Figure 2.2).

2.2.1.6. Performance evaluation of CMIP6 models

Assessing the accuracy of climate model output is essential before using them for projections (Wagener et al., 2022; Yimer et al., 2022). This study used the hydroGOF R package, which offers a comprehensive set of performance metrics to evaluate model accuracy. The study assessed how well the CMIP6 simulations matched the observed data. Five evaluation metrics were used: Pearson's correlation coefficient (r), Nash–Sutcliffe Efficiency (NSE), root mean square error (RMSE), coefficient of determination (R^2), and percentage bias (PBias%). Together, these statistical measurements provide useful information about the models' performance and reliability.

Pearson correlation coefficient

The Pearson correlation coefficient (r), which ranges from -1 to 1, quantifies the strength and direction of the relationship between two variables. In this analysis, it was employed to evaluate the degree of alignment between the model predictions and the actual observed data.

$$r = \frac{n(\sum XY) - (\sum X)(\sum Y)}{\sqrt{[n(\sum X^2) - (\sum X)^2][n(\sum Y^2) - (\sum Y)^2]}} \quad (1)$$

- X represents the observed climate data.
- Y represents the model-predicted climate data generated from CMIP6
- n denotes the number of observations used in the analysis.

Thus, the coefficient r indicates how closely the predicted climate values correspond with the observed climatic records. Values of r close to +1 indicate a strong positive agreement between the predicted and observed data, whereas values close to 0 suggest a weak or no linear relationship.

Nash–Sutcliffe Efficiency (NSE)

The NSE determines the relative size in measured data and residues. The ideal value is 1, with a range between -∞- and 1. Any score above 0 points indicates satisfactory performance, while any score below 0 indicates unacceptable performance. Nash-Sutcliffe Efficiency (NSE) measures how well a model predicts data by comparing its errors with the variability in the observed data.

$$NSE = 1 - \frac{\sum_{i=1}^{n} (x_i - \bar{y_i})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (2)$$

Root Mean Square Error (RMSE)

The root mean square error (RMSE) quantifies the difference between the simulated and observed values. An RMSE value of 0 represents a perfect fit, indicating no deviation between predicted and observed data (Müller-Plath & Lüdecke, 2024). This metric is frequently used to assess the accuracy of mathematical models or simulations. Smaller RMSE values reflect higher model precision, demonstrating closer alignment with observed data and fewer extreme errors.

$$\text{RMSE} = \frac{\sqrt{\sum_{i=1}^{n}(x_i - Y_i)^2}}{n} \tag{3}$$

Percentage Bias (PBias)

PBias is a metric that assesses bias, indicating whether the data from CMIP6 GCMs deviate positively or negatively from the observed data (Kesavavarthini et al., 2023). A PBias value close to zero signifies a better alignment between the CMIP6 GCMs and the observed rainfall data. Negative Pbias values indicate underestimation, while positive values suggest overestimation (Ignacio-Reardon & Luo, 2023).

$$PBias = \frac{\sum(\acute{p} - \acute{\hat{o}})}{\sum \acute{\hat{o}}} \times 100 \tag{4}$$

where p' represents the average rainfall estimated by the model $\acute{\hat{o}}$ denotes the mean of the observed rainfall measurements.

2.2.2. Methods of Data Analysis

2.2.2.1. Trend analysis

Trend analysis was performed using the non-parametric Mann–Kendall (MK) test, which is widely used for detecting monotonic trends in hydroclimatic time series (Chepkoech et al., 2018). The MK test does not require normally distributed data and is suitable for environmental datasets characterized by nonlinearity and variability (Sang et al., 2014; Wang et al., 2020). The test statistic is based on pairwise comparisons of data values over time, where positive differences indicate increasing trends and negative differences indicate decreasing trends (Almazroui & Şen, 2020). To address a key methodological limitation identified in the literature, the study accounted for serial autocorrelation by applying a pre-whitening procedure prior to trend estimation, ensuring that trend significance was not inflated by temporal dependence.

For a ranked set of *n* observations, *X*= $x_1, x_2, x_3, \ldots x_n$, the Mann-Kendall (MK) trend statistic *S* is calculated using

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}\,(x_j - x_i) \tag{5}$$

The sign function is expressed as

$$sgn\,(x_j - x_i) = \begin{cases} +1 \ldots\ldots\ldots x_j > x_i \\ 0 \ldots\ldots\ldots\ldots x_j = x_i \\ -1 \ldots\ldots\ldots x_j < x_i \end{cases} \tag{6}$$

Here, S represents the Mann-Kendall test statistic, while xj and xi denote sequential data values of the time series for a long time i and j ($j > i$). N refers to the total length of the time series. A positive S value indicates an increasing trend, whereas a negative SSS value indicates a decreasing trend in the data series.

The variance of S can be calculated using

$$V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right] \tag{7}$$

where n is the number of data, q is the number of linked groups and t_p is the number of data points in the i^{th} group

Sen's Slope Estimator (SSE) test

This study used the Sen slope estimate (SSE) to assess the strength of trends in time series data (Esayas et al., 2019; Tofu & Mengistu, 2023). The slope estimator β is a reliable indicator of the strength of a trend. A positive β value indicates a growing trend (showing higher values over time), while a negative β value indicates a decreasing trend. We calculated the Sen slope using the following formula to determine the slopes (T_i) for each pair of data points (x_j and x_k).

$$T_i = \frac{x_j - x_k}{\mathrm{j-k}}, for\ i = 1, 2, \ldots, N, \tag{8}$$

where x_j and x_k are taken as data values at time j and k ($j > k$), respectively. The median of these N values of T_i is indicated as the Sen estimator of slope, which is expressed as
The Sen Slope (Q_i) is calculated by

$$Q_i = \begin{cases} T_{\frac{N+1}{2}}, & if\ \ N\ is\ odd \\ \frac{1}{2}\left(T_{\left(\frac{N}{2}\right)} + T_{(N+2)/2}\right) & if\ \ N\ is\ even \end{cases} \tag{9}$$

The Sen estimator is calculated as $Q_{med} = T_{(N+1)/2}$ if N appears odd, and it is used as $Q_{med} = T_{N/2} + T_{(N+2)/2}$ if N appears even. A positive value of Q_i suggests an increasing trend, and a negative value of Q_i offers a decreasing trend in the time series. Both the MK and SSE tests were performed using R software.

Z-statistics test: The Z-value determines the statistical significance of a trend. A positive Z value indicates an upward trend, while a negative Z-value signals a downward trend (Tofu et al., 2022). This study used significance levels of 0.01 (high), 0.05 (medium), and 0.1 (low). The p-value was calculated for each time series to determine its significance.

$$Z = \begin{cases} \frac{S-1}{\sqrt{var\ (s)}}\ if\ s > 0, Z = 0\ if\ S = 0 \\ \frac{S+1}{\sqrt{var\ (s)}}\ \ if\ S < 0 \end{cases} \tag{10}$$

2.2.2.2. Variability analysis

The coefficient of variation (CV) is a statistical measure that expresses the standard deviation relative to the mean, making it a useful indicator of dispersion. It is particularly important to compare the variability between datasets with different units or scales. In this study, CV was applied to evaluate annual and seasonal variations, which revealed the variability of climatic factors such as temperature and precipitation. Previous studies, including Amare & Simane (2017) and Asfaw et al. (2018), highlight CV as the most widely used method for analysing precipitation variability and its significance in evaluating the extent of temperature and rainfall fluctuations within a given region.

Thus, CV can be expressed using the following formula:

$$CV = \frac{\sigma}{X} \times 100 \tag{11}$$

The coefficient of variation (CV) was used to measure the degree of variability in precipitation over time. In this case, x represents the mean precipitation, σ denotes the standard deviation of the precipitation, and CV indicates the coefficient of variation of precipitation. The CV provides a standardized measure of the relative variability of precipitation around its mean. Consequently, CV values below 20% indicate low variability in precipitation, values between 20% and 30% indicate moderate variability in precipitation, and values above 30% indicate high variability in precipitation. Therefore, a higher CV value reflects greater variability in precipitation over the study period.

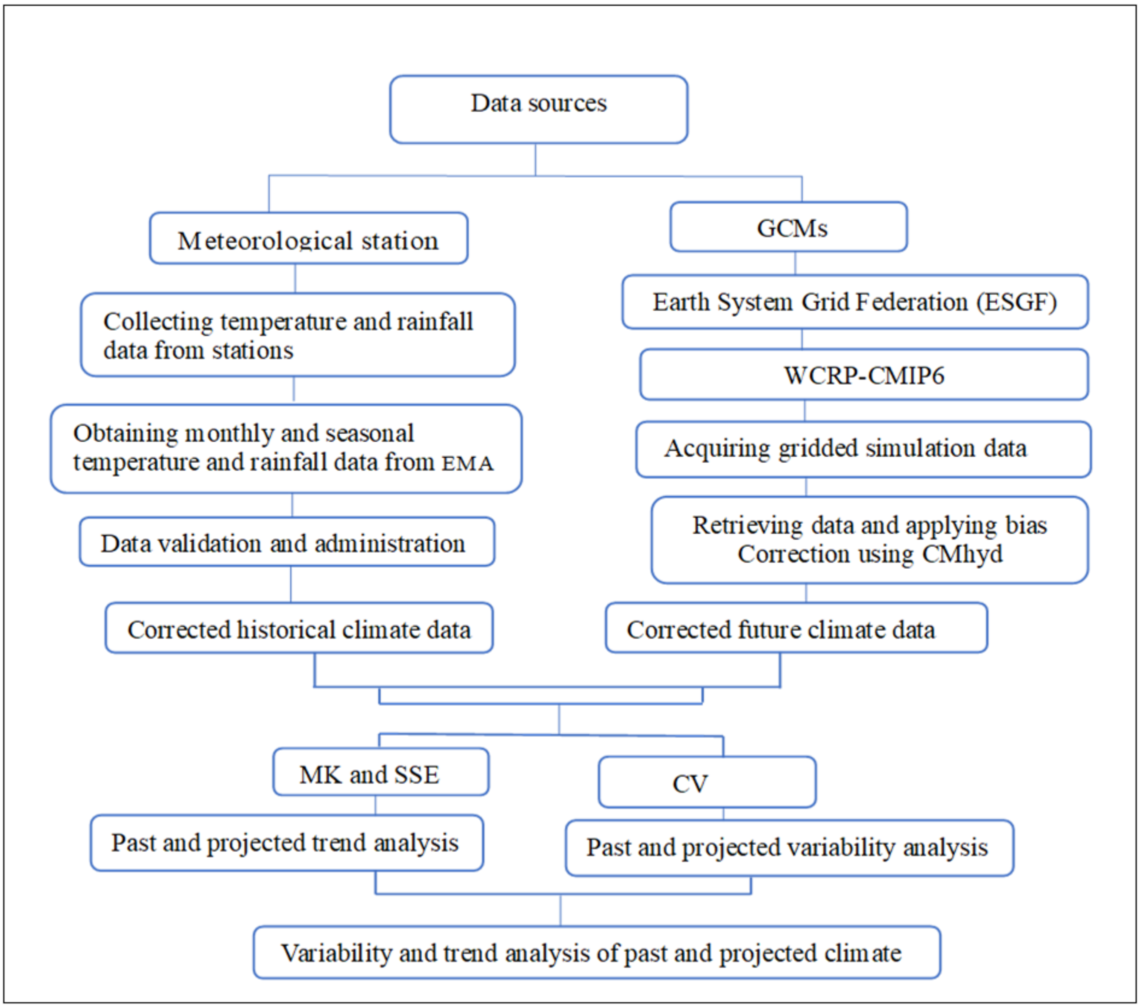

Figure 2.1 Methodological flow chart

2.3. Results and Discussion

2.3.1 Evaluation of historical rainfall and trend analysis

Annual rainfall analysis

The Mann–Kendall trend test revealed a slight declining tendency in annual rainfall over the 1992–2022 period; however, the trend was not statistically significant ($p = 0.30$; $p > 0.05$), indicating insufficient evidence for a long-term directional change in total annual precipitation in the study watershed. The linear regression slope of −1.528 mm $year^{-1}$ confirms a weak negative tendency, while the low coefficient of determination ($R^2 = 0.026$) shows that temporal variation explains only 2.6% of the observed variability in annual rainfall (Table 2.2). This indicates that annual rainfall dynamics are dominated by interannual fluctuations rather than systematic long-term change.

Such high variability, rather than a clear trend, poses challenges for agricultural and water resource planning due to unpredictable rainfall availability. Similar non-significant rainfall trends have been reported in the Awash River Basin and Amhara region (Mulugeta et al., 2019; Alemu & Bawoke, 2020). Likewise, Alemayehu & Bewket (2017a) documented strong interannual rainfall variability across Ethiopia's central highlands, while Suryabhagavan (2017) reported statistically insignificant declining rainfall trends in several parts of the country. These findings suggest that rainfall variability in many Ethiopian regions is largely governed by natural climatic fluctuations rather than persistent long-term decline (Thornton et al., 2014). In contrast, studies by Abegaz & Abera (2020), Tofu & Mengistu (2023), and Weldegerima et al. (2018) reported increasing rainfall trends in other regions, highlighting strong spatial heterogeneity in rainfall behavior across Ethiopia.

Belg (spring) rainfall analysis

In contrast to annual rainfall, the Mann–Kendall test revealed a statistically significant declining trend in Belg rainfall ($p < 0.05$). The estimated regression slope of −2.78 mm year^{-1} indicates a consistent reduction in Belg rainfall over the study period, while the coefficient of determination ($R^2 = 0.196$) suggests that approximately 19.6% of the variability is explained by time, with the remaining variation driven by interannual and climatic fluctuations (Table 2.2). Despite noticeable year-to-year variability, the statistically significant trend indicates a sustained decline in Belg rainfall.

This decline has important implications for early-season agricultural activities, particularly planting and crop establishment, which rely heavily on Belg rainfall. Similar findings of declining Belg rainfall and its implications for agricultural productivity and food security have been reported by Alemayehu & Bewket (2016) and Haile et al. (2019). Comparable reductions in short rainy season rainfall were also documented by Gummadi et al. (2018), while Hu et al. (2020) and Cherian et al. (2021) attributed such declines to large-scale climate variability, including ENSO-related ocean–atmosphere interactions.

Kiremit (summer) rainfall analysis

The Kiremit season exhibited a statistically significant increasing trend of 7.84 mm year^{-1} ($p < 0.01$) during the study period. The regression model indicates an R^2 value of 0.369, implying that 36.9% of the variability in Kiremit rainfall is explained by temporal change (Table 2.2), despite persistent interannual fluctuations.

The observed increase in Kiremit rainfall aligns with findings from Bekele et al. (2017), Belay et al. (2021), Mekonen & Berlie (2020), Bayable et al. (2021), Alemayehu et al. (2020), and

Mulugeta et al. (2019), who also reported increasing Kiremit rainfall in various parts of Ethiopia. However, contrasting evidence from Asfaw et al. (2018) highlights declining Kiremit rainfall in other regions, further confirming strong spatial heterogeneity in seasonal rainfall dynamics across the country.

Overall, the rainfall analysis reveals a pronounced seasonal redistribution pattern characterized by a significant decline in Belg rainfall and a significant increase in Kiremit rainfall, while annual rainfall shows no statistically significant trend. This divergence suggests a shift in intra-annual rainfall distribution rather than uniform changes in total precipitation. Such seasonal asymmetry has important implications for cropping calendars, soil moisture availability, and climate adaptation strategies in rainfed agricultural systems.

Table 2. 2 Descriptive statistics and Mann–Kendall trend test of annual and seasonal rainfall (1992-2022)

Rainfall /mm	Min.	Max.	Mean	SD	CV (%)	S	β	P-value	Trend
Annual	1187.02	1620.71	1391.53	139.32	10.02	-0.12	-1.53	0.3	↓
Belg	149.9	287.20	197.80	36.58	18.49	-0.25	-2.78	0.04**	↓
Kiremit	1120.30	1692.70	1499.08	118.14	7.88	0.41	7.84	0.001*	↑
Bega	23.56	274.3	84.69	65.33	77.14	-0.13	-1.02	0.29	↓

Note: S= Mann–Kendall test; β = Sen's slope; SD = standard deviation; CV = coefficient of variation; * & ** = significant at $p < 0.01$ and <0.05, respectively.

2.3.2 Evaluation of Historical Temperature and Trend Analysis

Analysis of historical minimum temperature

The analysis of minimum temperature indicates a clear and persistent warming trend across both annual and seasonal scales during the 1992–2022 period. Annual minimum temperature increased at a rate of 0.04°C year^{-1}, with a strong explanatory relationship over time (R^2 = 0.6048), indicating a robust long-term warming signal in the study watershed (Table 2.3). This consistent increase suggests that nighttime temperatures have been rising steadily over the study period, contributing significantly to overall climatic warming.

Seasonal analysis further confirms this pattern, with warming observed across all seasons, particularly during Belg and Kiremit. The Kiremit season exhibited a similar increasing trend of 0.04°C year^{-1}, reinforcing the presence of consistent seasonal warming. In contrast, Belg minimum temperature showed weaker temporal association (R^2 = 0.217), indicating higher interannual variability despite an overall upward trend. The Bega season also displayed statistically significant warming ($p = 0.002$; $\beta = 0.05$), although the relatively moderate explanatory power ($R^2 = 0.2997$) suggests that additional atmospheric and regional factors contribute to seasonal variability.

From an agronomic perspective, rising minimum temperatures have mixed implications. While increased nighttime temperatures may reduce frost occurrence during colder periods, as noted by Taye et al. (2021), it may also elevate evapotranspiration rates and intensify heat stress on crops and livestock. These combined effects highlight the need to carefully consider both beneficial and adverse consequences of nighttime warming when designing adaptation strategies for agricultural systems.

The observed warming trends are consistent with multiple studies across Ethiopia, which have reported increasing minimum temperatures over recent decades. Similar findings have been documented by Alemayehu et al. (2022b), Alemayehu & Bewket (2017a), Gebremichael et al. (2022), Belay et al. (2017), Asfaw et al. (2018), Ketema & Siddaramaiah (2020), and Mekonen & Berlie (2020), confirming that minimum temperature increase is a widespread phenomenon across different agroecological and geographical settings in the country.

Table 2. 3 Descriptive statistics and Mann–Kendall trend test of annual and seasonal minimum temperature

Temp /°C	Min.	Max.	Mean	SD	CV (%)	S	*β*	P-value	Trend
Annual	19.06	21.76	20.26	0.50	2.74	0.54	0.04	0.14	↑
Belg	21.19	23.96	22.84	0.77	3.37	0.37	0.05	0.003*	↑
Kiremit	18.03	20.37	19.08	0.53	2.78	0.49	0.04	0.000*	↑
Bega	17.23	20.44	19.14	0.78	4.08	0.38	0.05	0.002*	↑

Note: S= Mann–Kendall test; β = Sen slope; SD = Standard deviation; CV = coefficient of variation; * = Significant at $p < 0.01$

Analysis of historical maximum temperature

Analysis of maximum temperature trends showed a persistent warming signal throughout all seasons in the study watershed, with significant implications for hydrological processes and agricultural systems. Although the annual maximum temperature increased modestly at a rate of 0.0084 °C per year and exhibits low explanatory power ($R^2 = 0.0355$), seasonal analyses revealed more pronounced and consequential warming patterns, particularly during the *Belg* and *Kiremit* seasons (Fig. 2.2).

The *Belg* season showed the most pronounced increase in maximum temperature (0.0799°C per year; $R^2 = 0.3219$), accompanied by high interannual variability (CV = 5.15%) and a broad temperature range (25.90-31.0 °C). These conditions increase the risk of early-season heat stress, disrupt traditional planting calendars, and increase the likelihood of seasonal water shortages. Similarly, the *Kiremit* season, which is critical for crop production, is experiencing a statistically significant warming trend (0.0357°C per year; $p = 0.001$; $R^2 = 0.3336$). Rising temperatures during this period may accelerate soil moisture depletion, influence rainfall–temperature interactions, and ultimately restrict crop yields. In contrast, while the *Bega* season records the fastest warming rate (0.08 °C per year), this trend is characterized by substantial variability and lacks statistical significance, suggesting the influence of additional climatic drivers (Figure 2. 2).

The results of this study are consistent with the findings of multiple studies across Ethiopia. For example, Alemayehu et al. (2020), Asfaw et al. (2018), and Bayable et al. (2021a) documented significant increases in maximum temperature. Similarly, Mekonen and Berlie (2020) and Zeleke et al. (2023) reported persistent warming trends in different agroecological zones. This trend mirrors observations by Matewos (2019) and Ware et al. (2023), who reported significant warming trends in northeastern Sidama. In addition, Getnet et al. (2023) observed that maximum temperatures have increased at a faster rate than minimum temperatures.

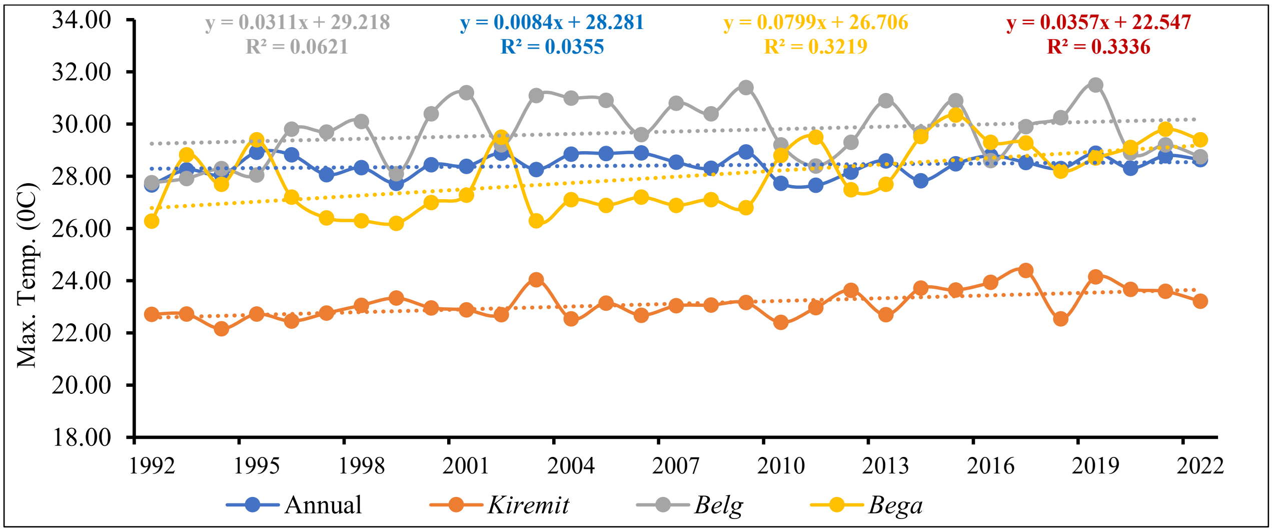

Figure 2. 2 Historical trends of annual and seasonal maximum temperatures in the Ayehu (°C) watershed

2.3.3. Future rainfall and temperature trend analysis

2.3.3.1. Performance evaluation of CMIP6 models

Accurate climate projections are essential for informed decision-making in climate-sensitive sectors such as agriculture, water resource management, and ecosystem conservation (Tanimu et al., 2024). General circulation models (GCMs), particularly those developed under the Coupled Model Intercomparison Project Phase 6 (CMIP6), are widely used to simulate future climate conditions and incorporate improved representations of atmospheric, oceanic, cryospheric, and land-surface processes (Khan et al., 2018; Getnet et al., 2023). However, because model performance varies across regions and climatic variables, rigorous evaluation is necessary before their application in climate impact assessments.

This study evaluated ten CMIP6 models using observed monthly rainfall, minimum temperature, and maximum temperature data (1992–2022) from the Injibara, Gimjabet Mariam, and Ayehu Farm Development stations. Following quality control, homogeneity testing, and consistency checks, areal averages were computed to represent watershed-scale climate conditions. Model performance was assessed using the correlation coefficient (r), Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS), and root mean square error (RMSE), which collectively provide a robust framework for evaluating model skill (Ekwueme, 2024; Worku et al., 2018).

The results revealed substantial inter-model variability, reflecting uncertainties associated with differences in model structure, parameterization schemes, and climate sensitivity. For rainfall simulations, MPI-ESM1-2-LR demonstrated the best overall performance, followed by MIROC6 and IPSL-CM6A-LR, whereas GFDL-ESM4 and CanESM5 showed relatively poor predictive skill. For both minimum and maximum temperature simulations, IPSL-CM6A-LR exhibited the highest agreement with observed records, while MIROC6, BCC-CSM2-MR, and GFDL-ESM4 performed less satisfactorily. Based on this multi-criteria evaluation, MPI-ESM1-2-LR was selected for rainfall projections, whereas IPSL-CM6A-LR was selected for minimum and maximum temperature projections.

Previous studies in the Upper Blue Nile Basin have reported different best-performing CMIP6 models. For example, Enyew et al. (2024) and Gebisa et al. (2023) identified INM-CM5-0 as the most suitable model for precipitation projections, while Alaminie et al. (2021) reported BCC-CSM2-MR as the best-performing model. Similarly, Alemayehu et al. (2020) ranked BCC-CSM2-MR, MIROC6, and NorESM2-MM among the most reliable models for rainfall simulations. These differences demonstrate that model performance varies across climatic variables and spatial scales, highlighting the importance of location-specific and variable-specific model evaluation before applying climate projections. Although the selected models reproduced historical climate conditions reasonably well, the use of individual best-performing models rather than a multi-model ensemble remains a limitation. Therefore, future studies should adopt ensemble approaches to better characterize projection uncertainty and improve the robustness of climate change assessments in the Ayehu watershed.

Table 2. 4 Performance evaluation of selected CMIP6 models for rainfall and temperature

Models	RMSE	PBIAS (%)	NSE	r
Rainfall (mm/month)				
ACCESS-CM2	62.01	44.2	0.56	0.92
BCC-CSM2MR	56.27	38.5	0.67	0.96
CanESM5	96.02	49.2	-0.04	0.88
CMCC-ESM2	76.14	42.12	0.42	0.94
CNRM-CM6	48.23	22.91	0.73	0.96
GFDL-ESM4	112.4	84.6	-0.05	0.85
IPSL-CM6A	37.16	13.5	0.84	0.96
MIROC 6	34.67	10.23	0.88	0.98
MPI-ESM1-2-LR	**23.77**	**5.66**	**0.94**	**0.98**
MRI-ESM2-0	59.34	39.7	0.62	0.96
Min. Temperature (^{0}C)				
ACCESS-CM2	1.56	6.2	0.58	0.92
BCC-CSM2MR	2.67	7.8	0.07	0.94
CanESM5	1.72	6.4	0.40	0.90
CMCC-ESM2	2.15	0.96	0.86	0.92
CNRM-CM6	1.47	5.1	0.59	0.85
GFDL-ESM4	1.89	-7.2	0.39	0.88
IPSL-CM6A-LR	**0.73**	**0.32**	**0.92**	**0.94**
MIROC 6	3.26	12.6	-0.82	0.87
MPI-ESM1-2-LR	2.27	8.4	0.09	0.92
MRI-ESM2-0	1.78	6.3	0.50	0.90
Max. Temperature (^{0}C)				
ACCESS-CM2	2.16	-0.42	0.61	0.86
BCC-CSM2MR	1.87	1.22	0.09	0.84
CanESM5	1.78	0.43	0.50	0.92
CMCC-ESM2	3.56	0.21	0.73	0.90
CNRM-CM6	2.98	3.14	0.42	0.88
GFDL-ESM4	1.69	-6.1	0.28	0.87
IPSL-CM6A-LR	**0.81**	**0.00**	**0.93**	**0.96**
MIROC 6	2.12	9.6	-0.79	0.80
MPI-ESM1-2-LR	1.32	4.4	0.46	0.92
MRI-ESM2-0	1.28	6.3	0.70	0.89

Note: The bold values in Table 2.4 represent the climate models based on their statistical performance in simulating the observed climate data.

2.3.3.2. Evaluation of future rainfall and trend analysis

Projected total annual rainfall in the Ayehu Watershed based on the MPI-ESM1-2-LR model exhibits strong scenario-dependent variability (Table 2.5; Fig. 2.3b). Relative to the baseline annual rainfall of 1391.53 mm, the near-future period (2030–2060) is projected to experience declines under SSP1-2.6 (−7.6%; 1292.79 mm), SSP2-4.5 (−6.7%; 1307.13 mm), and SSP3-7.0 (−5.4%; 1320.62 mm), whereas SSP5-8.5 projects an increase of 7.2% (1491.54 mm). A similar pattern is projected for the far-future period (2071–2100), with decreases of −7.3% under SSP1-2.6, −4.9% under SSP2-4.5, and −3.7% under SSP3-7.0, while SSP5-8.5 indicates a 9.6% increase (1525.71 mm). For the overall 21st century (2030–2100), rainfall is projected to decline by −7.1%, −5.8%, and −5.4% under SSP1-2.6, SSP2-4.5, and SSP3-7.0, respectively, whereas SSP5-8.5 projects an increase of 6.6%, accompanied by greater interannual variability (Table 2.5; Fig. 2.3b).

These projections indicate contrasting rainfall futures across emission pathways. The consistent decreases projected under SSP1-2.6, SSP2-4.5, and SSP3-7.0 suggest a tendency toward drier conditions relative to the historical baseline, while SSP5-8.5 indicates a wetter future characterized by increased rainfall variability. The results therefore highlight substantial uncertainty in future precipitation patterns and underscore the importance of considering multiple climate scenarios in long-term planning and adaptation strategies.

The projected changes are generally consistent with studies reporting declining rainfall under future climate scenarios in Ethiopia and the Upper Blue Nile Basin. For example, Arfasa et al. (2024), Mengistu et al. (2023), and Takele et al. (2022) reported decreasing or statistically insignificant changes in future rainfall across parts of the basin. Similarly, Mengistu et al. (2021) projected reductions in seasonal rainfall under selected climate scenarios. Conversely, Teshome et al. (2021a), Tessema et al. (2021), Feyissa et al. (2023), Alaminie et al. (2021), Almazroui et al. (2020), Gebisa et al. (2023), Getachew and Manjunatha (2021), and Moges and Bhat (2021) reported increasing precipitation under various CMIP- and RCP/SSP-based projections. These contrasting findings reflect the inherent uncertainty of precipitation projections arising from differences in climate models, emission scenarios, spatial scales, and methodological approaches. Nevertheless, the present results fall within the range of projected rainfall responses reported for Ethiopia and the Upper Blue Nile Basin and further emphasize the need for scenario-based climate adaptation planning.

Table 2. 5 Changes in projected rainfall for two future periods relative to the baseline period (1922-2022)

Model runs Time	Scenarios			
MPI-ESM-1-2-LR Total annual rainfall (mm)	SSP1-2.6	SSSP2-4.5	SSP3-7.0	SSP5-8.5
Baseline	1391.53	1391.53	1391.53	1391.53
2030-2060	1292.79	1307.13	1320.62	1491.54
2070-2100	1298.96	1326.21	1342.35	1525.71
2030-2100	1295.76	1314.82	1319.79	1484.23
Change of near future (%)	7.6	6.7	5.4	7.2
Change of far future (%)	7.3	4.9	3.7	9.6
Change of 21st century (%)	7.1	5.8	5.4	6.6

Projected JJAS (June–September) rainfall also exhibits contrasting responses among emission scenarios (Fig. 2.3a). Rainfall is projected to decrease under SSP1-2.6, SSP2-4.5, and SSP3-7.0, whereas SSP5-8.5 indicates an increasing trend, with seasonal totals potentially exceeding 1500 mm toward the end of the century. The SSP5-8.5 scenario also demonstrates greater year-to-year variability compared with the lower-emission pathways. These findings are consistent with the annual rainfall projections and further illustrate the uncertainty surrounding future rainfall dynamics in the watershed. The projected seasonal decline under low- and medium-emission scenarios agrees with Mengistu et al. (2021), while the increasing rainfall projected under SSP5-8.5 aligns with the findings of Feyissa et al. (2023), Alaminie et al. (2021), Almazroui et al. (2020), Gebisa et al. (2023), Getachew and Manjunatha (2021), and Moges and Bhat (2021). Overall, the results indicate that future rainfall in the Ayehu Watershed is highly sensitive to emission pathways, with projections ranging from modest declines to moderate increases depending on the scenario considered.

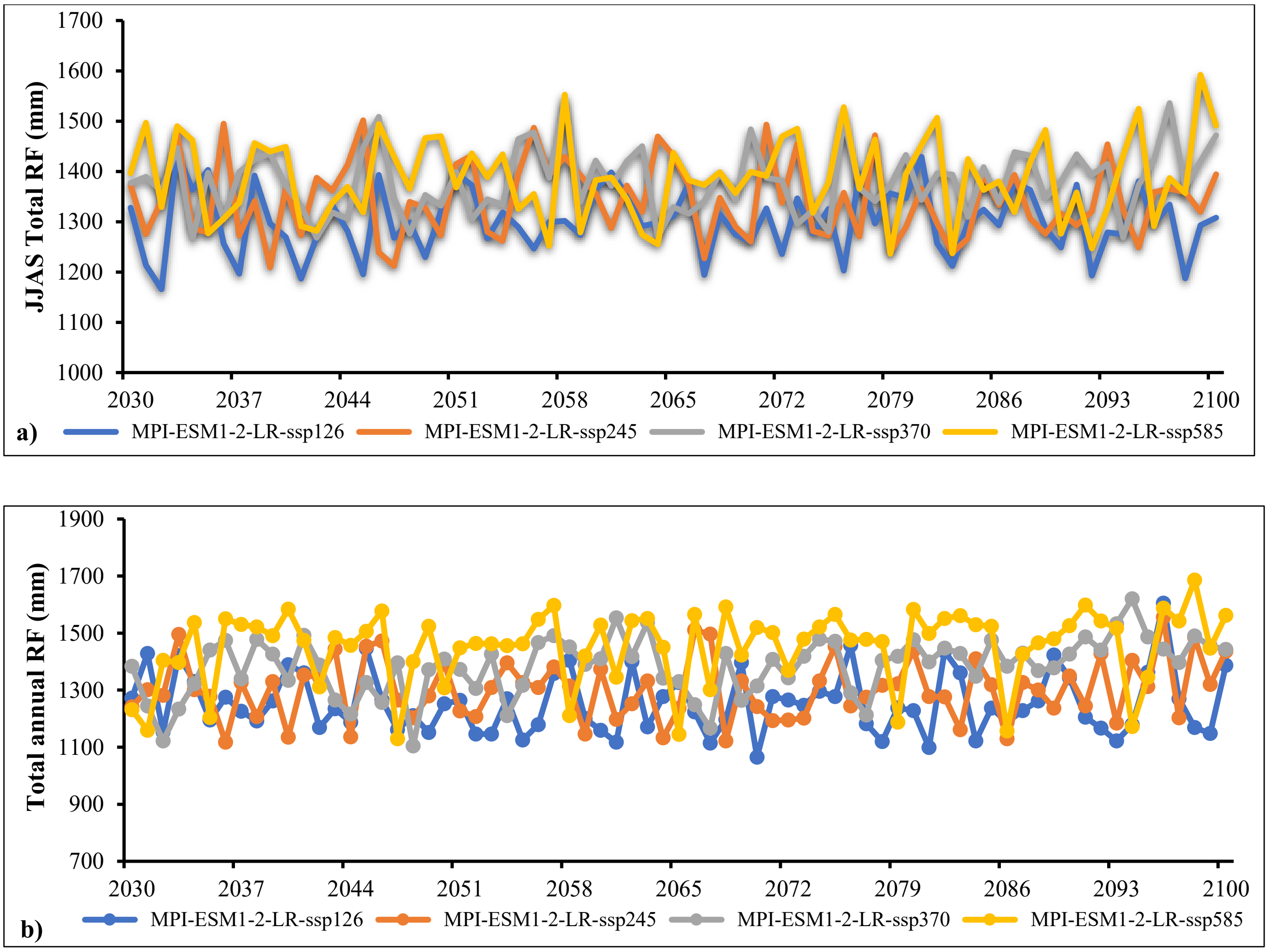

Figure 2. 3 projections of the MPI-ESM1-2-LR model in the SSP126, SSP245, SSP370, and SSP585 scenario for two future eras (2030s, 2070s). (a) Mean rainfall (mm/month) of the major rainy season (JJAS) and (b) Total annual rainfall (mm).

2.3.3.3. Evaluation of future minimum temperature and trend analysis

The analysis of projected minimum temperature indicated consistent warming trends across all Shared Socioeconomic Pathways (SSPs), although the magnitude of warming varied according to the emission scenario. The baseline annual minimum temperature for the reference period (1992–2022) was 18.26°C and served as the benchmark for future projections. During the near-future period (2030–2060), the mean minimum temperature is projected to increase by 0.92°C under SSP1-2.6, 2.1°C under SSP2-4.5, 2.3°C under SSP3-7.0, and 2.9°C under SSP5-8.5, resulting in projected temperatures ranging from 19.18°C to 21.22°C. The warming trend is projected to continue into the late-century period (2071–2100), with increases of 1.6°C, 2.3°C, 2.7°C, and 3.3°C under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, respectively. Consequently, projected mean annual minimum temperatures are expected to range from 19.84°C to 21.56°C during this period (Table 2.6). Overall, the projections indicate a progressive increase in minimum temperatures throughout the twenty-first century under all SSP scenarios, with greater warming occurring under higher-emission pathways. The projected differences among scenarios become more pronounced toward the end of the century, reflecting the increasing influence of future greenhouse gas emissions on regional temperature patterns.

Table 2. 6 Changes in the mean minimum temperature for the future periods (2030-2060 & 2070–2100) relative to the base line period (1992–2022)

Model runs Time	Scenarios			
IPSL-CM6A-LR Min. Temperature (°C)	SSP1-2.6	SSSP2-4.5	SSP3-7.0	SSP5-8.5
Baseline	18.26	18.26	18.26	18.26
2030-2060	19.18	20.37	20.56	21.22
2070-2100	19.84	20.57	20.97	21.56
2030-2100	19.42	20.29	20.65	21.34
Change of near future (°C)	0.92	2.1	2.3	2.9
Change of far future (°C)	1.6	2.3	2.7	3.3
Change of 21st century (°C)	1.2	2.0	2.4	3.1

Figure 2.4a shows the projected rate of change in minimum temperature from the IPSL-CM6A-LR model under four SSPs, indicating a clear emission-dependent warming signal. The lowest increase occurs under SSP1-2.6 (0.001°C yr^{-1}), suggesting near-stabilization under strong mitigation, while SSP2-4.5 shows moderate warming (0.0308°C yr^{-1}). Higher-emission pathways exhibit stronger warming, with SSP3-7.0 (0.0597°C yr^{-1}) and SSP5-8.5 (0.0853°C yr^{-1}) showing the most pronounced increases.

Scenario divergence becomes more evident after mid-century, with relatively constrained changes under SSP1-2.6 and progressively stronger warming under SSP3-7.0 and SSP5-8.5. Seasonal projections confirm consistent warming across all months, with larger increases during warmer months (March–April) and the highest warming under SSP5-8.5, followed by SSP3-7.0, SSP2-4.5, and SSP1-2.6 (Figure 2.4b). This indicates intensified late-century warming under high-emission pathways.

The projected increase in minimum temperature is likely to reduce frost occurrence while simultaneously intensifying heat stress, evapotranspiration demand, and pressure on water resources and ecosystem functioning. The SSP5-8.5 scenario represents a high-end warming pathway and should therefore be interpreted as a conditional projection under continued high greenhouse gas emissions, rather than an observed or inevitable outcome. Similar warming trends in minimum temperature have been reported by Arfasa et al. (2024), Teshome et al. (2021a), Gebisa et al. (2023), Mengistu et al. (2021), and Enyew et al. (2024), all of which consistently document an upward trajectory of minimum temperatures across Ethiopia under different emission scenarios.

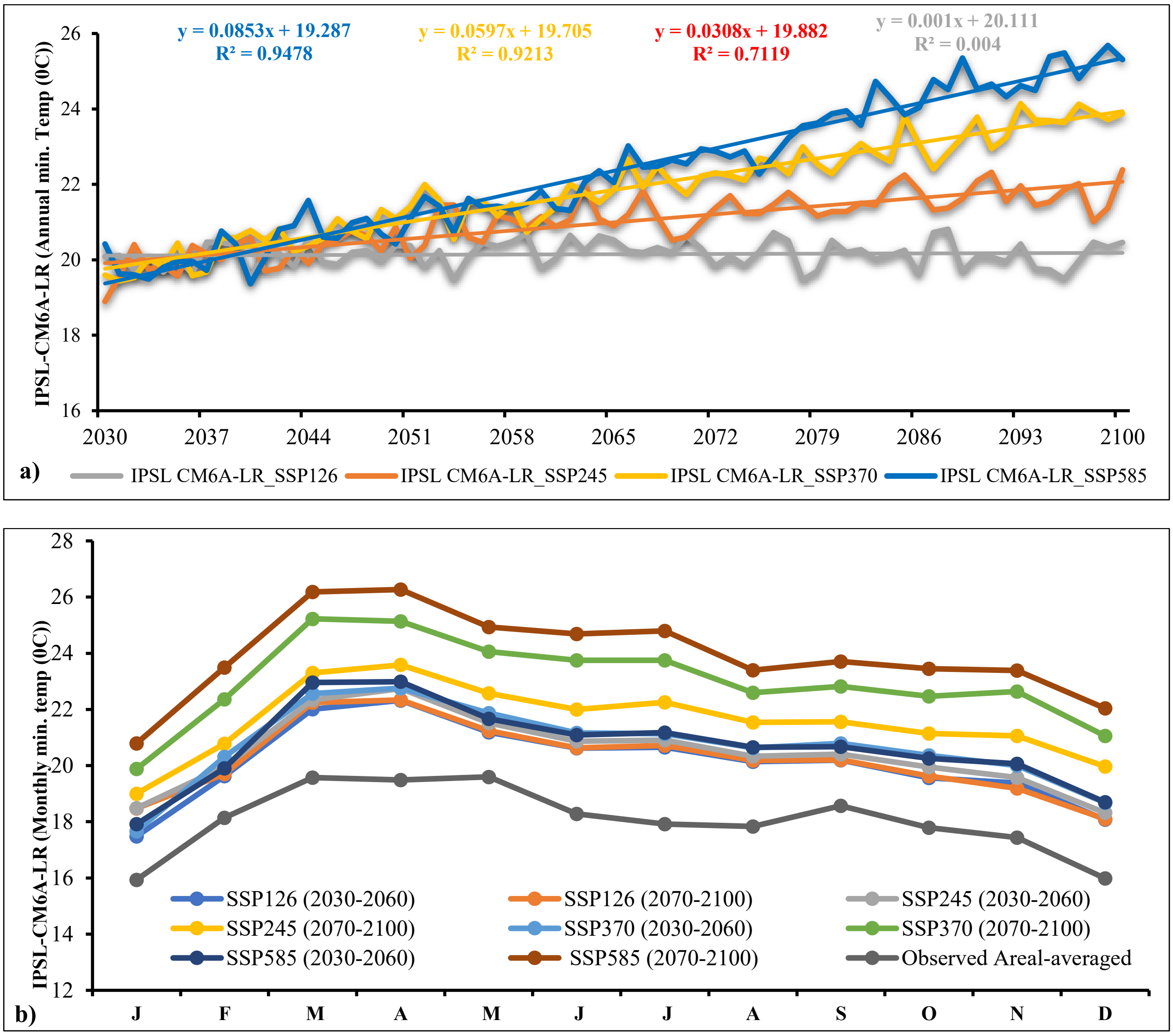

Figure 2.4. IPSL-CM6A-LR model projections under SSP126, SSP245, SSP370, and SSP585 scenario for two future eras (2030s, 2070s). (a) Mean annual min. temperature (^{0}C) and (b) Mean monthly min. temperature (^{0}C)

2.3.3.4 Evaluation of future maximum temperature and trend analysis

Table 2.7 presents projected changes in mean maximum temperature for the near future (2030–2060) and far future (2071–2100) relative to the baseline period (1992–2022) using the IPSL-CM6A-LR model under different SSPs. The baseline mean maximum temperature is 26.20°C. All scenarios show consistent warming, with progressively higher increases under higher-emission pathways. In the near future, temperature increases are 0.8°C (SSP1-2.6), 1.2°C (SSP2-4.5), 2.2°C (SSP3-7.0), and 4.2°C (SSP5-8.5), reaching 26.97°C, 27.35°C, 28.42°C, and 30.41°C, respectively.

In the far future (2070–2100), warming intensifies further, with increases of 1.5°C (SSP1-2.6), 2.02°C (SSP2-4.5), 2.9°C (SSP3-7.0), and 4.9°C (SSP5-8.5), corresponding to 27.68°C, 28.22°C, 29.05°C, and 31.18°C. The 21st-century mean changes also confirm a consistent warming gradient across scenarios, indicating higher temperature increases under higher-emission pathways and stronger late-century warming.

Table 2. 7 Changes in the mean maximum temperature for the future periods (2030-2060 & 2070–2100) relative to the base line period (1992–2022)

Model runs Time	Scenarios			
IPSL-CM6A-LR Max. Temperature (°C)	SSP1-2.6	SSSP2-4.5	SSP3-7.0	SSP5-8.5
Baseline	26.20	26.20	26.20	26.20
2030-2060	26.97	27.35	28.42	30.41
2070-2100	27.68	28.22	29.05	31.18
2030-2100	27.52	28.16	28.93	30.77
Change of near future (°C)	0.8	1.2	2.2	4.2
Change of far future (°C)	1.5	2.02	2.9	4.9
Change of 21st century (°C)	1.3	1.96	2.7	4.6

Figure 2.5a further illustrates the temporal evolution of maximum temperature, revealing a consistent warming trend across all SSP scenarios, with the intensity of warming increasing under higher emission pathways. The strongest warming is projected under SSP5-8.5, followed by SSP3-7.0, SSP2-4.5, and SSP1-2.6. Although the annual trend slope for SSP3-7.0 appears relatively small (0.0002°C year^{-1}), this does not contradict the pronounced decadal warming presented in Table 2.7. Rather, it reflects the sensitivity of regression-based trend estimates to interannual variability, which may obscure the cumulative magnitude of long-term temperature increases. Consequently, Table 2.7 and Figure 2.5a should be interpreted as complementary representations of future warming, with the former highlighting projected changes over time and the latter depicting linear temperature trends.

Figure 2.5b shows a consistent seasonal cycle, with peak temperatures in April–May and secondary peaks in October, while lower values occur in July–August. Across all SSPs, temperatures increase from 2030–2060 to 2070–2100, with SSP5-8.5 consistently showing the highest values and SSP1-2.6 the lowest, and scenario differences becoming more pronounced toward the end of the century.

These findings are consistent with previous studies. Getachew & Manjunatha (2021) reported increases of 1.38–3.59 °C in the Lake Tana sub-basin, while Enyew et al. (2024) projected rises of 1.8 °C, 2.1 °C, and 2.8 °C under SSP1-2.6, SSP2-4.5, and SSP5-8.5. Similarly, Alaminie et al. (2021) and Gebisa et al. (2023) reported comparable warming across the Upper Blue Nile and Baro River Basins, while Moges & Bhat (2021) identified strong warming trends in the Rib watershed. Collectively, these studies confirm consistent increases in maximum temperature under future climate scenarios.

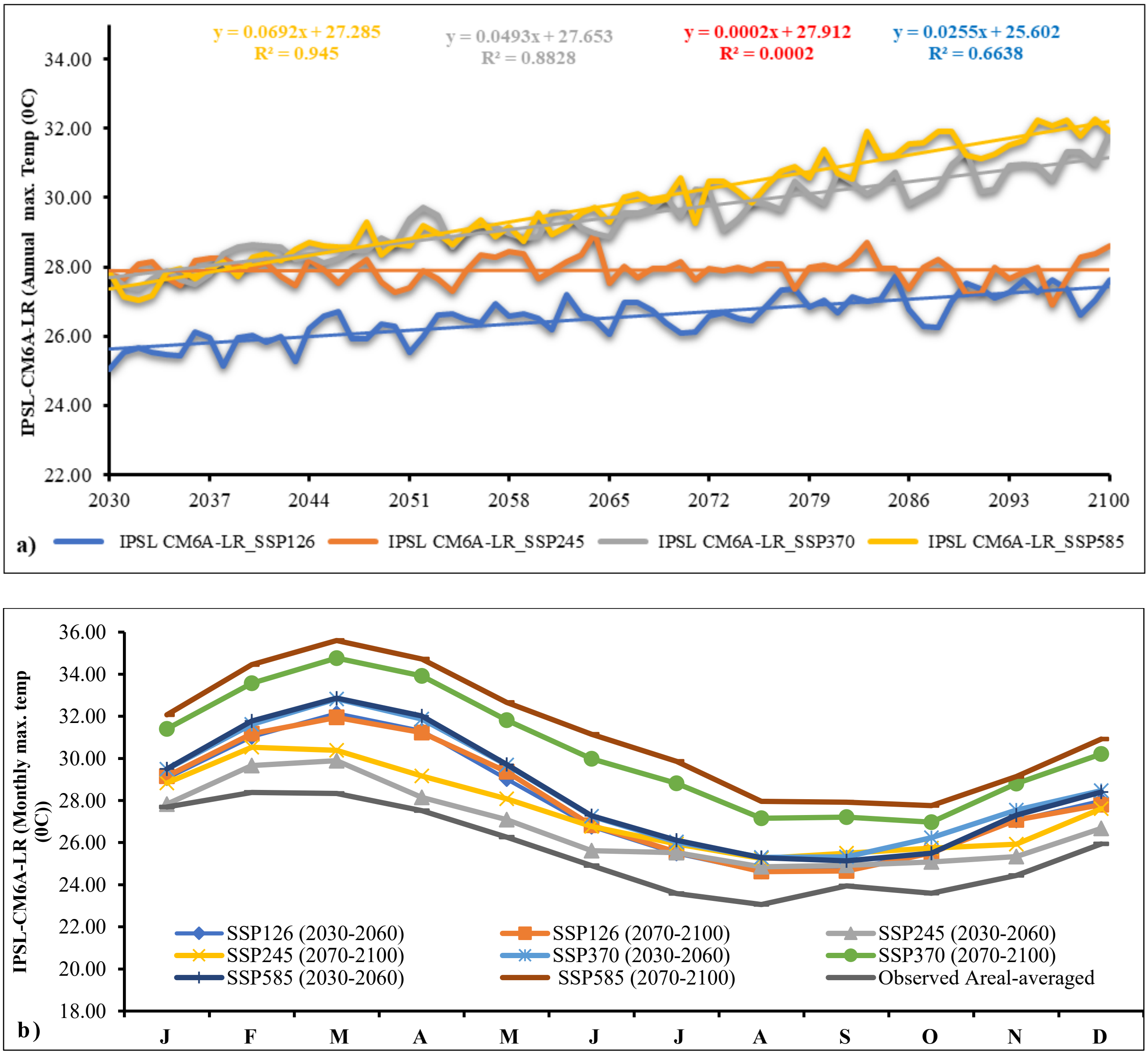

Figure 2.5 IPSL-CM6A-LR model projections under the SSP126, SSP245, SSP370, and SSP585 scenario for two future eras (2030s, 2070s). (a) Mean annual max. temperature (0C) and (b) mean monthly max. temperature (0C)

2.3.4 Implications of observed climate trends on water resources and climate change adaptation and mitigation

Over the past three decades, the Ayehu watershed has experienced notable shifts in rainfall and temperature, affecting water resources, agricultural productivity, and climate adaptation capacity. Annual rainfall shows a slight decline of 1.528 mm per year; however, this trend is not statistically significant and is dominated by strong interannual variability. Such rainfall irregularity in timing and amount complicates key agricultural decisions, including planting, irrigation planning, and harvesting (Markos et al., 2023b; Megersa et al., 2019), increases risk exposure for farming communities (Yeleliere et al., 2023), and heightens vulnerability to droughts and excessive rainfall, thereby reducing yields and farm income (Mengistu et al., 2021). Strengthening climate resilience therefore requires improved water management and reliable climate information services.

Seasonal analysis shows a significant decline in *Belg* rainfall (−2.78 mm $year^{-1}$; $p < 0.05$), a critical season for land preparation and early crop growth. This decline may disrupt planting schedules, germination, and crop development, ultimately reducing yields and threatening food security (Feke et al., 2021; Tesfamariam et al., 2019). Adaptation options such as drought-tolerant crops, improved water management, and enhanced forecasting services are essential to reduce these risks.

In contrast, *Kiremit* rainfall shows a significant increasing trend (7.84 mm $year^{-1}$; $p < 0.01$), which may enhance soil moisture, water availability, and agricultural production during the main growing season. Similar benefits have been reported by Tegegn et al. (2024). However, increasing rainfall variability also raises risks of flooding, waterlogging, and soil erosion (Mandal & Roy, 2024), which can damage crops, reduce soil fertility, and affect infrastructure. Integrated water resource management, improved drainage, and soil conservation are therefore important.

Temperature trends further indicate rising climate stress. Minimum temperature increases steadily by 0.04°C per year ($R^2 = 0.605$), reducing frost risk but increasing heat stress, pest incidence, and disease pressure (Bita & Gerats, 2013; Skendžić et al., 2021). Maximum temperature also rises, particularly during the *Belg* season (0.0799°C per year), increasing evapotranspiration, reducing soil moisture, and raising irrigation demand during critical crop growth stages (Djaman et al., 2018; Vahmani et al., 2022). Overall, these combined changes intensify agricultural vulnerability in the watershed.

2.4. Conclusion

The analysis of historical observations and CMIP6-based climate projections provides important insights into climate variability and future climate change in the Ayehu watershed. The results reveal notable changes in rainfall distribution and temperature patterns over the past three decades, with increasing variability in rainfall and significant warming trends in both minimum and maximum temperatures. While annual rainfall exhibited a slight declining tendency, the trend was not statistically significant and was characterized by substantial interannual variability. In contrast, seasonal analysis showed declining *Belg* rainfall and increasing *Kiremit* rainfall, indicating shifts in the temporal distribution of precipitation that may influence climate-sensitive sectors.

Future climate projections suggest that temperature will continue to increase throughout the twenty-first century under all SSP scenarios, with the magnitude of warming becoming more pronounced under higher-emission pathways. Both minimum and maximum temperatures are projected to rise, although the extent of warming varies among scenarios and projection periods. Rainfall projections are less consistent, showing decreases under SSP1-2.6, SSP2-4.5, and SSP3-7.0, but increases under SSP5-8.5, highlighting considerable uncertainty in future precipitation patterns. These contrasting projections indicate that future climate conditions in the watershed will be strongly influenced by the trajectory of greenhouse gas emissions.

Overall, the findings demonstrate that the study area is likely to experience continued warming accompanied by changes in rainfall characteristics and variability. The combination of rising temperatures and uncertain precipitation trends underscores the importance of incorporating climate information into long-term planning and adaptation efforts. The study contributes locally relevant evidence on historical climate variability and future climate projections, providing a scientific basis for climate risk assessment and future research in the watershed and the broader Upper Blue Nile Basin.

CHAPTER THREE

SPATIO-TEMPORAL DYNAMICS OF CLIMATE VARIABILITY AND ITS IMPACT ON MAJOR CROP YIELDS ACROSS DIFFERENT AGROECOLOGICAL ZONES OF THE AYEHU WATERSHED, UPPER BLUE NILE BASIN, NORTHWEST ETHIOPIA

Based on publication:

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Abstract

Climate variability poses a growing challenge to agricultural production and the livelihoods of smallholder farmers in Ethiopia, yet its effects across diverse agroecological settings remain insufficiently understood. This study examined the spatial and temporal patterns of climate variability and their relationships with major cereal crop yields in the Ayehu Watershed, Northwest Ethiopia, using trend analysis, spatial interpolation techniques, and an autoregressive distributed lag (ARDL) model. The findings revealed marked agroecological differences in rainfall distribution, with annual rainfall decreasing from the highland to the lowland zones. Seasonal rainfall showed declining trends during the Belg and Bega seasons and increasing trends during the Kiremit season in parts of the watershed. In contrast, both minimum and maximum temperatures exhibited significant upward trends across the study area. The crop–climate analysis indicated that minimum temperature was positively associated with cereal yields in several agroecological zones, suggesting that moderately warmer conditions may have supported crop growth under prevailing local conditions, while excessive rainfall was generally associated with reduced yields, likely due to moisture-related stresses during critical growth stages. Overall, the results demonstrate that the impacts of climate variability on crop production vary across agroecological zones and highlight the importance of climate-smart, location-specific adaptation strategies to enhance agricultural resilience and food security.

Keywords: Agroecological zone; ARDL model; Ayehu Watershed; Climate variability; Crop yields; Temperature trends

3.1. Introduction

Climate variability and change represent one of the most pressing challenges to global agricultural systems, with far-reaching implications for food security, rural livelihoods, and sustainable development (FAO, 2021; IPCC, 2023). Anthropogenic greenhouse gas emissions driven by fossil fuel combustion, land-use change, and industrial activities have intensified global warming, resulting in altered temperature and precipitation regimes and an increased frequency and intensity of climate extremes (Kumar et al., 2024; Sandal et al., 2024). These climatic shifts directly affect agricultural productivity by modifying growing-season conditions, disrupting crop phenology, and increasing yield instability, particularly in rainfed farming systems that are highly climate-sensitive (Mehta, 2024; Rahman et al., 2024).

Sub-Saharan Africa remains one of the most climate-vulnerable regions globally due to its strong dependence on rainfed agriculture, limited irrigation infrastructure, and constrained adaptive capacity among smallholder farmers (Lombe et al., 2024; Mutengwa et al., 2023). Observed increases in temperature and variability in rainfall patterns have already contributed to declining and unstable crop yields, undermining food security and rural livelihoods across the region (Benjamin et al., 2024; Kone et al., 2024). Within this context, Ethiopia represents a particularly critical case, as agriculture contributes approximately 37.6% of national GDP and supports the livelihoods of nearly 85% of the population (Belay et al., 2022; Mammo, 2022). Over recent decades, the country has experienced increasing climatic variability characterized by rising temperatures and erratic rainfall, which have intensified production risks for major staple crops and exacerbated food insecurity in many regions (Adunya & Benti, 2020; Grossi & Dinku, 2022; Abera et al., 2025; Teku & Eshetu, 2024).

A growing body of empirical research in Ethiopia has documented long-term trends in temperature increase, rainfall variability, and associated impacts on agricultural production (Amare & Simane, 2017; Takele et al., 2023; Alemayehu et al., 2023; Berhanu et al., 2024). However, existing studies exhibit three important limitations. First, most analysis are conducted at broad regional or basin scales, which mask localized climate dynamics and obscure heterogeneity in crop response. Second, many studies examine either climate trends or crop productivity independently, without explicitly integrating climate variability with yield response modeling. Third, limited attention has been given to agroecological differentiation, despite clear evidence that elevation, slope, and microclimatic variation strongly influence both climate exposure and agricultural performance. These limitations constrain the development of precise, location-specific adaptation strategies.

The Ayehu Watershed, located within the Upper Blue Nile Basin, provides a critical but under-researched agroecological context for addressing these gaps. The watershed is characterized by pronounced spatial variation in elevation, rainfall distribution, and temperature regimes, which create distinct agroecological zones with differing agricultural potentials and climate sensitivities. Despite its importance for cereal production, empirical evidence on how climate variability evolves spatially and temporally within the watershed, and how such variability influences crop productivity across agroecological gradients, remains limited. This gap restricts a nuanced understanding of localized climate risks and limits the formulation of targeted agricultural adaptation and planning strategies (Alemayehu et al., 2023; Berhanu et al., 2024; Takele et al., 2023).

Addressing these limitations, this study investigates the spatiotemporal dynamics of rainfall and temperature and quantifies their effects on the yields of major cereal crops across agroecological zones of the Ayehu Watershed. Methodologically, the study integrates long-term climate trend analysis, spatial interpolation techniques, and an Autoregressive Distributed Lag (ARDL) modeling framework to capture both temporal dynamics and climate–yield relationships under heterogeneous agroecological conditions. By combining spatial and econometric approaches at the watershed scale, the study advances empirical understanding of climate–agriculture interactions in complex landscapes.

The contribution of this research is threefold. First, it provides high-resolution evidence on spatial and temporal climate variability within a heterogeneous watershed system. Second, it empirically quantifies the dynamic relationship between climate variables and cereal crop yields using a robust time-series modeling approach. Third, it explicitly incorporates agroecological differentiation, allowing for more precise interpretation of climate–crop interactions across environmental gradients. The findings are expected to enhance the scientific understanding of climate impacts on agriculture in the Upper Blue Nile Basin and provide actionable insights for location-specific climate adaptation, agricultural planning, and policy formulation in Ethiopia and similar agroecological contexts (Singh, 2020; Alemayehu et al., 2024).

3.2. Research Methods

3.2.1. Research design

This study used a longitudinal research design, a widely acknowledged methodological approach for its strength in capturing temporal dynamics and developmental processes within complex systems (Ployhart & Ward, 2011). By repeatedly observing the same units over extended periods, longitudinal research enables a rigorous examination of long-term trends, interannual variability, and potential causal links among key variables (Wang et al., 2017). Guided by this framework, the study systematically analyzed the long-term spatiotemporal dynamics of climate variability and its effects on major crop yields in different agroecological zones of the Ayehu watershed.

3.2.2. Data type and source

This study employed a combination of ground-based meteorological observations and satellite-derived gridded climate datasets to provide a comprehensive assessment of climate variability in the Ayehu Watershed. Monthly rainfall and temperature data for the period 1992–2022 were obtained from three meteorological stations, Injibara, Gimja Bēt Maryam, and Ayehu Farm Development, from the Ethiopian National Meteorological Institute (EMI) (Table 3.1). The study period was selected based on the availability of complete and reliable climate records at the time the research commenced in 2023. In addition, the 31-year record satisfies the climatological requirement for long-term climate analysis and trend detection.

The three stations were selected because they represent the major agroecological zones of the watershed and possess the most complete and continuous records available within the study area. Although the limited number of stations may constrain the spatial representation of climatic conditions, their distribution across the highland, midland, and lowland agroecological zones provides the best available observational coverage for assessing climate variability within the watershed.

Prior to analysis, all station records underwent quality-control procedures, including consistency checks, outlier detection, and screening for missing observations. Stations with substantial data gaps were excluded from the analysis. Short gaps comprising less than 5% of the monthly observations were filled using linear interpolation based on adjacent observations, while records with larger proportions of missing data were omitted to minimize potential bias.

These procedures ensured the reliability and consistency of the climate datasets used in the study.

To complement the limited station network and characterize spatial climate variability across the watershed, gridded rainfall data from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and temperature data from the NASA POWER database were utilized (Table 3.2). These datasets were used independently rather than merged with station observations. Station data were employed primarily for temporal trend analysis, whereas satellite-derived products were used to assess spatial variability and generate climate surfaces across the watershed.

To evaluate the reliability of the gridded datasets, CHIRPS rainfall and NASA POWER temperature data were validated against observed station records using correlation coefficients (r), coefficients of determination (R^2), and Percent Bias (PBIAS). Validation was conducted using monthly data for the common observation period. PBIAS was expressed as a percentage, where positive values indicate overestimation and negative values indicate underestimation relative to observed records. The results showed strong agreement between satellite and observed datasets, with correlation coefficients of 0.96 for rainfall, 0.94 for minimum temperature, and 0.92 for maximum temperature, and corresponding R^2 values of 0.94, 0.88, and 0.86. The PBIAS values of 0.12%, 0.04%, and 0.26%, respectively, were well within the accepted range for excellent model performance, confirming the suitability of the CHIRPS and NASA POWER datasets for climate analysis in the study area (Table 3.3).

To assess the effects of climate variability on cereal crop production, annual yield data for maize (Zea mays), teff (Eragrostis tef), and wheat (Triticum aestivum) were obtained from the Ethiopian Central Statistical Agency (CSA) and local agricultural offices for the period 1992–2022. These crops were selected because they constitute the dominant cereal crops in the watershed and contribute substantially to local food production and rural livelihoods.

Table 3. 1 Location of meteorological stations in the study watershed

No	Station name	Latitude	Longitude	Elevation
1	Injibara	10.96	36.93	2672m
2	Gimja Bēt Maryam	10.85	36.89	2407m
3	Ayehu Farm Development	10.66	36.79	1874m

Table 3. 2 Data source/website for observed climate data from 1992 to 2022

No	Data Source	Website/Office/	Measurements
1	EMA	Ethiopian Meteorological Agency	°C/month for temperature & mm/month for rainfall
2	NASA	https://power.larc.nasa.gov/data-access-viewer/	°C/month for temperature
3	CHIRPS	https://data.chc.ucsb.edu/products/CHIRPS-2.0/	mm/month for rainfall

Table 3. 3 Validation of CHIRPS & NASA power data with observed (station data)

Variables	Correlation coefficient	R^2	Pbias
Rainfall	0.96	0.94	0.12
Minimum temperature	0.94	0.88	0.04
Maximum temperature	0.92	0.86	-0.26

3.2.3. Methods of data analysis

Mann Kendall trend test

To capture climate variability across the major agroecological zones of the Ayehu Watershed, the Injibara, Gimja Bēt Maryam, and Ayehu Farm Development meteorological stations were selected to represent the highland, midland, and lowland zones, respectively. Temporal trends in rainfall and temperature were then evaluated using the Mann–Kendall (MK) trend test, a widely used non-parametric statistical method that is particularly suitable for hydroclimatic time series because it does not require the data to follow a normal distribution and is relatively robust to outliers (Agbo et al., 2023; Malik & Kumar, 2020).

Because serial correlation can influence the significance of the MK statistic, lag-1 autocorrelation was first examined for each climate time series. Where significant autocorrelation was detected, a trend-free pre-whitening procedure was applied before conducting the MK test to remove the effects of serial dependence while preserving the underlying climatic trend. This approach improves the reliability of trend detection and reduces the likelihood of Type I errors.

The significance of trends was evaluated at the 1%, 5%, and 10% significance levels. Positive Z-values indicate increasing trends, whereas negative Z-values indicate decreasing trends. The magnitude of statistically detected trends was quantified using Sen's slope estimator, which provides a robust estimate of the rate of change over time (Asfaw et al., 2018; Esayas et al., 2019). Together, the MK test and Sen's slope estimator provide a rigorous assessment of climate variability across the agroecological zones of the watershed.

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(a_j - a_k) \tag{1}$$

where n is the number of data points, k and j are data values in time series k and j (j > k), and sgn (j-k) is a sign function as:

$$sgn = \begin{bmatrix} 1\,for\,(a_j - a_k) > 0 \\ 0\,for\,(a_j - a_k) = 0 \\ -1\,for\,(a_j - a_k) < 0 \end{bmatrix} \tag{2}$$

It is also assumed that for n = 8, the S test statistics is normally distributed, with a mean value of zero and a variance calculated using equation (3).

$$V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right] \tag{3}$$

where n is the number of data, q is the number of linked groups and t_p is the number of data points in the i^{th} group

$$Z = \begin{cases} \frac{S-1}{\sqrt{var\,(s)}}\ if\ s > 0, Z = 0\ if\ S = 0 \\ \frac{S+1}{\sqrt{var\,(s)}}\ if\ S < 0 \end{cases} \tag{4}$$

The Sen Slope Estimator (SSE) is used in time series data analysis to determine the extent of trends (Esayas et al., 2019; Tofu & Mengistu, 2023). The slope estimator β, which is calculated as the median of all possible pairs of data points, provides a reliable indicator of the strength of the trend. While a negative β value indicates a downward trend, a positive β value indicates an upward trend (increasing values over time). The following formula is used to calculate the slopes (T_i) for each pair of data points (X_j and X_k) in the Sen slope calculation process.

$$T_i = \frac{X_j - X_k}{\mathrm{j-k}}, for\ i = 1, 2, \ldots, N, \tag{5}$$

where X_j and X_k are taken as data values at time j and k (j > k), respectively. The median of these N values of Ti is indicated as the Sen estimator of slope, which is expressed as
The Sen Slope (B_i) is calculated by

$$Q_i = \begin{cases} T_{\frac{N+1}{2}}, & N \text{ is odd} \\ \frac{1}{2}\left(T_{\left(\frac{N}{2}\right)} + T_{(N+2)/2}\right) & N \text{ is even} \end{cases} \quad (6)$$

Coefficient of Variation

The coefficient of variation (CV) is a popular statistic for evaluating data variability, offering a relative measure by expressing standard deviation as a percentage of the mean (Gebrechorkos et al., 2019; Gummadi et al., 2018). Unlike the standard deviation, which measures absolute dispersion, CV enables meaningful comparisons between data sets with differing units or significantly changing means. In this study, we used the CV to determine the variability of yearly and seasonal climate variables, namely temperature and precipitation. According to Amare & Simane (2017) and Asfaw et al. (2018), the CV is particularly useful for assessing precipitation variability since it correctly represents changes in meteorological conditions within a specific region.

$$CV = \frac{\sigma}{X} \times 100 \quad (7)$$

Here, X stands for the average precipitation, while σ represents its standard deviation, and CV is the coefficient of variation. CV helps us understand precipitation variability: values below 20% suggest low variability, 20% to 30% indicate moderate variability, and anything above 30% signifies high variability. Essentially, a higher CV in precipitation means greater variability.

Precipitation Concentration Index (PCI)

The precipitation concentration index (PCI) was employed to analyze the temporal distribution of rainfall. This index quantifies whether precipitation is evenly distributed or concentrated within a few months, allowing researchers to analyze rainfall variability and its implications for agriculture and water management (Alemayehu et al., 2022b; Salameh, 2024). Mathematically, PCI is calculated using monthly rainfall totals (*Pi*) and is a strong sign of how rainfall changes with seasons. Based on established classifications (Al-Shamarti, 2016; Valli et al., 2013), PCI values below 10 indicate a uniform rainfall distribution, 11–15 denote moderate concentration, 16–20 represent irregular patterns, and values above 20 reflect highly irregular rainfall. This categorization provides a clear framework for evaluating the degree of rainfall concentration throughout the watershed.

$$PCI_{annual} = \frac{\sum_{1=1}^{12} \text{pi}^2}{(\sum_{1=1}^{12} \text{pi})^2} * 100 \tag{8}$$

The Rainfall Anomaly Index (RAI)

The Rainfall Anomaly Index (RAI) is a widely used hydroclimatic indicator designed to quantify and characterize wet and dry conditions within a region by standardizing deviations of observed rainfall from the long-term mean (Sharma et al., 2020; Singha et al., 2024). By expressing rainfall anomalies in a standardized form, the RAI provides a reliable and comparable measure of precipitation surplus and deficit, enabling the identification of unusually wet or dry periods. In this study, annual rainfall variability in the Ayehu Watershed was assessed using the RAI methodology proposed by Tilahun (2006). Unlike simple analyses based solely on rainfall totals, the RAI captures the magnitude and persistence of rainfall anomalies, thereby providing valuable insights into the occurrence and severity of droughts and excessively wet conditions. This makes the index particularly useful for evaluating the impacts of climate variability on agricultural production and water resources. Furthermore, because the RAI standardizes rainfall deviations, it facilitates meaningful comparisons of precipitation anomalies across different time periods and locations, regardless of differences in their absolute rainfall amounts.

The calculation for positive anomalies (indicating wetter conditions than average) is formulated as follows:

$$RAI = +3\left(\frac{RF - MRF}{Mean\,H10 - MeanRF}\right) \tag{9}$$

And for negative anomalies;

$$RAI = -3\left(\frac{RF - MRF}{M\,mean\,L10 - MeanRF}\right) \tag{10}$$

Here, RAI signifies the rainfallrain anomaly index. RF is the actual rainfall for a specific year, while MRF is the mean annual rainfall throughout the historical record. MH10 represents the average of the ten highest annual rainfall values recorded, and ML10 is the average of the ten lowest. Years with a positive RAI indicate high rainfall, whereas those with a negative RAI signify low rainfall, both relative to the long-term average. Similarly, the annual temperature anomaly is simply calculated as the difference between a given year's average temperature and the long-term mean.

Inverse Distance Weighted (IDW) interpolation

The Inverse Distance Weighted (IDW) method is a key tool for showing the geographic patterns of climate data, such as rainfall and temperature (Koç et al., 2022; Ozelkan et al., 2015). This technique is particularly robust, especially when dealing with complex terrain, such as mountainous regions, where intricate rain-orography interactions significantly influence precipitation patterns (Gilewski, 2021). IDW operates on the principle that locations closer to an observed data point are more similar to it than those farther away (Moussa & Abboud, 2024). In essence, it calculates values for unmeasured areas by assigning greater weight to observations from nearby meteorological stations in a time series (Kim et al., 2022). This approach allows us to create continuous spatial surfaces from discrete point data, effectively bridging the gaps between individual measurement stations (Liang et al., 2018).

Spatial interpolation was performed using the Inverse Distance Weighting (IDW) method. IDW was selected because of its simplicity, computational efficiency, and suitability for areas with relatively sparse meteorological networks. Unlike geostatistical approaches such as Kriging, which require robust estimation of spatial autocorrelation structures and generally perform best with denser station networks, IDW provides a practical and transparent approach for interpolating climate variables when the number of observation points is limited. The interpolated surfaces should therefore be interpreted as indicative representations of spatial patterns rather than precise estimates at unsampled locations.

Auto-regressive distributed lag (ARDL) model

This study used the Autoregressive Distributed Lag (ARDL) model, commonly referred to as the bounds testing approach, to analyze the dynamic relationship between climatic factors and crop yields. The ARDL framework was chosen because it best fit the data and aligned with the study's research goals. Preliminary stationarity tests revealed that the variables were integrated at mixed orders, I (0) and I (1). In contrast, the ARDL model can accommodate a mix of stationary and nonstationary variables. This feature provides greater flexibility and improves statistical robustness when examining short- and long-run relationships in climate–agriculture interactions.

Prior to ARDL estimation, stationarity was assessed using the Augmented Dickey–Fuller (ADF). Appropriate lag lengths were selected using the Akaike Information Criterion (AIC), while deterministic intercept and trend components were included where justified by the datagenerating process. The results confirmed that the variables were integrated at mixed orders, thereby satisfying the prerequisites for ARDL modelling.

Furthermore, the ARDL technique is particularly well suited for relatively small sample sizes, such as the 30-year climate and crop yield time series used in this analysis. The ARDL model allows simultaneous estimation of short- and long-run equilibrium relationships within a single regression framework. This capability enables it to capture the delayed and cumulative effects of climatic variables, such as rainfall, minimum temperature, and maximum temperature, on crop productivity. This feature is essential for agricultural impact studies, where the influence of climate variables often manifests itself over multiple growing seasons. Empirically, the model's application has been extensively validated in similar climate-agriculture scenarios. Begum et al. (2025), Hussein & Hmood (2024), Singh et al. (2024), and Tirfeessa et al. (2025) have demonstrated that ARDL provides valid estimates of crop yield responses to climate variability, both immediately and in the long run.

Let us denote:

- Y_t: Crop Yield at time t (dependent variable)
- $T_{min,\,t}$: Minimum temperature at time t (independent variable)
- $T_{max,\,t}$: Maximum temperature at time t (independent variable)
- R_t: Rainfall at time t (independent variable)
- Δ: First difference operator (e.g., $\Delta Y_t = Y_t - Y_{t-1}$)
- p, q_1, q_2, q_3: Optimal lag lengths for Y_t, $T_{min,\,t}$, $T_{max,\,t}$, and Rt, respectively.

1. General ARDL Model equation

The general ARDL model *(p, q1, q2, q3)* for crop yield (Y_t) as the dependent variable and minimum temperature ($T_{min,\,t}$), maximum temperature (Tmax, t) and rainfall (R_t) as independent variables can be written as:

$$Y_t = a_0 + a_1 t + \sum_{i=1}^{p} \phi i Y_{t-i} + \sum_{j=0}^{q_1} B_{1j}\, T_{min,t-j} + \sum_{k=0}^{q_2} B_{2k}\, T_{max,t-k} + \sum_{l=0}^{q_3} B_{3l}\, R_{t-l} + \epsilon t$$

(11)

Where:

- α_0: Intercept term
- $\alpha_1 t$: Deterministic time trend (optional, included if there is a trend in the data)
- ϕ_i: Coefficients of the Lagged Dependent Variable Y_{ti}
- β_{1j}, β_{2k}, β_{3l}: Coefficients of the current and lagged independent variables
- ϵ_t: Error term

2. ARDL short-run equation (Error Correction Model - ECM)

The short-run dynamics and the speed of adjustment to the long-run equilibrium are captured by the Error Correction Model (ECM) representation of the ARDL. This is derived by re-parameterizing the general ARDL model.

$$\Delta Y_t = a_0 + a_1 t + \sum_{i=1}^{p-1} \gamma i \Delta Y_{t-i} + \sum_{j=0}^{q_1-1} \delta_{1j} \Delta T_{min,t-j} + \sum_{k=0}^{q_2-1} \delta_{2k} \Delta T_{max,t-k} + \sum_{l=0}^{q_3-1} \delta_{3l} \Delta R_{t-l} + \lambda ECT_{t-1}\, \epsilon t$$
(12)

Where:

- ΔY_t, $\Delta T_{min,\, t}$, $\Delta T_{max,t}$, ΔR_t: Short-term dynamic coefficients representing the immediate impact of changes in the variables.
- γ_i, δ_{1j}, δ_{2k}, δ_{3l}: Short-term coefficients of the differenced lagged variables.
- ECT_{t-1}: The error correction term, representing the lagged deviations from the long-run equilibrium. It is obtained from the residuals of the long-run co-integrating regression.
- λ: The error correction coefficient, which measures the speed at which Yt adjusts back to the long-run equilibrium after a shock. It is expected that the cointegration is negative and statistically significant for cointegration to exist ($-1<\lambda<0$).

3. ARDL long run equation

If cointegration is established, there is a stable long-term relationship between the variables. Long-term coefficients are derived from the general ARDL model. They represent the equilibrium impact of the independent variables on the dependent variable. The long-run equation is obtained by setting all difference terms and the error term to zero in the ECM and solving for Yt. Alternatively, it can be derived directly from the general ARDL equation by setting $Y_t=Y_{t-i}$ and $X_t=X_{t-j}$ (where X represents the independent variables) for the long run.
The long-run equation can be expressed as

$$Y_t = \theta_0 + \theta_1 T_{min,t} + \theta_2 T_{max,t} + \theta_3 R_t + v_t \qquad (13)$$

Where:

- $\theta_0 = \frac{a_0}{1-\sum_{i=1}^{p} \phi i}$
- $\theta_1 = \frac{\sum_{j=0}^{q_1} B_{1j}}{1-\sum_{i=1}^{p} \phi i}$
- $\theta_2 = \frac{\sum_{k=0}^{q_2} B_{2k}}{1-\sum_{i=1}^{p} \phi i}$

- $\theta_3 = \frac{\sum_{l=0}^{q_3} B_{3l}}{1-\sum_{i=1}^{p} \phi i}$
- v_t: Long-term error term.

These θ coefficients represent the long-term elasticities or propensities of crop yield with respect to minimum temperature, maximum temperature, and rainfall, respectively.

4. Cointegration (ARDL bound test)

Cointegration in the ARDL framework is tested using the bounds test (Pesaran et al., 2001). This test examines the joint significance of the lagged-level variables in the unrestricted error correction model.

The null hypothesis for no cointegration is as follows:

H0: $\lambda=\theta_1=\theta_2=\theta_3=0$ (no long-term relationship)

The alternative hypothesis:

H1: $\lambda \# 0$ or $\theta_1 \# 0$ *or* $\theta_2 \# 0$ or $\theta_3 \# 0$ or 3 # 0 (there is a long-term relationship)

The F-statistic from the regression of the ECM form is compared with the critical values. Critical values are provided as a range (lower bound for I (0) variables and upper bound for I (1) variables).

- If the F-statistic is greater than the upper bound, the null hypothesis of no cointegration is rejected, indicating a long-run relationship.
- If the F-statistic is less than the lower bound, the null hypothesis cannot be rejected.
- If the F-statistic falls between the lower and upper bounds, the result is inconclusive.

The ARDL model focused on climatic variables, rainfall, minimum temperature, and maximum temperature, as the primary explanatory variables because the study objective was to quantify the influence of climate variability on crop yields. Although other factors such as fertilizer use, improved seed varieties, farm management practices, technological change, and market conditions also influence agricultural production, consistent long-term time-series data for these variables were unavailable for the study period. Therefore, the estimated climate effects should be interpreted within the context of this limitation, and the potential for omitted-variable bias should be acknowledged when interpreting the results.

Table 3. 4 Variable Definitions and Units

Variable Type	Variable Symbol	Description	Unit of Measurement
Dependent Variable	CY_t	Crop Yield	Quintal/Hectare
Independent Variable 1	R_t	Rainfall	Millimetre (mm)
Independent Variable 2	$T_{min,\ t}$	Minimum Temperature	Degree Celsius (°C)
Independent Variable 3	$T_{max,\ t}$	Maximum Temperature	Degree Celsius (°C)

3.3 Result and Discussion

3.3.1 Temporal variability and trends of rainfall in agroecological zones (AEZs)

Rainfall in the Ayehu Watershed (1992–2022) exhibited a clear bimodal pattern, characterized by a dominant Kiremit (main rainy season) and a comparatively shorter Belg season. Spatially, rainfall showed a pronounced altitudinal gradient, with higher totals in the highland agroecological zone and progressively decreasing amounts toward the midland and lowland zones. This pattern underscores the strong control of topography on rainfall distribution within the watershed.

Seasonal analysis indicates that Kiremit rainfall contributes the largest share of annual precipitation across all agroecological zones and constitutes the primary water source for rainfed agriculture. In contrast, Belg and Bega seasons are characterized by lower rainfall amounts and higher interannual variability, particularly in the midland and lowland zones. The elevated coefficients of variation (CV) and precipitation concentration index (PCI) values in these zones (Table 3.5) further confirm a more irregular and less predictable rainfall distribution at lower elevations.

Although Kiremit rainfall remains relatively more stable across the study period, the higher variability observed in Belg and Bega seasons suggests increasing uncertainty in early- and late-season agricultural water availability. Such instability has important implications for planting dates, crop establishment, and the viability of short-cycle cropping systems, particularly in moisture-sensitive agroecological zones. Similar patterns of seasonal rainfall instability have been widely documented in Ethiopia, where increasing intra-annual variability persists even in the absence of strong long-term monotonic trends, with Belg rainfall identified as particularly sensitive to climatic fluctuations (Adane & Asmerom, 2025; Feke et al., 2021; Gashaw et al., 2023; Jury & Funk, 2013; Shawul & Chakma, 2020).

Table 3.5 Annual and seasonal rainfall (mm), CV, and PCI (1992–2022) in the Ayehu watershed

Agroecology	Annual			*Kiremit* season			*Belg* season			*Bega* season		
	Mean	CV	PCI	Mean	CV	PCI	Mean	CV	PCI	Mean	CV	PCI
Highland	1573.6	12.3	13.2	1603.7	9.5	22.7	318.8	41.5	22.5	126.3	57.2	42.8
Midland	1452.5	12.9	15.4	1446.7	11.2	20.2	254.7	48.6	25.4	116.8	59.3	44.0
Lowland	1244.1	14.2	18.1	1271.5	13.3	18.5	189.6	52.3	28.2	98.2	61.9	46.1

CV = coefficient of variation, PCI = precipitation concentration index.

Trend analysis using the Mann–Kendall test and Sen's slope estimator revealed pronounced spatial and seasonal heterogeneity in rainfall dynamics across the agroecological zones. At the annual scale, rainfall exhibited a general declining tendency across all zones, although the magnitude and statistical significance of the trends varied spatially. Seasonally, Kiremit rainfall showed an increasing trend in the highland and midland zones, while the lowland zone exhibited a non-significant decreasing trend. In contrast, Belg rainfall consistently declined across all agroecological zones, with statistically significant reductions observed in the midland and lowland zones. Bega rainfall also showed an overall decreasing tendency, though with spatial variation in magnitude and statistical significance.

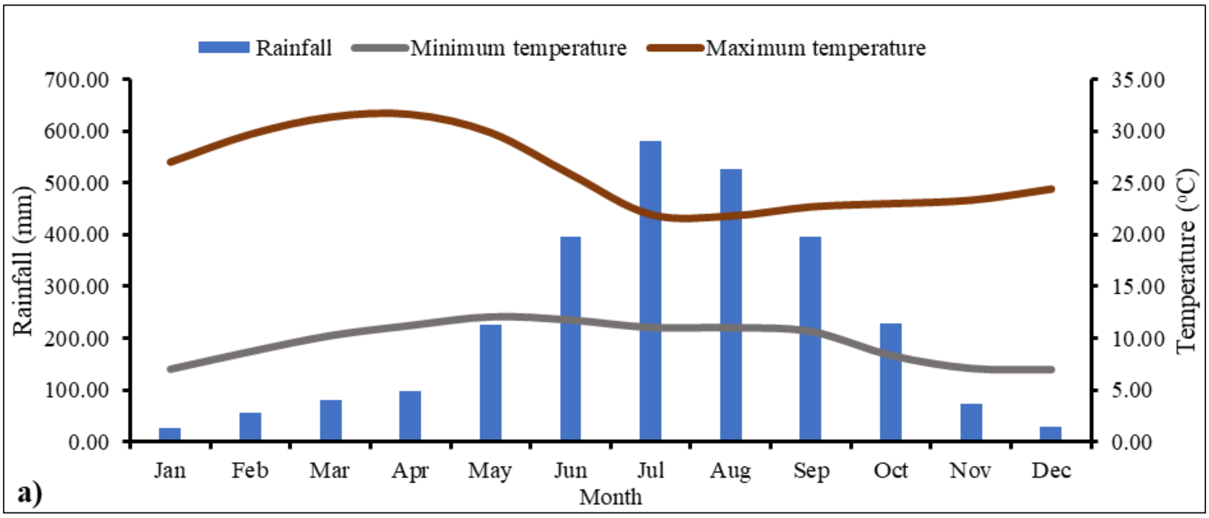
These results, based strictly on Sen's slope estimates, indicate that observed changes are not characterized by uniform annual rainfall decline but rather by a redistribution of rainfall within the annual cycle. Specifically, rainfall is becoming increasingly concentrated in the Kiremit season, while the contributions of Belg and Bega seasons are diminishing. This shift in intra-annual rainfall distribution has important implications for crop calendars, soil moisture availability, and agricultural water management in rainfed systems.

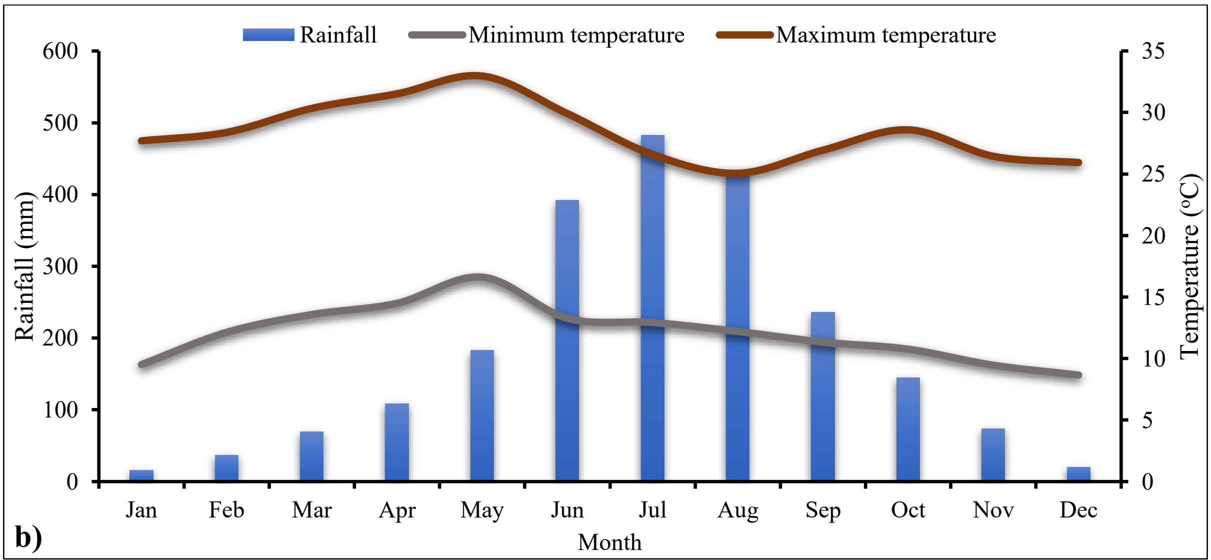
Overall, the findings suggest that the midland and lowland agroecological zones are more exposed to rainfall variability than the highlands. The combined effects of declining Belg rainfall, variable Bega conditions, and intensified concentration of rainfall in the Kiremit season increase the risk of intra-seasonal moisture stress, particularly during crop establishment and maturation periods. Such conditions can exacerbate drought impacts and food insecurity in rainfed farming systems (Enyew & Wassie, 2024; Mohammed et al., 2025). Although some highland areas show modest increases in Kiremit rainfall, the broader regional context still reflects increasing rainfall variability and a tendency toward greater climatic unpredictability (Sahilu et al., 2024).

Table 3. 6 Trends of rainfall in the Ayehu watershed in the AEZ (1992-2022)

AEZs	Annual			*Kiremit* season			*Belg* season			*Bega* season		
	Mean	Z	S	Mean	Z	S	Mean	Z	S	Mean	Z	S
Highland	1573.6	-1.7***	-3.8	1603.7	1.58***	7.2	318.8	-0.7**	-2.2	126.3	-0.3**	-2.4
Midland	1452.5	-0.42	-5.2	1446.7	0.53**	4.9	254.7	-1.3**	-3.2	116.8	-0.5**	-1.7
Lowland	1244.1	-1.3**	-6.2	1271.5	-0.42	-8.2	189.6	-1.5**	-4.2	98.2	-0.25	-2.9

*Significance levels: *p<0.1, **p<0.05, ***p<0.01; Z = Mann-Kendall test statistic; S = Sen's slope.





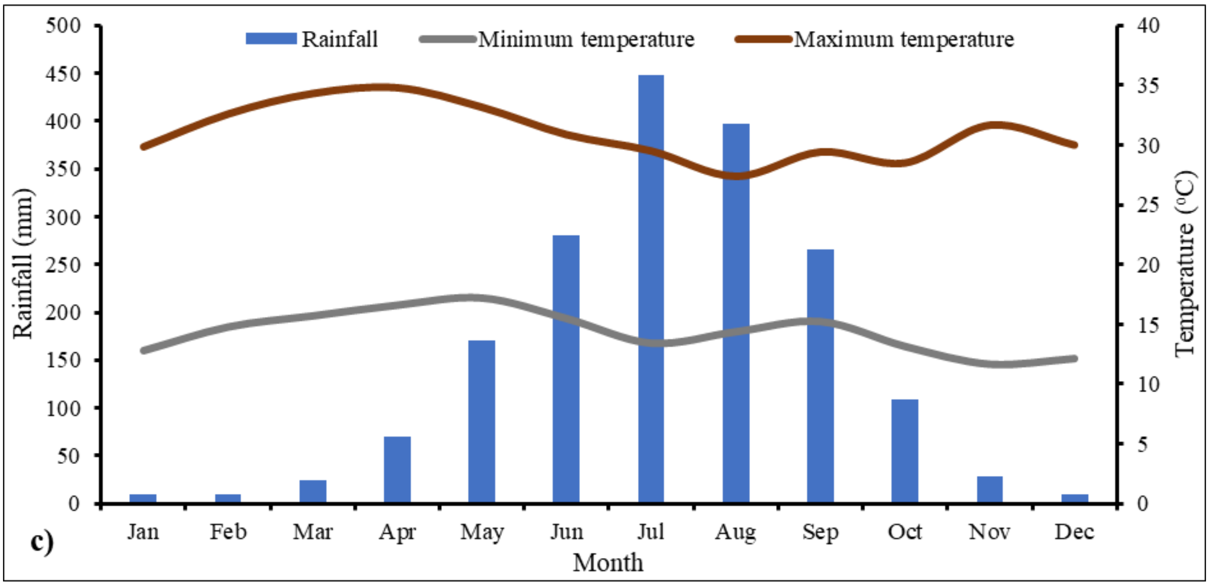


Figure 3.1 Monthly distribution of rainfall, minimum temperature, and maximum temperature in the study area across AEZ: (a) Highland, (b) Midland, and (c) Lowland

3.3.2 Analysis of rainfall anomalies across agroecological zones

Rainfall anomaly index (RAI) analysis for 1992–2022 revealed pronounced agroecological differences in rainfall variability across the watershed. In the highland zone, rainfall conditions were relatively stable, with a near-balanced distribution of wet and dry years (53% above and 47% below the long-term mean). Seasonally, Kiremit rainfall showed a slight dominance of positive anomalies (approximately 60% of seasons above average), whereas Belg and Bega seasons exhibited moderate interannual fluctuations without a consistent directional pattern (Figure 3.3), consistent with Zeleke et al. (2023). This relative stability may be associated with elevation-driven climatic moderation, which tends to buffer rainfall variability in high-altitude environments.

The midland zone exhibited a tendency toward wetter conditions, with approximately 60% of years recording above-average rainfall. Positive anomalies were particularly evident during the Kiremit (65%) and Belg seasons (Figure 3.4), especially in recent years, consistent with Sahilu et al. (2024). However, this pattern reflects interannual variability rather than a statistically consistent long-term shift, suggesting strong short-term climate fluctuations possibly driven by broader atmospheric variability.

In contrast, the lowland zone demonstrated higher rainfall instability, with dry years occurring more frequently (58%), particularly during the early 2000s. Seasonally, Kiremit rainfall was dominated by negative anomalies (55% of years), Belg rainfall showed strong temporal fluctuations, and Bega rainfall remained predominantly below the long-term mean (Adane &

Asmerom, 2025). These patterns indicate greater exposure to rainfall deficits and heightened climatic stress compared to the highland and midland zones.

Overall, the rainfall anomaly patterns reveal strong spatial heterogeneity in hydro-climatic conditions across the watershed. While such variability may be partly influenced by large-scale climate drivers such as ENSO-related variability and shifts in the Inter-Tropical Convergence Zone (ITCZ), these mechanisms were not explicitly analyzed in this study and are therefore interpreted as plausible explanatory factors rather than confirmed causal relationships (Ademe et al., 2020; Bayable et al., 2021; Zeleke et al., 2023). These findings underscore the importance of agroecology-specific adaptation strategies, including soil moisture conservation, supplemental irrigation, and crop diversification, to enhance resilience to rainfall variability (Balcha et al., 2023).

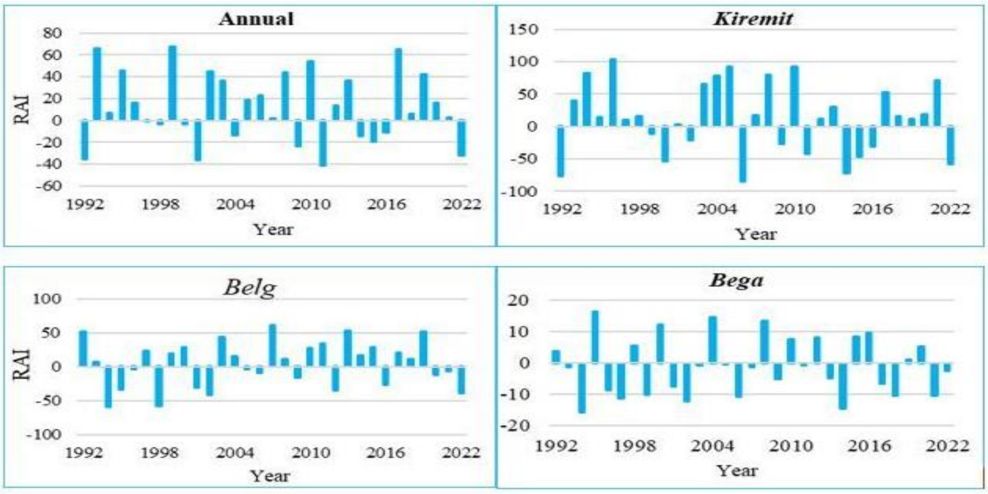


Figure 3.2 RAI in Highland AEZ

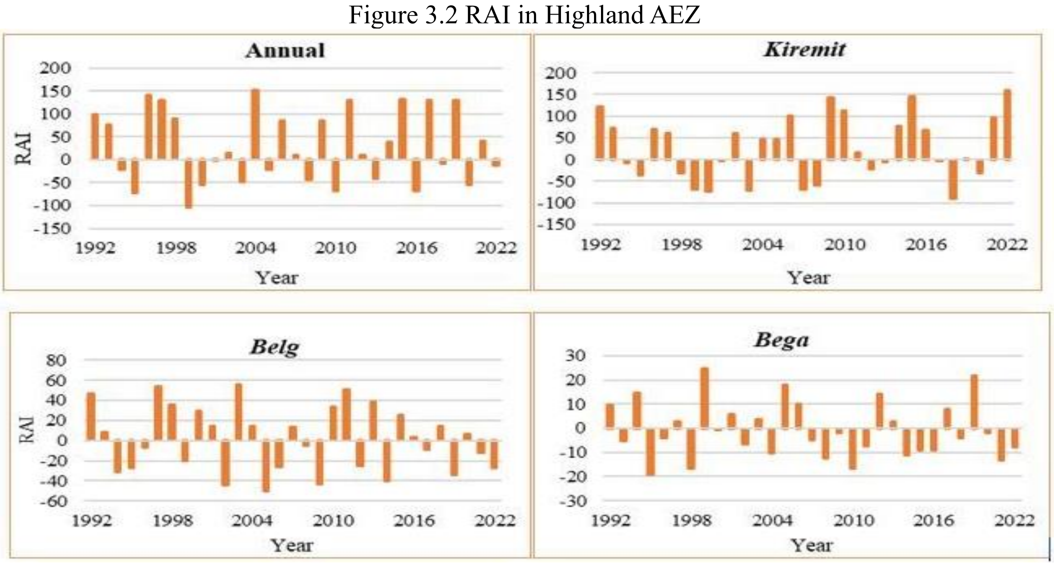


Figure 3.3 RAI in Midland AEZ

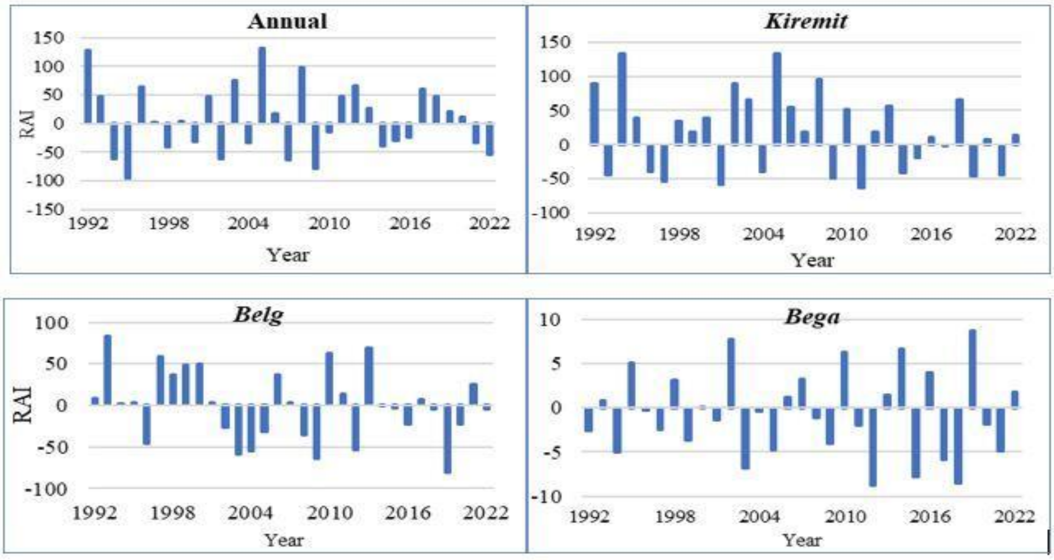


Figure 3.4 RAI in lowland AEZ

3.3.3 Temporal variability and trend of temperature across agroecological zones

Both minimum and maximum temperatures exhibited overall increasing tendencies across the watershed; however, the magnitude, direction, and statistical significance of these trends varied across seasons and agroecological zones. For minimum temperature, pronounced spatial heterogeneity was observed, particularly in the highland zone. As shown in Table 3.7a, the highlands exhibited a slight decline in annual mean minimum temperature ($Z = -0.05$, Sen's slope $= -0.01$°C year^{-1}). Seasonally, however, warming was observed during Kiremit ($Z = 0.24$, Sen's slope $= 0.01$°C year^{-1}) and Belg ($Z = 1.9$, Sen's slope $= 0.03$°C year^{-1}), while a slight cooling tendency occurred during the Bega season ($Z = -0.1$, Sen's slope $= -0.01$°C year^{-1}). In contrast, the midland and lowland zones showed more consistent increases in minimum temperature across both annual and seasonal scales, indicating a stronger and more uniform warming signal at lower elevations.

These patterns suggest that minimum temperature increase is more stable and spatially consistent in lower agroecological zones, while highland areas exhibit greater seasonal variability. Similar findings have been reported in Ethiopia, where widespread increases in minimum temperature have been documented across different agroecological contexts (Esayas et al., 2019; Nasir et al., 2025; Mohammed et al., 2025; Teyso & Anjulo, 2016), particularly in midland and lowland environments.

Maximum temperature also showed a generally coherent warming trend across all agroecological zones, although the magnitude and seasonal expression varied (Table 3.7b). In the highland zone, annual maximum temperature showed a slight increasing trend (Z = 0.04, Sen's slope = 0.01°C year^{-1}), driven mainly by significant warming during the Kiremit (Z = 8.8, Sen's slope = 0.01°C year^{-1}) and Belg seasons (Z = 5.3, Sen's slope = 0.02°C year^{-1}), while the Bega season trend was not statistically significant. In the midland zone, maximum temperature increased consistently across annual and seasonal scales, indicating sustained warming conditions. The lowland zone exhibited the strongest warming signal, particularly during the Bega season (Z = 2.3, Sen's slope = 0.03°C year^{-1}), reflecting intensified dry-season thermal stress.

Overall, the results indicate a clear intensification of thermal conditions across the watershed, with relatively stronger and more consistent warming in the midland and lowland zones compared to the highlands. This spatial gradient suggests increasing thermal stress in lower elevations, which may have important implications for crop water demand, evapotranspiration, and yield stability. Similar warming patterns have been reported in Ethiopia by Gashaw et al. (2023) and Zeleke et al. (2023), who documented consistent increases in both maximum and minimum temperatures across diverse agroecological settings.

Table 3. 7 Temperature trends in the Ayehu watershed across AEZs (1992–2022)

a. Minimum temperature

AEZs	Annual			*Kiremit* season			*Belg* season			*Bega* season		
	Mean	Z	S	Mean	Z	S	Mean	Z	S	Mean	Z	S
Highland	12.6	-0.05**	-0.01	11.2	0.24**	0.01	13.3	1.9**	0.03	10.4	-0.1***	-0.01
Midland	13.9	0.06***	0.01	13.0	0.4***	0.02	14.8	1.3***	0.02	12.7	2.2	0.02
Lowland	16.3	0.12	0.02	14.4	1.2***	0.03	17.1	0.14**	0.04	13.7	0.02**	0.01

b. Maximum temperature

AEZs	Annual			*Kiremit* season			*Belg* season			*Bega* season		
	Mean	Z	S	Mean	Z	S	Mean	Z	S	Mean	Z	S
Highland	26.4	0.04***	0.01	23.1	8.8***	0.01	28.6	5.3**	0.02	24.5	0.21	0.01
Midland	29.4	0.13**	0.01	25.5	0.3***	0.02	29.7	0.2**	0.03	26.6	0.14**	0.02
Lowland	33.9	0.19	0.02	28.4	0.14**	0.02	33.5	0.3***	0.03	28.6	2.3***	0.03

AEZs=Agroecological zones, Z = Mann Kendal test, S = Sen slope, ** and ** significant at 1% and 5%, respectively.

3.3.4 Spatial distribution of annual and seasonal rainfall

This section presents the results of GIS-based spatial interpolation analysis of annual and seasonal rainfall in the Ayehu Watershed. The findings reveal pronounced spatial and temporal heterogeneity in rainfall distribution, characterized by substantial variation in both magnitude and seasonal timing across the landscape. This climatic heterogeneity has important implications for agricultural production, underscoring the need for localized and context-specific adaptation strategies.

The highest annual rainfall was concentrated in the northern and northeastern highland areas, where more than 32% of the watershed received between 1,556 and 1,667 mm. Even higher rainfall amounts were observed in localized moisture-rich micro-regions of the northeastern highlands, with annual totals ranging from 1,668 to 1,779 mm (Fig. 3.6). These spatial patterns reflect the strong influence of topography on rainfall distribution, particularly elevation-driven orographic effects.

This spatial distribution is consistent with findings from other Ethiopian watersheds, where highland regions typically receive greater rainfall than lowland areas. Similar patterns have been reported by Adane & Asmerom (2025) in Wollo, Ayalew (2023) in the Hare catchment, Feke et al. (2021) in the Horro Guduru Wollega Zone, and Taye et al. (2019) in the Jema watershed, all of which highlight consistently higher rainfall in northern highland zones relative to southern lowlands.

Seasonally, rainfall exhibited a clear spatial gradient during both the Kiremit (main rainy) and Belg (short rainy) seasons. During the Kiremit season, the southern and southwestern lowland agroecological zones received relatively low rainfall (898–1,021 mm), whereas the northern and northeastern highlands recorded the highest amounts, reaching up to 1,517 mm (Fig. 3.5). The Belg season also contributed meaningfully to annual rainfall and played a critical role in supporting early planting and crop establishment, although its spatial distribution remained highly uneven across the watershed. In contrast, the Bega (dry) season was characterized by very limited and spatially uniform rainfall deficits across all agroecological zones, particularly in the midland and lowland areas.

Overall, the pronounced seasonal and spatial disparities in rainfall availability highlight the high climatic sensitivity of rainfed agriculture in the watershed. These conditions increase production risk and reinforce the importance of season-specific water management practices, including soil moisture conservation, supplemental irrigation, and adaptive cropping calendars.

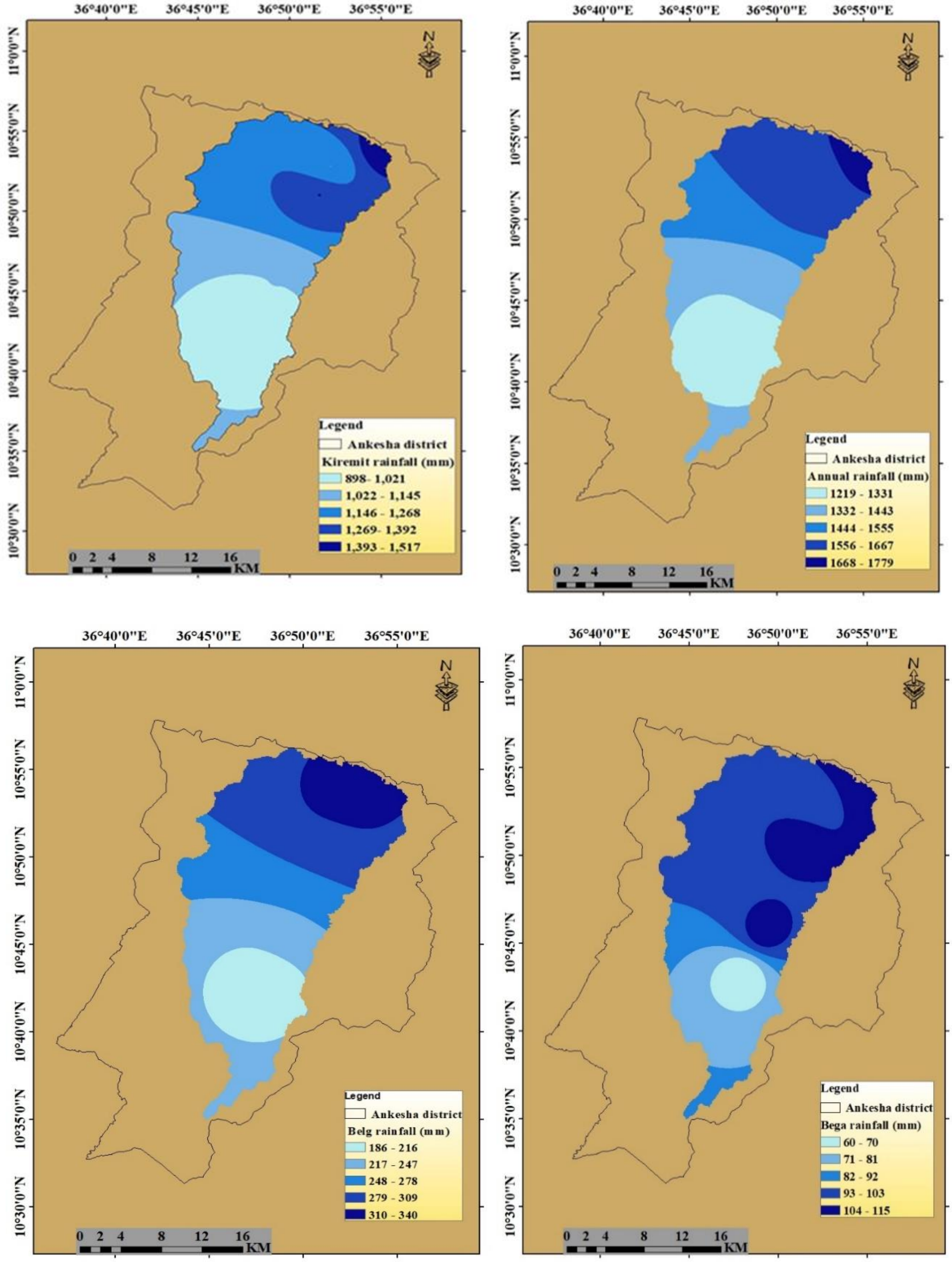


Figure 3.5 Spatial distribution of annual and seasonal rainfall in the Ayehu watershed *(1992–2022)*

3.3.5 Spatial distribution of minimum and maximum temperatures

Both minimum and maximum temperatures exhibited a clear inverse relationship with elevation, increasing progressively from the cooler, high-altitude northern and northwestern zones toward the warmer low-lying eastern and southeastern parts of the watershed. This elevation-dependent thermal gradient represents one of the dominant controls on the spatial climate structure of the watershed.

The spatial distribution of mean minimum temperature shows that the highest values (15.2–16.5°C) were concentrated in the southern and southwestern lowland areas, while substantially lower values (9.6–12.4°C) were observed in the northern highlands. A similar altitudinal pattern was evident for maximum temperature. The highest mean maximum temperatures (29.8–30.5°C) occurred in the southern and central-western lowlands, whereas cooler conditions prevailed in the higher northern and northeastern zones, where values declined to 25.2–27.5°C. Collectively, these results highlight the strong thermal contrast between lowland and highland environments, underscoring the dominant role of topography in shaping the watershed's thermal regime (Figure 3.6).

Such spatial thermal gradients are likely to influence key hydrological and agroecological processes, particularly evapotranspiration rates, soil moisture dynamics, and crop water demand. In this context, lower elevation zones are expected to experience higher evaporative demand and greater climatic stress on agricultural systems compared to cooler highland areas.

These elevation-driven temperature patterns are consistent with broader climatic characteristics observed across Ethiopia, where temperature generally increases from high-altitude northern regions toward lower southern and eastern lowlands. This inverse relationship between elevation and temperature has been widely documented and represents a fundamental feature of the country's climate system (Gedefaw, 2023; Hordofa et al., 2021; Mengistu et al., 2014; Tariku et al., 2021; Ware et al., 2023).

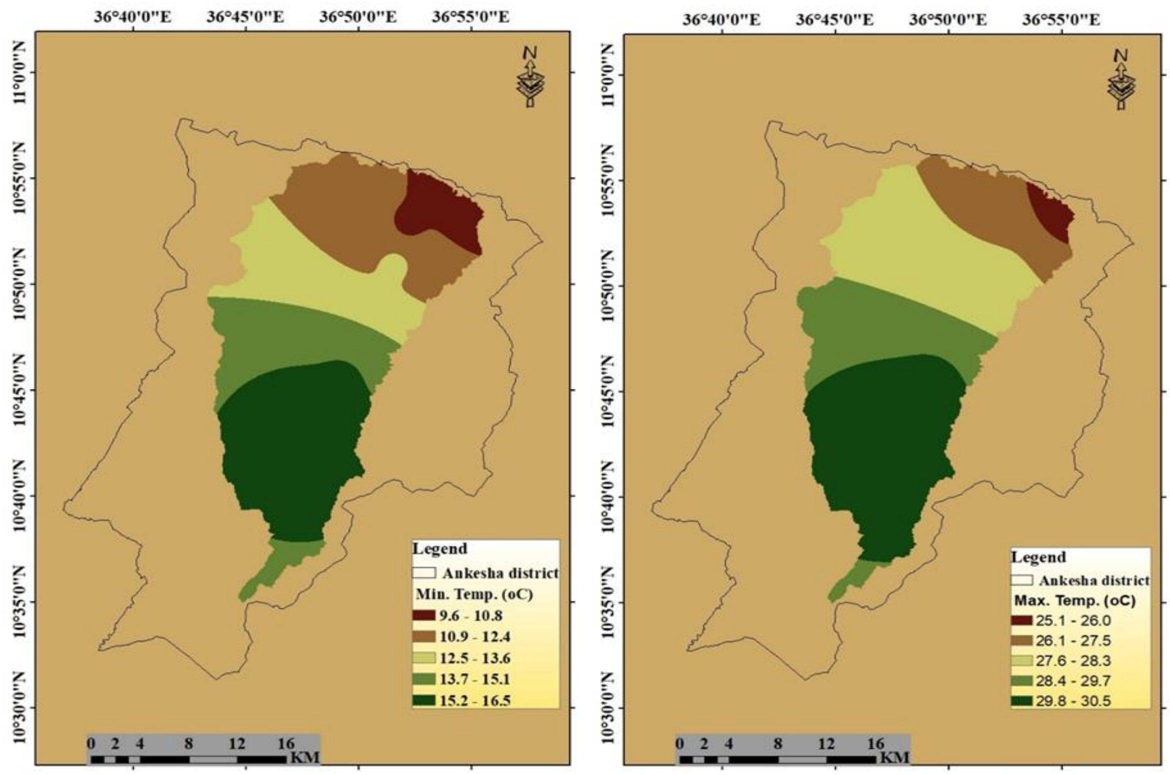


Figure 3.6 Spatial distribution of minimum and maximum temperatures in the Ayehu watershed (1992–2022)

3.3.6. Impacts of climate variability on crop yields across AEZs

Descriptive statistics of crop production

Table 3.8 presents the main crop yields, teff, maize, and wheat, in the agroecological zones (AEZs) of the Ayehu watershed, expressed as the mean total production in quintals over the cultivated area. The results show substantial variations that reflect both the diverse agricultural landscapes and the different potential and limitations of each zone. The midland zone had the highest teff production, with an average total yield of 58,924.35 quintals in the cultivated area. This could mean that the growing conditions were good or that the management practices were more intensive. In contrast, the lowland zone recorded the lowest mean total yield of 27,532.92 quintals, likely due to higher temperatures, lower soil fertility, and limited rainfall. Maize followed the reverse trend, doing best in the lowlands with a mean total yield of 754,962 quintals, while the highlands produced the least at 531,789.03 quintals, suggesting milder temperatures and other environmental restrictions. Wheat demonstrated relative adaptability across all zones, with the highlands leading with 219,754.63 quintals, followed by the lowlands with 182,048.42 quintals and the midlands with 164,714.90 quintals.

Table 3.8 Summary of major crop yields in AEZs

AEZs	Teff (*quintal*)		Maize (*quintal*)		Wheat (*quintal*)	
	Mean	SD	Mean	SD	Mean	SD
Highland	42583.02	15928.42	531789.03	385089.20	219754.63	74995.24
Midland	58924.35	8672.84	675427	186734.04	164714.90	41457.36
Lowland	27532.92	11387.31	754962	143575.16	182048.42	80533.32

Augmented Dickey–Fuller (ADF) unit root test

Table 3.9 presents the results of the Augmented Dickey–Fuller (ADF) unit root test for rainfall, minimum temperature (T-Min), maximum temperature (T-Max), and the yields of teff, maize, and wheat across the Highland, Midland, and Lowland agroecological zones (AEZs) of the Ayehu Watershed. The test was conducted to examine the stationarity properties and order of integration of the variables, which are prerequisites for appropriate time-series model specification, particularly the ARDL framework.

The results indicate mixed orders of integration across variables and agroecological zones. Minimum temperature (T-Min) is stationary at level [I (0)] in the Highland (t-statistic = −5.02, p-value = 0.001) and Midland (t-statistic = −2.52, p-value = 0.002) zones, while it becomes stationary after first differencing [I (1)] in the Lowland zone. In contrast, maximum temperature (T-Max) is non-stationary at level but achieves stationarity after first differencing [I (1)] across all agroecological zones, indicating a more persistent stochastic trend in maximum temperature dynamics.

Rainfall exhibits greater spatial heterogeneity in its time-series properties. It is stationary at level [I (0)] in the Highland zone (t-statistic = −2.08, p-value = 0.002), whereas it remains non-stationary at level in both the Midland and Lowland zones. After first differencing, rainfall becomes stationary in the Lowland zone [I (1)], but remains non-stationary in the Midland zone, suggesting more complex dynamic behavior in this agroecological setting.

Overall, the results confirm that the variables are integrated of order I (0) and I (1), satisfying the key precondition for the application of the ARDL modeling approach. The mixed order of integration also reflects the heterogeneous climatic dynamics across agroecological zones of the watershed. These findings provide a statistically valid foundation for estimating both short-run and long-run relationships between climate variables and crop yields in subsequent analyses.

Table 3. 9 Trends of the Augmented Dicky-Fuller Unit Root Test (ADF).

AEZs	Variables	ADF at *I* (*0*)		ADF at *I* (*1*)	
		T-stat	P-value	T-stat	P-value
Highland	Teff	-2.71	0.035	-3.62	0.005
	Maize	-3.16	0.002	-3.49	0.002
	Wheat	2.27	0.041	-2.86	0.007
	Tmin	-5.02	0.001	-2.24	0.081
	Tmax	-4.31	0.061	-3.42	0.032
	Rainfall	-2.08	0.002	-2.76	0.076
Midland	Teff	-2.41	0.004	-3.12	0.27
	Maize	-2.81	0.006	-4.76	0.004
	Wheat	-2.87	0.432	-2.95	0.031
	Tmin	-2.52	0.002	-5.16	0.007
	Tmax	-3.44	0.253	-5.09	0.003
	Rainfall	-2.73	0.052	-2.69	0.348
Lowland	Teff	-4.24	0.003	-2.78	0.572
	Maize	-2.36	0.001	-2.66	0.004
	Wheat	-2.82	0.421	-2.93	0.002
	Tmin	-0.09	0.532	0.56	0.003
	Tmax	0.83	0.064	-3.62	0.001
	Rainfall	1.52	0.237	-0.56	0.001

ARDL Model Specification and Diagnostic Assessment

To examine the short- and long-run impacts of climate variability on crop production, the Autoregressive Distributed Lag (ARDL) modelling framework was employed because it accommodates variables integrated of order zero [I (0)] and order one [I (1)] and allows simultaneous estimation of short-run and long-run relationships. Prior to estimation, the optimal lag structure for each agroecological zone was selected using standard information criteria, particularly the Akaike Information Criterion (AIC), to ensure model parsimony and avoid over-parameterization. The general ARDL specification incorporated aggregated crop production as the dependent variable and rainfall, minimum temperature (Tmin), and maximum temperature (Tmax) as explanatory variables. Following model estimation, the existence of a long-run equilibrium relationship among the variables was evaluated using the ARDL bounds testing approach.

A comprehensive set of diagnostic tests (Table 3.10) confirms the reliability and suitability of the estimated ARDL models. The serial correlation test (F-statistic = 2.178, p = 0.422) indicates that the residuals are independent and free from autocorrelation. The heteroscedasticity test (F-statistic = 26.72, p = 0.526) confirms constant error variance, suggesting that coefficient estimates are efficient and unbiased. Similarly, the Ramsey RESET functional form test (F-statistic = 0.932, p = 0.731) indicates that the model is correctly specified and that no major functional form misspecification exists. The normality test (F-statistic = 0.59, p = 0.638) further confirms that the residuals are approximately normally distributed, supporting valid statistical inference. Collectively, these diagnostic results demonstrate that the estimated ARDL models satisfy the principal assumptions required for reliable interpretation.

Table 3.10 Diagnostic tests of the ARDL model

Diagnostic test	Chi^2/F-statistics	P > | t |
Serial correlation	2.178	0.422
Functional form	0.932	0.731
Heteroscedasticty	26.72	0.526
Normality	0.59	0.638

ARDL Bounds Cointegration Test

The ARDL bounds test results presented in Table 3.11 provide evidence of a long-run equilibrium relationship between climate variables and aggregated crop production across the agroecological zones. The calculated F-statistics for the highland (5.964), midland (3.872), and lowland (4.546) zones exceed the corresponding upper critical bounds at conventional significance levels, indicating rejection of the null hypothesis of no cointegration. This confirms the existence of a stable long-run relationship between crop production and climatic variables, thereby justifying the estimation of both long-run coefficients and the associated error-correction models.

The explanatory power of the models varies across agroecological zones. Climatic variables explain a substantial proportion of crop production variability in the highland ($R^2 = 0.82$; adjusted $R^2 = 0.80$) and lowland zones ($R^2 = 0.79$; adjusted $R^2 = 0.77$), indicating that long-term fluctuations in rainfall and temperature play an important role in shaping agricultural productivity in these environments. In contrast, the relatively lower explanatory power observed in the midland zone ($R^2 = 0.64$; adjusted $R^2 = 0.63$; F = 3.872) suggests that additional non-climatic factors contribute considerably to production outcomes.

Nevertheless, these findings should be interpreted with caution because crop production is influenced by a wide range of socioeconomic, institutional, and agronomic factors that were not explicitly included in the model. Variables such as fertilizer application, improved seed adoption, irrigation access, pest and disease incidence, soil fertility conditions, market access, agricultural extension services, and farm management practices may also affect crop yields. Excluding such variables may introduce omitted-variable bias and partially explain the unexplained variation in crop production, particularly in the midland agroecological zone.

Furthermore, although climatic variables are generally treated as exogenous in agricultural production studies, potential endogeneity concerns cannot be entirely ruled out. Climate–yield systems may involve indirect feedback mechanisms whereby crop performance influences subsequent land-management decisions, investment in irrigation infrastructure, input utilization, and adaptation strategies. Such interactions may create simultaneity effects that are not fully captured within the present ARDL framework. Consequently, the estimated coefficients should be interpreted as statistical associations rather than definitive causal effects. Future studies could address these limitations through the inclusion of additional control variables, instrumental-variable approaches, panel data techniques, or structural modelling frameworks that explicitly account for potential endogeneity and feedback relationships.

Table 3.11 ARDL long-run bound test

Agroecological zones	F-Statistics	R^2	Adjusted R^2
Highland	5.964	0.82	0.80
Midland	3.872	0.64	0.63
Lowland	4.546	0.79	0.77

Short- and long-term impacts of climate factors on crop yields

Taking into account both short-run and long-run dynamics, Table 3.12 presents the ARDL estimates of the relationships between rainfall, minimum temperature (Tmin), maximum temperature (Tmax), and aggregated crop production (teff, maize, and wheat combined) across the highland, midland, and lowland agroecological zones.

Long-run relationships

In the long run, minimum temperature (Tmin) exhibits a positive and statistically significant association with aggregated crop production across all agroecological zones: highland (1.465, t = 5.342), midland (1.527, t = 6.021), and lowland (1.728, t = 5.892). The magnitude of the effect is strongest in the lowland zone, suggesting that warmer minimum temperatures are more beneficial for crop production in lower elevations, possibly through reduced cold stress and improved growing conditions. Similar positive temperature–agriculture relationships have been documented by Abbas et al. (2024) and Jing et al. (2016).

By contrast, maximum temperature (Tmax) shows no statistically significant long-run relationship with aggregated crop production in any agroecological zone (highland: 0.235, $t = 0.493$; midland: 0.192, $t = 0.426$; lowland: 0.210, $t = 0.273$), indicating that long-term variations in daytime temperature do not exert a stable influence on crop output within the study period. This finding aligns with previous studies reporting weak or insignificant long-run effects of average temperature indicators on agricultural production (Asfew & Bedemo, 2022; Chandio et al., 2020; Khan et al., 2023; Sultan & Gaetani, 2016).

Rainfall, however, demonstrates a statistically significant negative long-run association with aggregated crop production across all agroecological zones, with the strongest effect observed in the midland zone (−1.462, $t = -4.824$), followed by the lowland (−0.643, $t = -2.617$) and highland zones (−0.597, $t = -2.785$). This indicates that, over the long run, higher rainfall is associated with lower crop production in the study area. Similar negative rainfall–production relationships have been reported by Asfew and Bedemo (2022), Kumar et al. (2018), Sahoo and Moharaj (2024), and Warsame et al. (2021), although contrasting evidence also exists, highlighting the context-dependent nature of rainfall impacts (Dumrul & Kilicaslan, 2017; Kumar et al., 2021; Li et al., 2023; Pickson et al., 2020; Singh et al., 2017; Singh et al., 2021).

Short-run dynamics

In the short run, changes in minimum temperature ($\Delta \ln Tmin$) are positively and significantly associated with aggregated crop production across all agroecological zones (highland: 0.579, $t = 2.541$; midland: 0.563, $t = 2.871$; lowland: 0.536, $t = 2.617$). Similarly, short-term changes in maximum temperature ($\Delta \ln Tmax$) also show positive and significant effects on crop production in the highland (1.302, $t = 2.672$), midland (1.572, $t = 2.583$), and lowland zones (1.382, $t = 2.479$). These results suggest that short-term temperature fluctuations are associated with corresponding short-run adjustments in crop output.

In contrast, short-run changes in rainfall ($\Delta \ln Rainfall$) are negatively and significantly associated with aggregated crop production across all agroecological zones (highland: −0.762, $t = -2.361$; midland: −0.883, $t = -4.632$; lowland: −0.921, $t = -4.532$), indicating that rainfall variability exerts immediate adverse effects on agricultural production.

Overall, the findings highlight clear agroecological heterogeneity in climate–crop relationships across the Ayehu Watershed. Minimum temperature shows a consistently positive and statistically significant association with crop production in both the short and long run, whereas maximum temperature influences production only in the short term. Rainfall, in contrast, exhibits a persistent negative association with crop production across both time horizons.

Although these results provide important insights into climate–crop dynamics, they should be interpreted as conditional statistical relationships rather than strict causal effects. Crop production is also influenced by agronomic practices, soil fertility, input use, and institutional and socioeconomic factors that were not explicitly included in the model. In addition, potential endogeneity between climatic conditions and farm management responses may affect coefficient estimates. Accordingly, the findings are best interpreted as robust empirical associations that characterize climate sensitivity of agricultural production in the study area.

Table 3.12 ARDL long-run and short-run results

Variable	Coeff.	T-stat	Prob	Variable	Coeff.	T-stat	Prob
Long run				Short run			
Highland				Highland			
Teff (t-1)	-0.623***	-9.142	0.000	ΔlnTeff	-0.321	-3.692	0.621
Maize(t-1)	0.987	5.964	0.000	ΔlnMaize	0.741**	4.729	0.030
Wheat(t-1)	-2.683***	-5.192	0.000	ΔlnWheat	-1.037*	-4.620	0.062
Tmin(t-1)	1.465**	5.342	0.000	ΔlnTmin	0.579***	2.541	0.000
Tmax(t-1)	0.235	0.493	0.762	ΔlnTmax	1.302**	2.672	0.042
Rainfall(t-1)	-0.597***	-2.785	0.000	ΔlnRainfall	-0.762***	-2.361	0.001
Midland				Midland			
Teff(t-1)	-0.784***	-8.211	0.000	ΔlnTeff	-0.463**	-4.241	0.028
Maize(t-1)	-2.567***	-6.204	0.000	ΔlnMaize	-1.421***	-4.982	0.000
Wheat(t-1)	2.121***	5.782	0.000	ΔlnWheat	0.872***	5.241	0.000
Tmin(t-1)	1.527***	6.021	0.003	ΔlnTmin	0.563**	2.871	0.021
Tmax(t-1)	0.192	0.426	0.512	ΔlnTmax	1.572**	2.583	0.030
Rainfall(t-1)	-1.462***	-4.824	0.000	ΔlnRainfall	-0.883***	-4.632	0.002
Lowland				Lowland			
Teff(t-1)	-0.921	-3.215	0.000	ΔlnTeff	-0.493**	-2.933	0.023
Maize(t-1)	-3.240***	-4.132	0.000	ΔlnMaize	-1.457**	-4.521	0.003
Wheat(t-1)	1.273***	5.764	0.000	ΔlnWheat	0.932***	5.314	0.000
Tmin(t-1)	1.728***	5.892	0.000	ΔlnTmin	0.536**	2.617	0.004
Tmax(t-1)	0.210	0.273	0.217	ΔlnTmax	1.382***	2.479	0.000
Rainfall(t-1)	-0.643***	-2.617	0.000	ΔlnRainfall	-0.921***	-4.532	0.001

Note: ***, ** represents the 1 % and 5 % significance level, respectively.

3.4. Conclusions and policy recommendations

The comprehensive analysis of climatic records reveals a progressively heterogeneous and climate-stressed agroecological system characterized by a significant warming trend and pronounced spatial and temporal variability in rainfall. The watershed is dominated by a bimodal rainfall regime, with the Kiremit season contributing the largest share of annual precipitation, while Belg and Bega rainfall have generally declined, particularly in the midland and lowland agroecological zones. Over time, rainfall has become increasingly variable and concentrated within shorter periods, indicating a shift toward a more erratic and uneven hydrological regime with heightened intra- and inter-seasonal instability.

Clear agroecological differences are evident in rainfall behavior. The highland zone exhibits relatively more stable (stationary) rainfall characteristics, whereas the midland and lowland zones show stronger non-stationarity and higher variability, reflecting greater climatic unpredictability in lower elevations. In contrast, temperature trends are consistently positive, statistically significant, and spatially pervasive across all agroecological zones and seasons, with stronger warming signals in the midland and lowland zones. This indicates a widespread intensification of thermal stress across the watershed, largely independent of elevation differences.

Overall, the findings demonstrate that rainfall variability and rising temperature constitute the dominant and interacting climatic drivers shaping recent hydroclimatic conditions in the watershed. The ARDL-based climate–yield analysis further shows that crop production responds asymmetrically to climatic conditions over time, with short-term temperature increases associated with productivity gains under certain conditions, while rainfall variability and extremes consistently reduce crop yields across agroecological zones. Long-run results similarly indicate persistent yield sensitivity to rainfall dynamics, reinforcing the role of moisture stress and excess rainfall as key production constraints.

CHAPTER FOUR

SMALLHOLDER FARMERS' PERCEPTIONS OF CLIMATE VARIABILITY AND ITS RISKS ACROSS AGROECOLOGICAL ZONES IN THE AYEHU WATERSHED, UPPER BLUE NILE BASIN, ETHIOPIA

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Abstract

Understanding how farmers perceive climate variability is crucial for designing adaptation strategies that are responsive to local environmental conditions and livelihood realities. This study examined smallholder farmers' perceptions of climate variability and associated risks across agroecological zones in the Ayehu Watershed, Upper Blue Nile Basin, Ethiopia. A survey of 338 randomly selected farm households was conducted, complemented by analysis of historical rainfall and temperature records to assess observed climatic trends and their relationship with farmers' perceptions. Meteorological analysis revealed a non-significant decline in annual rainfall (-0.53 mm year^{-1}), alongside a significant increase in Kiremit season rainfall (7.48 mm year^{-1}). Both annual minimum and maximum temperatures increased significantly at rates of 0.03°C year^{-1} and 0.02°C year^{-1}, respectively, indicating a clear warming trend despite mixed rainfall signals. Farmers broadly perceived increasing temperatures and declining rainfall, although the intensity and consistency of these perceptions varied significantly across agroecological zones ($P < 0.01$). Risk perception analysis further showed that crop pests and diseases, declining yields, drought, and water scarcity were the most frequently reported climate-related risks, with notable spatial variation across zones. Econometric results indicate that access to climate information, farming experience, and extension services significantly shape farmers' perceptions of climate variability. The findings demonstrate that climate perceptions are not uniform but are shaped by both biophysical exposure and socio-institutional conditions. This misalignment between observed climate trends and perceived variability across agroecological zones highlights the importance of strengthening localized climate information systems and extension services. Targeted, zone-specific adaptation strategies are therefore essential to improve farmers' awareness, risk response, and resilience under increasing climate variability.

Keywords: Agroecological zones; Binary logit model; Climate variability; Perception; Smallholder farmers

4.1 Introduction

Climate variability has emerged as a major challenge to sustainable development, affecting environmental systems, economic activities, and human well-being across multiple scales (Getahun et al., 2021; IPCC, 2018). It is primarily driven by increasing greenhouse gas concentrations from anthropogenic activities such as fossil fuel combustion and land-use change, which have altered global temperature and precipitation regimes (Kumar et al., 2018; Tofu & Mengistu, 2023). Given that temperature and precipitation are key determinants of ecosystem functioning and agricultural productivity, their variability has profound implications for climate-sensitive livelihoods, particularly in rainfed agricultural systems where production is highly dependent on seasonal rainfall patterns (Addis & Abirdew, 2021; Alemayehu et al., 2023; Ali & Kamraju, 2023; Malhi et al., 2020; Maxwell et al., 2019).

The impacts of climate variability are more pronounced in developing regions due to limited adaptive capacity, weak institutional support, and constrained access to climate services (Asfaw et al., 2021; Likinaw et al., 2023). In Sub-Saharan Africa, agriculture remains highly vulnerable because of its reliance on rainfall, limited irrigation infrastructure, and low adoption of climate-resilient technologies (Adeniyi, 2016; Gitz et al., 2016; Tessema & Simane, 2021; Kidane et al., 2022). Ethiopia reflects these vulnerabilities, where recurrent droughts, floods, erratic rainfall, and rising temperatures continue to threaten agricultural production and rural livelihoods (Alemu et al., 2019; Gebru et al., 2020; Aboye et al., 2023; Tessema & Simane, 2019).

Within this context, farmers' perceptions of climate variability play a central role in shaping adaptation decisions. Perception refers to how individuals interpret climatic changes based on lived experience, knowledge systems, and environmental interaction (Mairura et al., 2021; Muneer et al., 2024). These perceptions influence risk assessment, resource allocation, and household-level adaptation strategies (Abbas et al., 2022; Sertse et al., 2021). However, misperceptions or incomplete interpretation of climatic signals may lead to delayed or maladaptive responses (Singh, 2020; Wodaje et al., 2020). Therefore, understanding perception patterns is essential for linking observed climatic changes with behavioral adaptation processes (Bagagnan et al., 2019; Hassan & Knight, 2023; Mihiretu et al., 2020).

Although empirical studies in Ethiopia have examined farmers' perceptions of climate variability (Belay et al., 2017; Dendir & Simane, 2019; Sertse et al., 2021), evidence remains limited regarding systematic comparisons across agroecological zones. Agroecological zones differ in altitude, rainfall, temperature, soil characteristics, and livelihood systems, all of which shape both exposure to climate variability and perception of associated risks (Dendir & Simane, 2019; Tessema & Simane, 2019; Howe et al., 2019). However, most existing studies rely on aggregated analyses that mask intra-watershed heterogeneity, particularly in environments where climatic and socioeconomic conditions vary sharply over short spatial distances (Alemayehu et al., 2023; Gashure & Wana, 2023). This study addresses this gap by providing a comparative, agroecology-based assessment of climate variability perceptions and risk prioritization in the Ayehu watershed.

Methodologically, the study employs the Severity Index (SI) and the Standardized Climate-Related Risk Perception Index (SCRRPI) to quantify and compare perceived climate risks across agroecological zones. The SI captures the relative severity of climate-related problems as perceived by farmers, while the SCRRPI enables standardized comparison of perception intensity across spatial contexts. These indices provide a more rigorous and comparable alternative to conventional descriptive ranking methods. In addition, econometric analysis is used to identify the determinants of perception differences at the household level.

Farmers' perceptions are further shaped by socioeconomic, institutional, and environmental factors such as education, income, farm size, access to climate information, and extension services (Esayas et al., 2019; Mairura et al., 2021; Tesfahunegn & Gebru, 2021; Foguesatto & Machado, 2021). Prior experience with climate extremes also plays a critical role in shaping how climatic signals are interpreted (Belay et al., 2022; Howe et al., 2019). Given the spatial variability of these factors, localized analysis is essential for understanding perception formation and designing targeted adaptation interventions (Alemayehu et al., 2022a).

Conceptually, this study integrates observed climate variability, farmers' perceptions, perceived climate risks, and the socioeconomic determinants of perception. This framework allows for examination of how objective climatic changes are interpreted through subjective and contextual lenses, ultimately shaping risk awareness and adaptation behavior at the farm level.

Accordingly, the objectives of this study are to: (i) assess farmers' perceptions of temperature and rainfall variability and associated climate risks across agroecological zones, and (ii) identify the key socioeconomic and institutional factors influencing these perceptions.

4.2. Research Methods

4.2.1. Methods of data analysis

4.2.1.1. Trend analysis

In this study, trends in temperature and rainfall were analyzed using the non-parametric Mann–Kendall (MK) test, implemented in R Studio. The Mann–Kendall test is widely used for detecting monotonic trends in hydroclimatic time series because it does not assume a specific data distribution. However, it is not independent of sample size; rather, its statistical power and sensitivity increase with longer time series. The test evaluates whether there is a statistically significant upward or downward trend based on the relative ordering of data values in the series. The Mann–Kendall test statistic (S) is computed as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \qquad (1)$$

where x_j and x_i are the sequential data values, n is the data duration of the time series, and

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1 \ldots\ldots\ldots x_j > x_i \\ 0 \ldots\ldots\ldots\ldots x_j = x_i \\ -1 \ldots\ldots\ldots\ x_j < x_i \end{cases} \qquad (2)$$

A positive Z-value indicates an increasing trend, while a negative Z-value indicates a decreasing trend. The statistical significance of the trend was evaluated at the 5% significance level ($\alpha = 0.05$). However, before applying the Mann–Kendall test, the time series were examined for potential serial autocorrelation, since the presence of autocorrelation can inflate the significance of trends. Where necessary, pre-whitening considerations were applied to reduce the influence of serial dependence and improve the reliability of trend detection (Tofu et al., 2022; Zeleke et al., 2023).

$$\mathrm{Z} = \begin{cases} \frac{S-1}{\sqrt{var\ (s)}}\ if\ s > 0, Z = 0\ if\ S = 0 \\ \frac{S+1}{\sqrt{var\ (s)}}\ \ if\ S < 0 \end{cases} \qquad (3)$$

Missing or incomplete meteorological observations were identified during data preprocessing. Short gaps were handled using interpolation based on neighboring observations, while years with substantial missing records were excluded from the trend analysis to ensure data consistency and reliability.

Sen’s slope estimator

Sen’s slope estimator, a robust nonparametric method, assesses the magnitude of trends within a time series by calculating the slope of the trend (Da Silva et al., 2015; Tofu & Mengistu, 2023). The proposed method is a nonparametric method to evaluate trend strength in sequential data and is characterized by the following:

$$\beta = \text{median}\left(\frac{X_j - X_k}{j-k}\right),\ j > k \tag{4}$$

where x_j and x_k represent the data values at times j and k, correspondingly. β represents Sen's slope estimate. A positive value of β (>0) shows an upward trend in the sequence of time data, whereas a negative value shows a downward trend in the data series over time.

Overall, the combination of the Mann–Kendall test and Sen’s slope estimator allowed for a robust assessment of both the direction and magnitude of climate trends in the study area while accounting for key data quality considerations such as autocorrelation and missing observations.

4.2.1.2. Variability analysis

Variability was assessed using the coefficient of variation (CV), a relative statistical measure that expresses the ratio of the standard deviation to the mean. As an indicator of dispersion, the CV provides a standardized means of comparing the degree of variability across different datasets. In this study, the CV was applied to evaluate the variability of both annual and seasonal rainfall and temperature.

$$CV = \frac{\sigma}{X} \times 100 \tag{5}$$

Where, x represents the average rainfall, σ denotes the standard deviation, and CV refers to the coefficient of variation. The coefficient of variation can be interpreted in the following way: values <20% low variability, between 20 to 30% moderate variability, and >30% high variability.

Calculation of the Severity Index (SI)

The Severity Index (SI) was used to quantify farmers’ perceived intensity of climate variability, particularly changes in temperature and rainfall. It provides a structured approach for transforming Likert-scale responses into a single composite measure that reflects the perceived severity of climate-related changes at the household level. In this study, the SI was constructed following the methodology of Jawo et al. (2023) and Tofu and Mengistu (2023).

The index is based on a five-point Likert scale, where numerical weights are assigned according to respondents' level of agreement. This weighting scheme follows the standard ordinal structure of Likert scaling; whereby higher values represent stronger perceptions of climate variability severity:

This coding framework enables the aggregation of individual responses into a composite severity score, with higher SI values indicating stronger perceptions of climate variability. Since the scale ranges from 0 to 4, the resulting SI values are interpreted relative to these theoretical minimum and maximum limits. Accordingly, SI values approaching 0 indicate very low perceived severity, values around the midpoint (2) reflect moderate perceived severity, and values approaching 4 indicate very high perceived severity. The classification thresholds therefore derive directly from the underlying Likert-scale structure and provide a consistent basis for comparing the intensity of perceived climate variability across indicators and respondents (Jawo et al., 2023; Tofu & Mengistu, 2023).

$$\text{Severity Index (SI)} = \left(\frac{\sum_{i=0}^{4} a_i x_i}{\sum_{i=0}^{4} x_i}\right)(100) \tag{6}$$

where a_i is an index representing a category, a constant indicating the weight assigned to the class, and xi represents the frequency of responses. Moreover, i = 0, 1, 2, 3, 4 and x_0, x_1, x_2, x_3, and x_4 are the response frequencies corresponding to $a_0 = 0$, $a_1 = 1$, $a_2 = 2$, $a_3 = 3$, and $a_4 = 4$, respectively. The rating categories were as follows: a_0 = Strongly Disagree $0.0 < SI < 12.5$; a_1 = Disagree $12.5 < SI < 37.5$; a_2 = Neutral $37.5 < SI < 62.5$; a_3 = Agree $62.5 < SI < 87.5$; a_4 = Strongly Agree $87.5 < SI < 100$.

In this Severity Index (SI) calculation, the weight assigned to each class (represented by a_i) is based on the level of agreement indicated by respondents. The index assigns increasing values to each level of agreement, reflecting an escalating degree of perceived severity or agreement with the statement.

Climate-Related Risk Perception Index (CRRPI)

To assess smallholder farmers' perceptions of climate-related risks across the highland, midland, and lowland agroecological zones, a Climate-Related Risk Perception Score

(CRRPS) and a standardized Climate-Related Risk Perception Index (CRRPI) were computed. These measures quantify the extent to which farmers perceive climate variability as a threat to agricultural production and livelihoods based on their experiences and observations. The approach was adapted from established methodologies developed by Likinaw et al. (2023) and Mamun et al. (2021).

The Climate-Related Risk Perception Score (CRRPS) was calculated using a five-point ordinal scale that captures the intensity of perceived climate-related risks. Respondents rated each climate-related statement according to their perceived level of risk, and weighted scores were assigned as follows:

$$CRRPS = CRRPn \times 0 + CRRPvl \times 1 + CRRPl \times 2 + CRRPh \times 3 + CRRPvh \times 4,$$

Where:

- $CRRPn$ = the count of farm households with no perception;
- $CRRPvl$ = the count of farm households with very low perception;
- $CRRPl$ = the count of farm households with low perception;
- $CRRPh$ = the count of farm households with high perception;
- $CRRPvh$ = the count of farm households with very high perception of risk.

Because the study included 120 households in the highland, 118 in the midland, and 100 in the lowland agroecological zones, the maximum attainable CRRPS differed among zones (480, 472, and 400, respectively), while the minimum score was zero in all cases. To enable meaningful comparisons across agroecological zones with different sample sizes, the CRRPS values were standardized into a Climate-Related Risk Perception Index (CRRPI), expressed as a percentage of the maximum attainable score:

$$Standardized\ Climate\ Related\ Risk\ Perception\ Index\ (SCRRPI) = (Total\ CRRPS\ value)/\ (Respective\ Highest\ CRRPS\ value) * 100 \quad (7)$$

The SCRRPI ranges from 0 to 100, where higher values indicate stronger perceived climate-related risks and lower values indicate weaker perceptions of risk. This standardization ensures comparability of climate risk perceptions across agroecological zones (Ahmed et al., 2019; Likinaw et al., 2023).

To obtain an overall measure of perceived climate-related risks, a composite CRRPI was calculated by averaging the standardized indices of all identified climate risks:

$$Overall\ CRRPI = \frac{\sum (CRRPI_{risk1} + CRRPI_{risk2} + CRRPI_{risk3} \cdots + CRRPI_{riskn})}{N} \quad (8)$$

Where; $CRRPI_{risk1}$, $CRRPI_{risk2}$, $CRRPI_{risk3}$,…$CRRPI_n$ are the CRRPI values calculated for each climate risk and N is the number of different climate risks. This process provides a general measure of farmers' perceptions of climate risks across all identified risks in the study area, allowing for a comprehensive understanding of the overall climate risk perception.

Descriptive statistical techniques, including frequencies, percentages, means, and standard deviations, were used to summarize the socioeconomic and demographic characteristics of respondents. To examine differences in climate-related risk perceptions among agroecological zones, a one-way analysis of variance (ANOVA) was employed. The test assessed whether mean perception scores differed significantly across the highland, midland, and lowland zones. Although responses were initially collected using a five-point Likert scale, the aggregated perception scores were treated as continuous variables for inferential analysis, following established practice in social science research (Asare & Botchway, 2019).

Binary logistic regression model

A binary logistic regression model was employed to identify the factors influencing farm households' perception of temperature and rainfall variability. In this study, the dependent variable captured the existence of climate variability perception rather than its intensity. Accordingly, households that reported perceiving changes in temperature and rainfall patterns were coded as 1 (perceivers), whereas those who did not perceive such changes were coded as 0 (non-perceivers). This binary specification enabled the analysis of factors associated with the likelihood that a household recognizes climate variability based on its observations and experiences (Tofu & Mengistu, 2023).

The logistic regression function estimates the probability of the outcome as a function of explanatory variables using a logit transformation, expressed as $\text{logit}(p) = \ln[p/(1-p)] = \beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_kX_k$, where *p* represents the probability of perception, β_0 is the intercept, $\beta_1 \ldots \beta_k$ are the estimated coefficients, and $X_1 \ldots X_k$ denote the predictor variables (Kifle et al., 2022). The estimated coefficients were interpreted using odds ratios, obtained by exponentiating β, which reflect the change in the likelihood of perception associated with a one-unit increase in the predictor.

Prior to model estimation, diagnostic tests were conducted to verify the underlying assumptions of the binary logistic regression model. Multicollinearity among explanatory variables was assessed using Variance Inflation Factors (VIF) for continuous variables and Contingency Coefficients (CC) for categorical variables. The linearity of the logit was examined for continuous predictors, and the independence of observations was ensured through the survey design. Model adequacy was evaluated using the likelihood ratio chi-square statistic, while explanatory power was assessed using Cox and Snell and Nagelkerke pseudo-(R^2) measures. In addition, model goodness-of-fit was evaluated using the Hosmer–Lemeshow test, and predictive performance was assessed based on the model's classification accuracy. These diagnostic procedures confirmed the reliability and robustness of the estimated model.

The model is specified as follows:

$$\ln\left[\frac{P}{1-P}\right] = \beta 0 + \beta_1 X_1 + \beta_2 X_2 \ + \beta_3 X_3 \ \ldots + \ \beta_k X_k \qquad (9)$$

Explanatory variables examined in the study

The selection of independent variables was guided by theoretical foundations from the literature, expert consultations, and the lived experiences of local farmers, ensuring both conceptual rigor and contextual relevance. Accordingly, variables such as sex, age, farm size, agroecological setting, farming experience, education, access to extension services, access to climate information, and irrigation use were included, as they are widely recognized as key determinants of farmers' perceptions and responses to climate variability.

This specification is consistent with previous studies indicating that socio-demographic, socioeconomic, biophysical, and institutional factors, including household characteristics, landholding size, market access, off-farm income opportunities, credit access, extension services, and climate information, significantly influence climate change perceptions and adaptation decisions (Cherinet & Mekonnen, 2019; Ali & Rose, 2021; Asrat & Simane, 2018; Jawo et al., 2023). In addition, agroecological conditions have been shown to play a critical role in shaping farmers' perceptions of temperature and rainfall variability (Deressa et al., 2011; Esayas et al., 2019).

In this study, farmers' climate perception was specified as the dependent variable and coded as a binary outcome (1 = perceives climate variability; 0 = does not perceive climate variability) following Awoke & Agitew (2022). The explanatory variables were then modeled to explain variations in perception using a binary logit framework, consistent with Manh & Ahmad (2021).

Careful attention was given to the treatment of categorical variables. Agroecological zone was included as a nominal categorical variable and represented using dummy variables, with one zone serving as the reference category. Education level was treated as an ordinal categorical variable, reflecting increasing levels of educational attainment from illiteracy to secondary education and above. This specification ensures that the model appropriately captures differences in perception across agroecological and educational groups without imposing artificial numerical structure on inherently categorical variables.

Table 4.1 Description of predictor variables and their hypothesis

Explanatory variables	Description and measurement	Variable type	Sign	Mean	SD
Age	Age of household heads (years)	Continuous	+	49.21	13.69
Sex	1=male, 0=female	Dummy	±	0.86	0.54
Education	1=can't read & write, 2=read & write, 3= primary education, 4=secondary education	Categorical	+	2.38	1.05
Extension service	1=has access, 0=has no access	Dummy	+	0.52	0.47
Weather information	1=has access, 0=has no access	Dummy	+	0.44	0.49
Market information	1=has access, 0=has no access	Dummy	+	0.57	0.46
Agroecology	1=highland, 2=midland, 3=lowland	Categorical	±	1.94	0.80
Farming experience	Total farm experience of households (years)	Continuous	+	22.52	12.39
Off-farm activity	1=participated in off-farm activities 0=not participate in off-farm activities	Dummy	_	0.59	0.48
Farm size	Size of farm land (hectare)	Continuous	±	1.25	0.35
Access to credit	1= has access, 0=has no access	Dummy	±	0.62	0.50
Irrigation use	1=irrigation users, 0=non-users	Dummy	_	0.52	0.40

SD = Standard deviation

4.3. Results and Discussion

4.3.1. Socio-demographic characteristics of the respondents

Table 4.2 presented a summary of the sample households' characteristics with respect to continuous variables. The respondents had a mean age of 49.2 years, ranging from 24 to 67 years, with a standard deviation of 13.7 years, indicating a diverse age profile. The average household comprised 4.06 members, with family sizes varying between 1.9 and 8.2. Respondents reported an average of 22.5 years of farming experience, ranging from 6 to 52 years, reflecting a community with substantial agricultural expertise. The mean farm size was 1.25 hectares, with holdings spanning 0.55 to 2.96 hectares and a standard deviation of 0.35 hectares, highlighting variability in land ownership among households. Collectively, these statistics illustrated the heterogeneity in demographic, experiential, and landholding characteristics within the farming community.

Table 4. 2 Characteristics of the sample households for the continuous variables

Household characteristics	Min	Max	Mean	SD
Age (years)	24	67	49.2	13.7
Family size (number)	1.9	8.2	4.06	1.72
Farming experience (years)	6	52	22.5	12.4
Farm size (hectare)	0.55	2.96	1.25	0.35

SD = Standard deviation

Table 4.3 summarizes the characteristics of the sample households with respect to categorical variables. The majority of respondents were male (86.7%), with females representing only 13.3% of the sample, highlighting a notable gender disparity in household decision-making. In terms of education, nearly half of the participants were illiterate (46.4%), with smaller proportions able to read and write (25.4%), having completed primary education (17.5%), or secondary education (10.7%), indicating generally low levels of formal education. Just over half of the households (51.8%) reported access to credit, whereas 48.2% did not, suggesting potential limitations in financial resources that could affect agricultural investments and adaptive capacity. Together, these categorical characteristics highlight the importance of gender, education, and credit access in shaping farmers' livelihoods and their ability to respond to climate variability.

Table 4. 3 Characteristics of the sample households for the categorical variables

Household characteristics		Frequency	Percentage
	Male	293	86.7
Sex	Female	45	13.3
	Can't read and write	157	46.4
Education	Can read and write	86	25.4
	Primary education	59	17.5
	Secondary education	36	10.7
Access to credit	Yes	175	51.8
	No	163	48.2

4.3.2 Variability and trends of rainfall

Annual rainfall variability and trends

Analysis of annual rainfall during 1992–2022 revealed considerable interannual fluctuations, with values ranging from 1187.02 mm to 1620.71 mm. The mean annual rainfall showed a standard deviation of 139.32 mm and a coefficient of variation (CV) of 10.02%, indicating relatively low year-to-year variability. Trend analysis using the Mann–Kendall test and Sen's slope estimator indicated a slight but statistically non-significant declining trend of approximately 1.53 mm per year (Table 4.4), suggesting overall stability in long-term annual rainfall despite observable fluctuations.

Similar non-significant rainfall trends have been reported in other Ethiopian studies, including Feke et al. (2021), Moshe and Beza (2024), and Weldegerima et al. (2018). These results highlight the inherent temporal variability of rainfall and underscore the difficulty of detecting statistically robust long-term changes in annual precipitation, which has important implications for agricultural and water resource planning.

Seasonal rainfall variability and trends

The study area is characterized by a bimodal rainfall regime comprising two main rainy seasons. The Kiremit season (June–September) is the dominant rainfall period, contributing approximately 80% of total annual rainfall, while the Belg season (March–May) accounts for about 13%. Rainfall variability is markedly higher during the Belg and Bega seasons, with coefficients of variation of 18.49% and 77%, respectively (Table 4.4), indicating substantial interannual instability during these periods. This heightened variability increases production uncertainty for smallholder farmers by affecting planting decisions, water availability, and household food security. These findings are consistent with previous studies emphasizing the dominance of Kiremit rainfall in Ethiopia's hydroclimatic system. Mekonen and Berlie (2020) reported that Kiremit contributes about 68.4% of annual rainfall, while Belg contributes approximately 23%. Similarly, Alemayehu et al. (2020), Bayable et al. (2021), Feke et al. (2021), and Ketema and Siddaramaiah (2020) identified Kiremit as the principal rainy season across most Ethiopian regions. In contrast, Alemayehu et al. (2022b), Getahun et al. (2021), and Mekonen et al. (2020) highlighted the greater instability of Belg and Bega rainfall. Collectively, these patterns emphasize the need for climate-resilient agricultural practices that capitalize on the relative reliability of Kiremit rainfall while reducing vulnerability to secondary-season rainfall uncertainty.

Trend analysis further reveals contrasting seasonal dynamics. Kiremit rainfall shows a statistically significant increasing trend of 7.84 mm per year ($p < 0.01$), consistent with positive Mann–Kendall and Sen's slope estimates. In contrast, Belg and Bega rainfall exhibit declining tendencies of approximately 2.78 mm per year and 1.02 mm per year, respectively. The decline in Belg rainfall is statistically significant ($p < 0.05$), whereas the reduction in Bega rainfall is not statistically significant (Table 4.4).

These findings partially align with Belay et al. (2021), who reported increasing trends in Kiremit and Bega rainfall, and Tofu and Mengistu (2023), who observed increasing trends in both Kiremit and annual rainfall. Overall, the results suggest a strengthening of the main rainy season alongside weakening secondary rainfall seasons, with important implications for cropping calendars, soil moisture dynamics, and the sustainability of rainfed agricultural systems.

Table 4. 4 Seasonal and annual MK analysis of rainfall (1992–2022)

RF/mm	Min.	Max.	Mean	SD	CV (%)	MK	Trend	P-value	Sen's slope
Bega	23.56	274.3	84.69	65.33	77	-0.13	↓	0.29	-1.02
Belg	149.9	287.20	197.80	36.58	18.49	-0.25	↓	0.04**	-2.78
Kiremit	1120.30	1692.20	1499.08	118.14	7.88	0.41	↑	0.001*	7.84
Annual	1187.02	1620.71	1391.53	139.32	10.02	-0.12	↓	0.3	-1.53

MK; Mann–Kendall; ↑ increasing; ↓ decreasing; * & ** shows statistically significant at 0.01 & 0.05, respectively

4.3.3 Variability and trends of temperature

Seasonal analysis revealed relatively low but distinct temperature variability across the major agricultural seasons. Kiremit exhibited the lowest variability (CV = 2.14%), indicating relatively stable temperature conditions during the main rainy season, whereas Bega showed the highest variability (CV = 3.96%). The highest mean seasonal temperature was recorded during Belg (20.99°C), likely due to greater solar radiation and reduced cloud cover during this period. In contrast, Kiremit recorded the lowest mean temperature (17.16°C), reflecting the cooling influence of increased rainfall and persistent cloud cover, which reduce incoming solar radiation. Similar seasonal temperature patterns have been reported by Alemayehu et al. (2020), who observed that rainy seasons generally experience lower temperatures because of the moderating effects of precipitation and cloud cover.

Trend analysis further revealed a consistent warming pattern across all seasons. The Bega season exhibited a statistically significant warming trend of 0.04°C per year ($p < 0.05$), while Belg and Kiremit showed significant increases of 0.06°C per year ($p < 0.01$) and 0.03°C per year ($p = 0.03$), respectively (Table 4.5). The relatively stronger warming observed during Belg is particularly noteworthy because this season plays a crucial role in crop establishment, seed germination, and early vegetative growth. Rising temperatures during this period may alter planting schedules, accelerate crop development, and increase moisture demand, thereby affecting crop performance and production outcomes.

The implications of seasonal warming are likely to vary across agroecological zones. Lowland areas, which already experience relatively high temperatures, may become increasingly vulnerable to heat stress, water shortages, and declining crop productivity. Conversely, warming in highland areas may alter crop suitability patterns, extend growing periods for some crops, and encourage shifts in cropping systems. These differential impacts underscore the need for agroecology-specific adaptation measures that account for local climatic conditions and farming practices.

The observed seasonal warming trends are consistent with the findings of Alemayehu et al. (2022b), who reported increasing seasonal temperatures in the Suha watershed, and Belay et al. (2017), who documented widespread warming trends in Ethiopia's Central Rift Valley. Collectively, these studies suggest that warming has become a pervasive climatic feature across many parts of Ethiopia.

Overall, the analysis demonstrates a persistent and statistically significant warming trend across both annual and seasonal timescales in the Ayehu Watershed. The observed increase of approximately 0.9°C during the study period provides compelling evidence of ongoing climatic change in the region. The consistency between observed temperature records and farmers' perceptions further strengthens confidence in the findings and highlights the value of integrating scientific observations with local knowledge. Given the importance of temperature for crop growth, water demand, and ecosystem functioning, the observed warming trends have important implications for agricultural productivity and livelihood sustainability. These findings emphasize the urgent need for targeted adaptation strategies aimed at reducing heat-related risks, improving water-use efficiency, and enhancing the resilience of farming systems under a changing climate.

Table 4. 5 Seasonal and annual Mk analysis of temperature (1992–2022)

Tem. /^{0}C	Min.	Max.	Mean	SD	CV (%)	MK	Trend	P-value	Sen's slope
Bega	13.59	28.01	20.80	0.825	3.96	0.40	↑	0.03*	0.04
Belg	12.23	29.75	20.99	0.782	3.72	0.32	↑	0.002**	0.06
Kiremit	11.20	23.12	17.16	0.368	2.14	0.52	↑	4.19	0.03
Annual	12.21	26.20	19.22	0.273	1.42	0.59	↑	3.75	0.03

MK Mann–Kendall; ↑ increasing; ↓ decreasing; * & ** indicate statistically significant at 0.01 & 0.05, respectively.

4.3.4. Farmers' perceptions to temperature and rainfall variability

This study examined farm households' perceptions of temperature and rainfall variability across three agroecological zones based on the premise that perceptions of climate variability differ according to local environmental conditions and exposure to climate-related risks. The results revealed considerable variation in climate perceptions among the agroecological zones. Farmers in the lowland agroecological zone reported the highest level of awareness of climate variability, with 87% perceiving changes in rainfall and 91% perceiving changes in temperature. In comparison, the corresponding proportions were lower in the midland zone (71.2% for rainfall and 72.9% for temperature) and the highland zone (65% for rainfall and 68.3% for temperature) (Table 4.6). Across all agroecological zones, a large proportion of respondents perceived increasing temperatures, with the highest percentage recorded in the lowland zone (86%), followed by the midland (76%) and highland zones (69%). Similarly, perceptions of declining rainfall were more frequently reported in the lowland (78%) and midland (75%) zones than in the highland zone (69%). In contrast, reports of increasing rainfall, no noticeable change, or uncertainty regarding rainfall trends were relatively uncommon and occurred more frequently among respondents in the midland and highland zones (Figure 4.1).

The observed differences in perception across agroecological zones are likely associated with variations in climatic exposure, livelihood dependence on rain-fed agriculture, and the severity of climate-related shocks experienced by farming households. Lowland farmers are generally more exposed to recurrent droughts, high temperatures, erratic rainfall patterns, and prolonged dry spells, all of which have direct consequences for crop production and household livelihoods. As a result, farmers in these areas are more likely to recognize and remember climatic changes than their counterparts in the relatively cooler and less climate-stressed highland environments. The lower perception levels observed in the highland zone may reflect comparatively moderate climatic conditions, localized microclimatic variability, and differences in access to climate information and farming experiences.

Importantly, the perception results correspond closely with the meteorological analyses presented in the preceding sections. Trend analyses of observed climate data revealed a significant increase in annual and seasonal temperatures, while rainfall records exhibited considerable temporal variability and irregular distribution patterns over the study period. The widespread perception of increasing temperature and declining rainfall therefore aligns with the observed climatic trends, suggesting that farmers possess a reasonably accurate understanding of long-term climate variability in the watershed. This agreement between local perceptions and meteorological evidence enhances confidence in farmers' experiential knowledge and demonstrates the value of integrating scientific climate observations with local knowledge systems when assessing climate change impacts and adaptation needs.

These findings are consistent with previous studies. Lowland farmers' heightened awareness of climate variability reflects their frequent exposure to extreme climatic events, including droughts, erratic rainfall, and rising temperatures (Aidoo et al., 2021; Berhanu et al., 2024; Gebrehiwot & van der Veen, 2021). Similarly, Sertse et al. (2021) reported that Ethiopian farm households experience notable climate changes characterized by elevated temperatures, reduced precipitation, and altered rainfall patterns. In addition, Bitana et al. (2023) reported that in the Kolla agro-climatic zone, high vulnerability arises from greater exposure, sensitivity, and limited adaptive capacity, posing serious challenges for rural households. Nationwide studies also confirm a general consensus among farmers regarding increasing temperatures and declining rainfall (Megersa et al., 2022; Sohail et al., 2022).

Despite the widespread recognition of climate variability, a proportion of respondents reported no noticeable change or expressed uncertainty regarding temperature and rainfall trends. Such differences in perception may be influenced by variations in farming experience, educational background, access to climate information, and the localized nature of climatic conditions. The existence of these differences highlights that climate perception is not uniform across households and underscores the importance of strengthening climate information dissemination and awareness programs.

Farmers' perceptions of climate variability have important implications for adaptation planning because awareness of climatic changes often serves as a prerequisite for adopting adaptive responses. Households that recognize increasing temperatures and declining rainfall are more likely to adjust planting dates, diversify crops, adopt improved crop varieties, implement soil and water conservation practices, and engage in other climate adaptation measures. Consequently, understanding how climate perceptions vary across agroecological zones is essential for designing targeted and context-specific adaptation interventions.

Overall, the findings indicate that most farmers across the watershed are aware of ongoing climatic changes, particularly increasing temperatures and declining rainfall. The higher perception levels observed in the lowland agroecological zone reflect greater exposure to climate-related risks and suggest that climatic stressors play a critical role in shaping local understanding of climate variability. The strong correspondence between farmers' perceptions and observed climatic trends further demonstrates the reliability of local knowledge and highlights its potential contribution to climate adaptation planning and policy development.

A one-way analysis of variance (ANOVA) was conducted to examine whether mean perception scores for temperature and rainfall variability differed across the three agroecological zones (highland, $n = 120$; midland, $n = 118$; lowland, $n = 100$). All underlying assumptions of ANOVA were satisfied prior to the analysis. The results revealed statistically significant differences among agroecological zones for both temperature perception ($F = 7.23$, $p < 0.01$) and rainfall perception ($F = 8.91$, $p < 0.01$), indicating that farmers' perceptions of climate variability vary across agroecological settings. To identify the specific groups responsible for these differences, a Bonferroni post hoc test was subsequently performed. The post hoc analysis showed that significant differences existed between the lowland and highland zones and between the lowland and midland zones for both temperature and rainfall perceptions, whereas no statistically significant differences were detected between the highland and midland zones (Table 4.7). These findings suggest that farmers residing in the lowland agroecological zone perceive climate variability differently from those in the highland and midland zones, potentially reflecting differences in local climatic conditions and exposure to climate-related stresses.

Focus group discussions further illustrated the practical implications of these perceptions. Farmers across all zones reported increasingly unpredictable rainfall, particularly variable onset and duration of the rainy season, which complicates planting schedules and necessitates adjustments in farming practices. Many households, which previously relied solely on rain-fed agriculture, have adopted irrigation systems to mitigate the risks associated with irregular rainfall, demonstrating proactive adaptation to the challenges posed by climate variability.

An elderly key informant noted that climate variability has become more severe in recent years, especially in the lowland areas where heat has intensified and rainfall has become more unreliable. He explained that farmers in the lowland are more affected because they experience frequent droughts, declining soil moisture, and stronger heat stress compared to midland and highland areas. According to him, although all zones have noticed changes in climate, the highland communities still experience relatively stable conditions, while midland farmers face moderate but increasing variability. He further emphasized that "in the past, rains were predictable, but now the timing is uncertain everywhere, especially in the lowlands," highlighting a clear spatial difference in climate perception and impact across agroecological zones.

Table 4. 6 Household's climate perception based on agroecology

	Highland (%)	Midland (%)	Lowland (%)	F-value	Prob > F
Rainfall					
Perceived	65	71.2	87	7.23	0.000***
Not perceived	35	28.8	13		
Temperature					
Perceived	68.3	72.9	91	8.91	0.000***
Not perceived	31.7	27.1	9		

*** indicates level of significance at 1%

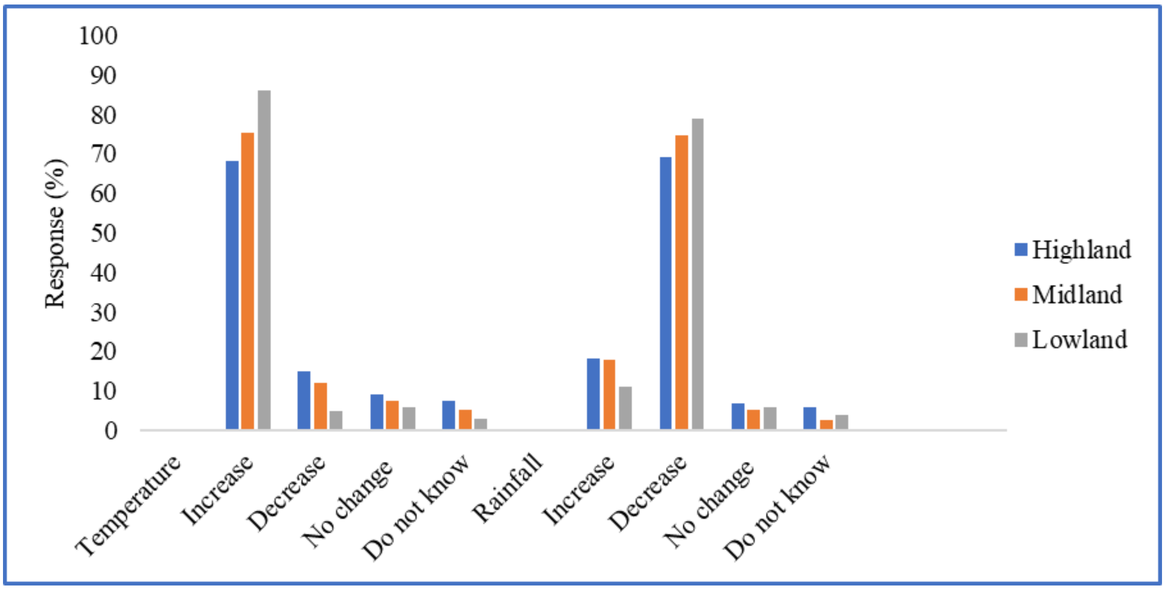

Figure 4.1 Households' perceptions to trends of temperature and rainfall

To further investigate differences in farmers' perceptions of temperature and rainfall variability across agroecological zones, a Bonferroni post hoc test was performed following the analysis of variance. The results revealed statistically significant differences in both temperature and rainfall perception scores between the highland and lowland zones, with mean differences of 0.227 ($p < 0.001$) and 0.220 ($p = 0.001$), respectively. Likewise, significant differences were observed between the midland and lowland zones for temperature (mean difference = 0.181, $p = 0.004$) and rainfall perceptions (mean difference = 0.141, $p = 0.049$).

In contrast, no statistically significant differences were detected between the highland and midland zones for either temperature perception (mean difference = 0.045, $p = 1.000$) or rainfall perception (mean difference = 0.079, $p = 0.475$) (Table 4.7). These findings indicate that farmers residing in the lowland agroecological zone perceived temperature and rainfall variability differently from their counterparts in the highland and midland zones. The observed differences may reflect the greater exposure of lowland areas to climate-related stresses, including higher temperatures, more frequent droughts, and greater rainfall variability.

It is important to note that the absence of statistically significant differences between the highland and midland zones should not be interpreted as evidence that farmers in these two zones hold identical perceptions of climate variability. Rather, the results indicate that the analysis did not provide sufficient statistical evidence to conclude that their perception scores differed at the specified significance level. Therefore, while climate perceptions were broadly similar between the highland and midland zones, they were distinctly different from those reported in the lowland zone (Table 4.7).

Table 4. 7 Multiple comparison of households' climate perceptions using Bonferroni

Agroecological location		Rainfall		Temperature	
		Mean difference	Sig.	Mean difference	Sig.
Highland	Midland	.079	.475	.045	1.000
	Lowland	.220	.001	.227	.000
Midland	Highland	-.079	.475	-.045	1.000
	Lowland	.141	.049	.181	.004
Lowland	Highland	-.220	.001	-.227	.000
	Midland	-.141	.049	-.181	.004

This study used a severity index to evaluate farmers' perceptions of temperature and rainfall variability. Farmers' severity scores ranged from 29.9% to 84.5%, highlighting varying levels of concern across different climate indicators. Several key indicators received notably high severity ratings: rising temperatures (84.5%), unpredictable rainfall distribution (79.7%), and extreme hot days (79.4%). Similarly, late onset of rainfall was rated at 75.6%, decreased rainfall at 74.7%, and abrupt cessation of precipitation at 74.8%. These findings reveal a strong consensus among smallholder farmers regarding the severity of these dimensions of climate variability. In contrast, climate features such as timely rainfall (29.9%), increased rainfall (30.4%), and decreased temperatures (30.8%) received low severity scores, suggesting that farmers generally perceive these conditions as less problematic or less frequent (Table 4.8). These findings are consistent with previous studies, which identified rising temperatures, erratic rainfall, heatwaves, delayed rainfall onset, and reduced precipitation as primary indicators of climate change (Jawo et al., 2023). Similarly, Pickson & He (2021) reported that farmers perceive drying water sources, uncertain rainfall, declining temperatures, and low precipitation as key impacts of climate variability.

FGD participants confirmed the survey results, emphasizing that rising temperatures, erratic and unpredictable rainfall, and extreme heat are the most serious climate challenges affecting agriculture. They particularly stressed that delayed onset and early cessation of rainfall disrupt cropping seasons and increase crop failure risks. In contrast, favorable conditions such as timely rainfall and cooler temperatures were rarely observed and considered less important. Overall, the discussions reflect a strong consensus that climate variability is intensifying and negatively affecting smallholder livelihoods.

Table 4. 8 Indicators of household's climate variability perception (n=338)

Climate variables		Likert scale					Severity index (SI) (%)	Rank
		SDA (0)	DA (1)	N (2)	A (3)	SA (4)		
Rise of temperature	NR	3	6	4	172	153	84.5	1
	PR	0.9	1.8	1.2	50.9	45.3		
No of hot days increased	NR	4	8	9	221	96	79.4	3
	PR	1.2	2.4	2.7	65.4	28.3		
No of warm nights increased	NR	27	56	34	112	109	66.3	7
	PR	8	16.6	10.1	33.1	32.2		
Decreased temperature	NR	95	122	80	30	11	30.8	8
	PR	40.5	28.1	19.2	8.9	3.3		
Increased rainfall	NR	129	90	59	37	23	30.4	9
	PR	46.1	38.8	7.7	6.8	0.6		
Decreased rainfall	NR	18	24	7	184	105	74.7	6
	PR	5.3	7.1	2.1	54.4	31.1		
Rainfall comes on time	NR	111	109	76	25	17	29.9	10
	PR	42.9	34.3	15.4	7.4	0		
Delayed onset of rainfall	NR	10	38	12	152	126	75.6	4
	PR	3	11.2	3.6	45	37.2		
Unpredictability of cession of rainfall	NR	9	35	18	164	112	74.8	5
	PR	2.7	10.4	5.3	48.5	33.1		
Uncertainty of rainfall distribution	NR	7	19	7	176	129	79.7	2
	PR	2.1	5.6	2.1	52	38.2		

SDA = strongly disagree; DA = disagree; N = neutral; A = agree; SA = strongly agree; NR= number of respondents; PR = percentage of respondents.

4.3.5. The link between farmers' climate perceptions and meteorological data

Household perceptions of climate variability alone do not provide a complete understanding of changes in temperature and precipitation. Climate perceptions are inherently subjective and location-specific, often shaped by personal experiences, livelihood dependence on agriculture, local agroecological conditions, and broader socioeconomic factors (Asrat & Simane, 2018; Usmail et al., 2023). Consequently, farmers' assessments may not always correspond precisely with observed climatic records. Nevertheless, integrating local perceptions with meteorological observations can improve the interpretation of climate variability by combining experiential knowledge with objective measurements (Salerno et al., 2022). Such an approach provides a more comprehensive basis for understanding climate change impacts and designing context-specific adaptation strategies. By incorporating both local knowledge and scientific evidence, policymakers and development practitioners can formulate adaptation interventions that are more responsive to local realities while remaining grounded in empirical data.

A key contribution of the present study is the comparison of farmers' perceptions with long-term meteorological records to evaluate the extent to which local experiential knowledge reflects observed climatic conditions across different agroecological settings. Understanding the degree of correspondence between perceived and observed climate change is particularly important because farmers' adaptation decisions are often based on their perceptions rather than on instrumental climate records. Consequently, assessing the consistency between local perceptions and observed climate trends can provide valuable insights into the effectiveness of perception-based adaptation responses and climate risk management strategies.

As discussed earlier, a substantial proportion of farm households perceived declining trends in annual, Kiremit, and Belg rainfall over the study period. Meteorological records partially supported these perceptions, revealing decreasing trends in annual, Belg, and Bega rainfall. However, the observed climate data also indicated a statistically significant increase in Kiremit rainfall, the principal rainy season, which contrasts with farmers' perceptions of declining rainfall during the same period. This finding suggests that the level of agreement between farmers' perceptions and meteorological observations varies across seasons and rainfall characteristics. The discrepancy may arise because farmers often evaluate rainfall based not only on total seasonal amounts but also on its timing, distribution, intensity, onset, cessation, and overall usefulness for agricultural production. Thus, even where Kiremit rainfall increased statistically, delayed rainfall onset, prolonged dry spells, uneven distribution, or rainfall occurring outside critical crop growth stages may have created the perception of declining rainfall from an agricultural perspective. Since farming households primarily assess climate through its effects on crop performance and livelihood outcomes, perceived rainfall trends may differ from meteorological measurements that focus on total precipitation amounts.

Similar discrepancies between perceived and observed rainfall trends have been reported in previous studies. For example, Esayas et al. (2019) identified notable differences between farmers' assessments of rainfall variability and instrumental climate records, while Megersa et al. (2022) documented inconsistencies between perceived declines in precipitation and observed meteorological trends. These findings indicate that farmers' perceptions provide valuable insights into local climate experiences but may not always fully reflect measured climatic changes. Therefore, combining local knowledge with scientific climate observations remains essential for obtaining a more comprehensive understanding of climate variability and its impacts.

In contrast to rainfall, a substantial proportion of farm households perceived increasing temperatures across the different agroecological zones. Meteorological records from the past three decades similarly indicated increasing trends in both annual and seasonal temperatures. This correspondence suggests that farmers are generally able to recognize long-term temperature changes occurring within their local environments. Temperature changes may be more readily perceived than rainfall variations because they are experienced directly through heat stress, changes in crop growth and livestock performance, water availability, and human comfort. As a result, warming trends are often more visible and easier for farming communities to detect than changes in rainfall, which may fluctuate considerably from season to season and location to location.

Although the observed warming pattern indicates broad consistency between farmers' perceptions and meteorological observations, the present study did not formally quantify the degree of agreement between perception data and climate records. Therefore, the findings should be interpreted as indicating general correspondence rather than complete alignment. Similar patterns have been reported elsewhere. Imran et al. (2020) found that farmers' perceptions of rising temperatures in Pakistan generally reflected trends observed in meteorological records. Likewise, Ankrah et al. (2023) and Moroda et al. (2018) reported that farmers were often able to recognize long-term temperature changes consistent with historical climate data.

4.3.6. The perceived risks of climate variability

The results revealed that farmers in different agroclimatic regions perceive several risks related to climate variability. These risks included decreased crop yields, drought, flooding, plant pests and diseases, reduced soil fertility, food shortages, and diminished water availability and quality. The climate-related risk perception index (CRRPI) showed that perceptions of these risks vary by agroecological region. In the highland zone, farmers primarily cited plant pests and diseases, decreased agricultural output, worsening soil fertility, and water shortages as significant risks. In contrast, farmers in the midland zone identified reduced crop yields, flooding, crop losses, and soil fertility depletion as major concerns related to climate fluctuations. In the lowland zone, farmers perceived recurrent droughts, reduced water availability and quality, declining crop yields, and crop pests and diseases as the major risks of climate variability. This zone exhibited the highest overall Climate-Related Risk Perception Index (CRRPI), with drought and water scarcity being the primary concerns. In contrast, the highland zone showed the lowest CRRPI, where pests and diseases were the most pressing issues. The midland zone fell in between, with reduced crop yields and harvest losses ranked as the top priorities (Table 4.9). These findings indicate that perceptions of climate-related risks vary significantly across agroecological zones, reflecting differences in local environmental conditions and exposure to climate stressors. Similar patterns have been reported in previous studies. For instance, Likinaw et al. (2023) noted that households perceive climate risks differently depending on socioeconomic and environmental factors. Likewise, Jawo et al. (2023) found that farmers in low-elevation areas perceived greater impacts of climate change compared to those in mid- and high-elevation zones.

FGD participants across all AEZs identified climate variability as a growing threat, with erratic rainfall, rising temperatures, and extreme events driving crop failure, water scarcity, pests, soil decline, and food insecurity, making farming increasingly uncertain and livelihoods less secure.

Table 4. 9 Households perceived risks of climate variability across AEZs

Highland (n=120)								
Climate risks	4	3	2	1	0	CRRPS	CRRPI	Rank
Decline in crop yield	36	48	24	9	3	345	71.9	2nd
Recurrent drought	15	17	32	41	15	216	45	8th
Flooding	28	37	31	18	6	303	63.1	6th
Crop pests and diseases	44	52	17	7	0	373	77.7	1st
Loss of soil fertility	42	33	26	19	0	338	70.4	3rd
Harvest loss	32	34	28	20	6	292	60.8	7th
Food shortage	29	46	22	16	7	314	65.4	5th
Reduce water availability & quality	31	49	20	11	9	322	67.1	4th
Overall CRRPI							64.9	
Midland (n=118)								
Climate risks	4	3	2	1	0	CRRPS	CRRPI	Rank
Decline in crop yield	46	32	23	17	0	343	72.7	1st
Recurrent drought	33	41	28	13	3	324	68.6	5th
Flooding	42	36	21	14	5	332	70.3	3rd
Crop pests and diseases	30	37	35	14	2	315	66.7	6th
Loss of soil fertility	32	47	26	7	6	328	69.5	4th
Harvest loss	35	41	29	12	1	333	70.6	2nd
Food shortage	31	38	25	20	4	308	65.3	7th

Reduced water availability & quality	24	49	23	16	6	305	64.6	8th
Overall CRRPI							67.4	
Lowland (n=100)								
Climate risks	4	3	2	1	0	CRRPS	CRRPI	Rank
Decline in crop yield	49	27	19	5	0	320	80	3rd
Recurrent drought	55	29	13	3	0	336	84	1st
Flooding	31	36	21	9	3	283	70.8	5th
Crop pests and diseases	44	25	17	12	2	297	74.3	4th
Loss of soil fertility	16	31	36	17	0	246	61.5	7th
Harvest loss	14	33	23	29	1	230	57.5	8th
Food shortage	28	32	24	15	1	271	67.8	6th
Reduced water availability & quality	52	28	16	4	0	325	81.3	2nd
Overall CRRPI							72.1	

Notes: 0: No perception; 1: Very low perception; 2: Low perception; 3: High perception; and 4: Very high perception, CRRPS=Climate Related Risk Perception Score, CRRPI= Climate Related Risk Perception Index

Key informants also revealed that both early and late rainfall have significantly disrupted planting and harvesting schedules. Delays during the *Belg* rainy season, which is critical for land preparation and crop cultivation, have posed additional challenges for agricultural production. Participants emphasized that irregular rainfall timing, whether too early or too late, has increasingly complicated their ability to plan for the farming season.

These observations are consistent with the findings of Belay et al. (2017) and Teshome et al. (2021b), who reported that variations in the onset of rainfall profoundly influence smallholder farmers' crop choices and the timing of planting and harvesting activities. The implications of such disruptions highlight the urgent need for adaptive strategies that consider shifting rainfall patterns to strengthen agricultural resilience and safeguard food security. Moreover, these insights underscore the importance of providing reliable climate information and incorporating farmers' experiential knowledge into broader agricultural policy and planning efforts.

This study employed one-way analysis of variance (ANOVA) to determine significant differences in climate-related risk perception indexes among the three agroecological zones. The analysis showed that there are statistically significant differences in risks from recurrent drought, crop pests and diseases, harvest losses, and reduced water availability and quality across the agroecological zones, with $p < 0.01$. Additionally, there were notable differences in crop yield reduction and soil fertility loss among farmers from distinct agroecological regions ($p < 0.05$). However, flooding and food scarcity did not differ significantly between the study groups. This indicates that households had similar views about the risks associated with flooding and food scarcity, regardless of the agroecological zone.

4.3.7. Factors affecting farmers' perceptions of climate variability

Farmers' perceptions of temperature and rainfall variability were shaped by a complex interplay of demographic, socioeconomic, biophysical, and institutional factors. To identify the key determinants, a binary logistic regression model was employed. The dependent variable was constructed based on whether households reported perceiving changes in key climatic elements (temperature and rainfall variability) relative to long-term local experience; households were categorized into "perceivers" and "non-perceivers" accordingly. This binary classification ensured that the analysis captured the existence of perception rather than its intensity.

As shown in Table 4.10, the model demonstrated strong explanatory power, with the likelihood ratio chi-square indicating overall significance ($\chi^2 = 363.91$, $p < 0.01$). The Cox and Snell R^2 value of 0.659 further indicates that the explanatory variables jointly account for 65.9% of the variation in farmers' climate variability perceptions. Multicollinearity diagnostics using VIF and tolerance values confirmed that there were no serious multicollinearity problems among the predictors.

Out of the 12 explanatory variables included in the model, eight significantly influenced farmers' perceptions of climate variability. Of these, five variables showed a negative relationship, while the remaining variables exhibited a positive association. Specifically, age, education level, access to climate information, extension services, farming experience, agroecological location, off-farm activities, and irrigation practices were statistically significant determinants of perception. In contrast, sex of household head, farm size, access to credit, and market information did not show statistically significant effects (Table 4.10).

The model results indicate that age is negatively associated with climate variability perception. A one-unit increase in age reduces the likelihood of perceiving climate variability by 28.8 percent ($p < 0.01$). This suggests that older farmers may be less responsive to newly emerging climate information, possibly due to lower engagement with training, extension, and modern communication platforms. In contrast, younger farmers tend to be more exposed to new information sources and therefore more likely to recognize climate variability. However, this finding contrasts with earlier studies such as Deressa et al. (2011), Gashure & Wana (2023), and Rapholo & Diko (2020), which reported that older farmers often have stronger perceptions due to accumulated experiential knowledge. The divergence may be explained by differences in institutional support systems, education levels, and access to climate information across study contexts.

Educational status also significantly influenced farmers' perceptions. Farmers who could not read and write were less likely to perceive climate variability compared to literate farmers by odds of 0.157, which is also statistically significant at $p < 0.05$). This suggests that education enhances farmers' ability to access, interpret, and utilize climate-related information from extension materials, media, and training programs. Consequently, literate farmers are more likely to detect and interpret changes in temperature and rainfall patterns. This result should be interpreted as an association rather than causation due to the cross-sectional nature of the data. Similar findings have been reported by Assan et al. (2020) and Poortinga et al. (2019), who emphasized education as a key factor shaping climate awareness and perception.

Access to agricultural extension services had a strong positive effect on perception of climate variability. Farmers with extension contact were 2.49 times more likely to perceive climate variability than those without access ($p < 0.01$). This suggests that extension services play an important role in disseminating climate-related knowledge and supporting farmers' interpretation of environmental changes. Key informants also confirmed that regular interaction with development agents enhances farmers' understanding of rainfall variability and appropriate farming calendars, including decisions on planting, ploughing, and crop selection. This finding is consistent with Adeagbo et al. (2021), Bekuma et al. (2023), and Fahad et al. (2020), who similarly reported the importance of extension services in shaping climate awareness.

Farming experience significantly increased the likelihood of perceiving climate variability. A unit increase in farming experience raises the probability of perception by a factor of 1.52. This indicates that accumulated years of farming enhance farmers' ability to recognize long-term changes in weather patterns and adjust their practices accordingly. Experienced farmers are more capable of identifying subtle climatic shifts and adapting crop and soil management strategies. This finding is consistent with Huong et al. (2017), Jawo et al. (2023), and Mamun et al. (2021).

Access to climate information also had a strong positive effect. Farmers with access to climate information were 2.17 times more likely to perceive climate variability ($p < 0.01$). This highlights the importance of timely and reliable climate information in shaping farmers' awareness and adaptive capacity. Access to forecasts and advisory services improves decision-making and enhances preparedness for climate-related risks. This finding aligns with Abrha (2015), Asrat & Simane (2018), and Hadgu et al. (2015).

Participation in off-farm activities showed a significant negative association with perception. Households engaged in non-farm activities were less likely to perceive climate variability (OR = 0.083, $p < 0.01$). This may be because such households are less dependent on climate-sensitive agricultural production and therefore have reduced daily exposure to weather-related changes. In contrast, agriculture-dependent households are more directly affected by climatic fluctuations, increasing their awareness. This result is consistent with Ali & Rose (2021), Esayas et al. (2019), and Mairura et al. (2021).

Agroecological location significantly influenced perception. Farmers in highland (Dega) and midland (Woina Dega) areas were less likely to perceive climate variability compared to those in lowland (Kolla) areas, with odds ratios of 0.424 and 0.034, respectively ($p < 0.01$). This difference is likely due to higher climate stress and greater rainfall and drought variability experienced in lowland areas, which increases sensitivity to climatic changes. Similar findings were reported by Cherinet and Mekonnen (2019), Asrat and Simane (2018), and Zeleke et al. (2023), who highlighted spatial variation in climate perception across agroecological zones.

Finally, irrigation practice had a significant negative effect on perception. Farmers using irrigation were 17.1 percent less likely to perceive climate variability ($p < 0.01$). This suggests that irrigation may buffer farmers from rainfall variability, thereby reducing their sensitivity to climate fluctuations. As a result, irrigating households may underestimate the severity of climate change impacts. This finding is consistent with Esayas et al. (2019), Adeagbo et al. (2021), and Aboye et al. (2023), who similarly noted that irrigation can reduce perceived climate risk despite improving resilience.

Overall, the model results demonstrate that farmers' perceptions of climate variability are shaped by a combination of human capital, institutional access, livelihood diversification, and environmental context. While the findings are robust, they should be interpreted as associations rather than causal relationships due to the cross-sectional nature of the data.

Table 4. 10 Binary logistic regression model for determinants of households' climate perception

Variables in the model	Odds ratio	Std. Err.	z	p>/z/	[95% conf.	interval]
Age	.288	.374	-1.243	.001***	.139	.600
Sex (1=male)	.599	.479	-.512	.285	.234	1.532
Education (1=Can't read and write)	.157	.932	-1.850	.047**	.025	.977
Extension service (1=yes)	2.49	.416	2.251	.000***	4.605	21.437
Climate information (1=yes)	2.17	.367	2.216	.000***	4.214	18.835
Market information (1=yes)	.65	.369	-.431	.243	.315	1.340
Agro-ecology (Highland)	.424	.232	-.857	.000***	.269	.668
Midland	.034	1.56	-4.707	.003***	.000	.193
Farming experience	1.52	1.86	1.609	.001***	.378	6.212
Off-farm activity (1=yes)	.083	.494	-2.489	.000***	.032	.218
Farm size	.76	.161	-.278	.142	.382	.775
Access to credit (1=yes)	1.09	.357	.085	.071	.541	2.194
Irrigation practice (1=user)	.171	.662	-1.765	.008***	.013	.371
Constant	41.31	1.526	3.721	.015	7.566	22.85
No of observation	338	-2 log likelihood= 466.566				
Prob >chi-square	0.000	Cox and Snell R square =.659				

*** and ** indicate levels of significance at p<0.01 and 0.05, respectively; no perception was the reference category.

4.4. Conclusion

The Mann-Kendall trend test showed a non-significant decreasing trend in annual rainfall with minimal overall variability, suggesting that rainfall patterns have remained relatively stable and providing a generally consistent environment for agricultural planning despite occasional fluctuations. However, the study area experiences significant rainfall variability during the *Bega* and *Belg* seasons, pointing to the need for adaptive agricultural practices to manage these seasonal changes effectively. The analysis further revealed that minimum temperature is rising faster than maximum temperature. This accelerated increase in nighttime temperature may reduce frost risk for sensitive crops but can simultaneously stress other crops, disrupt growth cycles, and increase water requirements, highlighting the necessity for targeted agricultural interventions.

Farmers across all agroecological zones reported long-term changes in temperature and rainfall, with lowland farmers exhibiting the greatest awareness of climate variability, likely due to higher exposure and vulnerability. Overall, farmers' observations of reduced rainfall align with meteorological records, except during the *Kiremit* season, when they perceived lower rainfall despite recorded increases. This discrepancy highlights a knowledge gap in understanding seasonal climate trends, reflecting the complexity of climate variability.

Farmers across agroecological zones face climate-related risks such as reduced crop yields, drought, and soil nutrient depletion, stresses the importance of integrating local perceptions into adaptation planning. The study emphasizes the need for region-specific interventions that enhance resilience and support sustainable agricultural practices tailored to the distinct challenges of highland, midland, and lowland areas.

Regression analysis showed that access to extension services, climate information, and farming experience significantly improve farmers' perceptions of climate variability. In contrast, factors such as household age, education level, agroecological zone, engagement in off-farm activities, and irrigation use were associated with lower climate perception. These results underscore the complex factors influencing farmers' climate awareness and highlight the importance of targeted interventions to enhance knowledge and adaptive capacity in agricultural communities.

Overall, the study calls attention to the need to align climate adaptation strategies with both local perceptions and empirical climate data. Policymakers should consider agroecological differences and region-specific vulnerabilities when designing targeted interventions to strengthen smallholder farmers' adaptive capacity and support sustainable agricultural development.

CHAPTER FIVE

FACTORS AFFECTING SMALLHOLDER FARMERS' CHOICES OF ADAPTATION STRATEGIES TO CLIMATE VARIABILITY IN THE AYEHU WATERSHED, UPPER BLUE NILE BASIN, ETHIOPIA

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Abstract

Climate variability continues to pose a major threat to rainfed agricultural systems in Ethiopia, yet smallholder farmers respond through a complex mix of indigenous knowledge and introduced technologies shaped by local biophysical conditions and institutional access. This study goes beyond merely cataloguing adaptation practices by empirically examining the pattern of adaptation choices and their determinants across agroecological zones, with attention to the statistical significance of influencing factors. Using data from 338 farm households, the analysis combines descriptive indices and a Multinomial Logit model to identify both the structure of adaptation responses and their underlying drivers. The results indicate that farmers predominantly rely on a transition from indigenous, knowledge-based strategies, such as crop diversification, use of local varieties, and adjustment of planting dates, to more input-intensive introduced measures, particularly chemical fertilizer application and improved seed use. However, the uptake and effectiveness of these strategies are significantly constrained by structural and statistically relevant limitations, including small landholdings, limited access to climate information services, declining soil fertility, and high input costs. The econometric results further show that adaptation choices are significantly influenced by socioeconomic and institutional variables, including education level, access to credit, extension services, household income, climate risk perception, and agroecological location. These factors exhibit statistically significant effects in shaping the likelihood of adopting specific adaptation strategies, underscoring that farmers' decisions are systematic rather than random. Overall, the findings suggest that adaptation in the study area is best characterized as a constrained hybrid system, where traditional and modern practices coexist under resource limitations and uneven institutional support. Rather than simply promoting general adaptation practices, the results highlight the need for targeted interventions that strengthen reliable climate information services, expand access to affordable credit, improve extension delivery with statistically evidence-based targeting, and design agroecology-specific support packages tailored to the most significant constraints faced by farmers.

Keywords: Climate variability; Determinants; Indigenous; Introduced; Multinomial logit model.

5.1 Introduction

Climate variability remains one of the most pressing global challenges, with far-reaching consequences for ecosystems, agriculture, water resources, and human livelihoods (Javadinejad et al., 2019; Kelman et al., 2016). It is increasingly associated with erratic weather patterns and extreme events such as droughts and floods, which undermine socioeconomic stability (Kiddle et al., 2021). Since the industrial revolution, the global climate system has undergone significant transformation, largely driven by rising greenhouse gas emissions (Abera & Tesema, 2019; Megersa et al., 2022). These changes have disproportionately affected smallholder farmers in developing countries through rising temperatures and altered rainfall regimes (Nautiyal et al., 2024). The IPCC Sixth Assessment Report (AR6) further confirms that the sustained increase in global mean temperatures provides clear evidence of ongoing global warming (Gemeda et al., 2023).

Agriculture remains central to rural livelihoods, food security, and economic development in developing countries (Myeni & Moeletsi, 2020; Von Loeper et al., 2016). However, it is inherently sensitive to climate variability due to its dependence on rainfall and temperature regimes (Belay et al., 2017; Saguye, 2016). In Sub-Saharan Africa, where smallholder farmers dominate agricultural production, the sector is particularly vulnerable to climate-related risks (Adeniyi, 2016; Matewos, 2019). Approximately 175 million smallholder farmers in the region depend largely on rainfed, low-input agriculture on increasingly degraded land with limited access to water resources (Matewos, 2019; Erdaw, 2023). This structural vulnerability necessitates the development of effective, context-specific adaptation strategies that are responsive to both historical climate variability and projected future change (Limantol et al., 2016; Usmail et al., 2023).

In Ethiopia, climate variability poses a major constraint to agricultural production and rural development (Tessema & Simane, 2021). Although agriculture contributes substantially to GDP, employment, and foreign exchange earnings, it remains highly vulnerable due to its reliance on rainfed production systems and limited technological transformation (Belay et al., 2022; Deressa et al., 2011; Megersa et al., 2022; Sinore & Wang, 2024). Productivity challenges are further exacerbated by recurrent extreme weather events, land degradation, and institutional constraints, leading to declining crop and livestock outputs and heightened food insecurity (Etana et al., 2020; Tesfahunegn et al., 2016; Wakweya, 2025). In response, strengthening adaptation capacity has become a central policy priority for enhancing agricultural resilience and productivity (Sertse et al., 2021).

Adaptation, as defined by the IPCC (2023), refers to adjustments in ecological, social, or economic systems in response to actual or expected climatic stimuli and their effects. In agricultural systems, adaptation aims to reduce vulnerability and enhance resilience, while also exploiting potential opportunities arising from climate change (Qin et al., 2023). In this context, understanding farmers' adaptation behavior across diverse agroecological settings is essential for strengthening resilience, improving food security, and promoting sustainable land management (Kahsay et al., 2019; Marie et al., 2020).

Effective adaptation policy design requires a nuanced, agroecology-sensitive understanding of farmers' responses to climate variability, as exposure and vulnerability differ across locations (Asrat & Simane, 2017a; Simane et al., 2016). In Ethiopia, farmers employ a wide range of adaptation strategies, including crop diversification, soil and water conservation, irrigation, agroforestry, and adjustment of planting dates (Addis & Abirdew, 2021; Bekuma et al., 2023; Sertse et al., 2021; Teshome et al., 2021b). However, the adoption and intensity of these practices vary significantly across regions due to differences in socioeconomic conditions, institutional support, and biophysical environments (Bawakyillenuo et al., 2016; Eshetu et al., 2021).

The Ayehu watershed in the Upper Blue Nile Basin provides a relevant case for examining these dynamics due to its marked agroecological heterogeneity, where highland, midland, and lowland areas experience distinct climate stressors (Alemayehu et al., 2023; Tofu et al., 2022). These zones are exposed to varying patterns of rainfall variability, temperature increase, and dry spell frequency, requiring location-specific adaptation responses (Hamer et al., 2025). This diversity underscores the importance of an integrated agroecological approach to climate adaptation.

Despite increasing research on climate change adaptation in Ethiopia, several gaps remain. First, most studies emphasize identification of adaptation practices and their determinants, with limited attention to the relative importance and comparative use of indigenous and introduced strategies. Second, little empirical evidence exists on how these two categories of strategies interact across different agroecological contexts. Indigenous practices such as crop diversification, use of local varieties, and adjustment of planting dates remain widely used (Mekonnen et al., 2021; Shumetie & Alemayehu, 2018), alongside promoted modern inputs such as improved seeds, fertilizers, and pesticides (Bekuma et al., 2023; Myeni & Moeletsi, 2020). However, the comparative adoption patterns of these strategies across agroecological zones remain insufficiently understood, despite evidence that effective adaptation requires integrating local knowledge with appropriate modern technologies (Nyong et al., 2007). Third, although previous studies identify socioeconomic and institutional determinants such as education, gender, farming experience, household size, extension access, and credit availability (Gebre et al., 2023; Jawo et al., 2023; Megabia et al., 2022), their effects are not consistent across contexts due to variations in agroecology, institutions, and livelihood systems (Asrat & Simane, 2017a; Marie et al., 2020). This highlights the need for localized empirical evidence to inform context-specific adaptation policies (Alemayehu et al., 2022a).

Against this background, this study advances the literature by conducting a comparative analysis of indigenous and introduced adaptation strategies across agroecological zones, rather than merely listing practices. By integrating a Weighted Average Index with econometric modeling, it captures both the relative importance of adaptation strategies and the key determinants of farmers' choices under different environmental conditions. The study therefore provides empirically grounded insights into how indigenous knowledge systems and modern agricultural technologies interact in shaping adaptation behavior. Accordingly, it aims to examine the determinants influencing farmers' choice of adaptation strategies to climate variability in the Ayehu watershed, Upper Blue Nile Basin, Ethiopia, with specific objectives to (i) assess the relative importance of indigenous and introduced adaptation strategies across agroecological zones and (ii) identify factors affecting smallholder farmers' choices of adaptation strategies.

5.2. Research Methods

5.2.1. Method of data analysis

Weighted Average Index (WAI)

The study used the Weighted Average Index (WAI) to rank adaptation measures according to their perceived importance among surveyed households. Fourteen adaptation strategies were identified and evaluated using a four-point Likert scale, ranging from 'not important' to "very important." Households evaluated the relative significance of each strategy in response to climate variability, allowing a systematic ranking of adaptation measures. The WAI captured both the frequency and intensity of household responses, providing a robust quantitative measure of the general importance of each strategy. By aggregating and normalizing these responses, the WAI offered a comprehensive assessment of the relative significance of different adaptation strategies. This method allows for a systematic ranking of strategies, allowing comparisons across agroecological zones and identifying region-specific priorities.

This approach has been widely used in previous research to evaluate climate adaptation practices because it is a robust method for capturing community preferences and the practical relevance of various strategies (Fagariba et al., 2018; Gemeda et al., 2023). Previous studies have shown that the WAI effectively identifies the priority of adaptation strategies. It helps highlight the most important measures from a community perspective, guiding targeted interventions and informing policy recommendations. Furthermore, WAI enables a clear comparison across different adaptation strategies, helping to pinpoint which methods are more widely adopted or considered more critical across varying agroecological zones. This evidence-based approach improves the study's capacity to recommend region-specific strategies to strengthen climate resilience among smallholder farmers (Simotwo et al., 2018; Williams et al., 2019).

$$\mathrm{WAI} = \frac{\Sigma \mathrm{FiWi}}{\Sigma\ \mathrm{Fi}} \tag{2}$$

where F = frequency of response; W = weight of each score; and i = score (0= not important; 1= less important; 2= moderately important; 3 = highly important).

In addition to the weighted average index (WAI), the study employed one-way analysis of variance (ANOVA) to investigate variations in the mean scores of adaptation strategies across the different agroecological zones. The purpose of one-way ANOVA was to determine whether there were statistically significant differences in how farmers in the highland, midland, and lowland rated the importance of various climate adaptation strategies. By comparing mean scores, the ANOVA test was used to assess whether certain strategies were prioritized differently depending on the specific agroecological challenges facing each zone, such as varying degrees of rainfall, temperature fluctuations, and soil quality (Masud et al., 2017; Popoola et al., 2020).

Problem Confrontation Index (PCI)

To identify the primary barriers to implementing adaptation strategies, this study used the Problem Confrontation Index (PCI) as an effective tool to rank and prioritizing obstacles. PCI has been widely recognized as a valuable method for systematically identify critical challenges that hinder the adoption of climate adaptation strategies, as demonstrated in several empirical studies (Manh & Ahmad, 2021; Popoola et al., 2020). The study employed a 4-point Likert scale to assign scores for exposure to problems, allowing farmers to evaluate ten specific climate-related issues. Each issue was rated as a major problem (3 points), moderate problem (2 points), minor problem (1 point), or no problem at all (0 points). This approach is highly effective because it provides a structured way to quantify and rank the significance of different barriers. By allowing farmers to directly assess the severity of the issues they face, PCI enables researchers to pinpoint the challenges that have the greatest impact on the successful implementation of climate adaptation strategies (Gemeda et al., 2023; Masud et al., 2017; Pickson & He, 2021). The PCI was estimated using the following equation:

$$\mathrm{PCI} = (\mathrm{PN} \times 0) + (\mathrm{PL} \times 1) + (\mathrm{PM} \times 2) + (\mathrm{PH} \times 3) \tag{3}$$

where PCI = the problem confrontation index, P_H = the number of farmers with high-level problems, P_M = the number of farmers with medium-level problems, P_L = the number of farmers with low-level problems, and P_N = the number of farmers with no problems.

Multinomial Logit Model (MNL)

The study used a multinomial logit (MNL) model to identify the key factors that influence farmers' choice of adaptation strategies to climate variability. The selection of the MNL model was guided by prior research that demonstrated its effectiveness in analyzing farmers' adaptive behaviors. The model also identifies critical barriers to adaptation. These barriers include financial limitations and inadequate institutional support. Recognizing them is crucial for designing targeted interventions. By assessing the relative importance of these determinants, the MNL model provides valuable information for policymakers to develop context-specific strategies that strengthen farmers' resilience to climate variability. The insights gained from this analysis contribute to an in-depth understanding of adaptive capacity within agricultural systems, making the MNL model an invaluable tool for researchers and practitioners working to address climate change challenges in the agricultural sector (Megersa et al., 2022; Teshome et al., 2021b). The MNL model is particularly advantageous as it allows for the estimation of probabilities across multiple categorical outcomes. Thus, it provides an in-depth understanding of how various factors influence decision making among farmers (Belay et al., 2017). The model is specified as follows:

Let farmer i decide to use the j^{th} adaptation option if the perceived benefit of option j is greater than the utility obtained from other available options (for example, k), depicted as:

$$U_{ij} = \left(\beta'_j X_i + \varepsilon_j\right) > U_{ik}\ (\beta'_k X_i + \varepsilon_k), k \neq j \tag{4}$$

In this context, U_{ij} and U_{ik} denote the perceived utility of farmer i for adaptation options j and k, respectively. Here, Xi represents a vector of explanatory variables that influence the choice of the adaptation option. βj and βk are the parameters to be estimated, whereas εj and εk serve as error terms.

To illustrate the MNL model, let Y be a random variable with values ranging from 1 to M, where M is a positive integer and X is a set of conditioning variables. In this context, Y denotes adaptation options or categories, and X includes household, institutional, and environmental attributes. The goal is to determine how the elements change. Because the probabilities must sum up to one, determining P (Y = j|X) depends on knowing the probabilities for j = 2 to M. Let X be a 1 × K vector, where the first element is 1. Consequently, the probability that household i with characteristics X will choose the adjustment option j is expressed as follows:

$$P(\gamma_i = j|\chi) = \frac{\exp(X_j\beta_j)}{\left[1+\sum_{j=1}^{M} exp(X_j\,\beta_j)\right]} \tag{5}$$

In this equation, P represents probability, j denotes adaptation options, X signifies explanatory variables, and βj = k × 1 represents coefficients, where j ranges from 1 to M.

Multicollinearity among continuous explanatory variables is a significant concern in regression analysis because it can distort estimated coefficients and lead to unreliable statistical inferences. To assess and identify multicollinearity in this study, the variance inflation factor (VIF) approach was employed. The VIF quantifies the extent to which the variance of a regression coefficient increases due to multicollinearity with other independent variables. Specifically, it provides a measure of how much a variable inflates the standard errors of the regression coefficients due to its correlation with other predictors.

The VIF for each explanatory variable was calculated using the formula:

$$VIF = \frac{1}{1-R_j{}^2} \tag{6}$$

The contingency coefficient (CC) is a useful statistical measure for assessing multicollinearity among categorical and dummy variables in regression analysis. It quantifies the degree of association between variables, helping researchers determine whether one variable influence another. A CC value close to one indicates a strong correlation, signaling potential multicollinearity that could bias model estimates. In contrast, a value near zero suggests little or no association, indicating that multicollinearity is unlikely to be a concern.

The formula for calculating the contingency coefficient was expressed as follows:

$$CC = \sqrt{\frac{x^2}{\mathrm{n}-x^2}} \tag{7}$$

In this formula, CC represents the contingency coefficient, x^2 denotes the chi-square test, and 'n' signifies the total sample size.

Description of explanatory variables

The explanatory variables in the multinomial logit model (MNL) were selected based on their relevance to climate adaptation, as highlighted in previous studies. They were also chosen based on their availability in the collected data. These variables encompass sociodemographic, economic, climatic, and institutional factors that influence farmers' adaptation decisions. Table 5.1 presented the independent variables used in the analysis, which included the age of the household head, educational level, family size, farm size, farm experience, household income, crop failure, recurrent drought, extension service, credit access, agroecology, climate perception, and climate information.

Age is a crucial determinant, as older farmers often rely on experience and traditional knowledge, while younger farmers tend to be more receptive to innovative techniques. Studies indicated that age affects how people see risk and how willing they are to use new farming technologies (Kassie et al., 2013). Similarly, education plays a vital role in adaptation, since higher educational attainment improves access to climate-related information and resources, allowing farmers to make informed decisions. Educated farmers are more likely to adopt climate-smart technologies and innovative agricultural practices (Sisay et al., 2023). In addition, family size affects both labor availability and resource allocation. While larger families can provide more labor for farming activities, they may also face financial constraints due to increased household expenditures, potentially limiting investment in adaptation strategies (Aryal et al., 2020). The size further determines farmers' capacity to implement adaptation measures. Larger farms typically have greater resources and flexibility to adopt new strategies, while smaller farms often encounter significant land and financial constraints (Deressa et al., 2009). In addition, farming experience improves resilience by improving farmers' understanding of local climate patterns and effective adaptation techniques. Experienced farmers tend to be better equipped to cope with climate shocks as they accumulate knowledge over time (Getahun et al., 2021).

Financial capacity also plays a critical role, as higher household income allows farmers to invest in adaptation measures such as drought-resistant seeds and irrigation systems. On the contrary, low-income households struggle to finance necessary adaptations (Teshome et al., 2021b). Additionally, exposure to crop failure significantly influences farmers' adaptation decisions. Repeated crop losses often push farmers to adopt new strategies, such as diversifying farming systems or using soil conservation techniques, to mitigate future risks (Megersa et al., 2022). The access to the extension service is an important factor that motivates farmers to practice different adaptation strategies. In this regard, Asrat & Simane (2018) highlighted the crucial role of extension services in improving adaptation by equipping farmers with new skills for the adoption of sustainable techniques. Recurrent droughts pose severe challenges to agricultural productivity, prompting farmers to adopt more resilient cropping systems and explore diversification options (Khanal et al., 2018). Access to credit also plays a pivotal role in facilitating adaptation, as it provides farmers with the financial resources needed to invest in improved inputs and technologies. However, limited access to credit can hinder adaptation efforts by restricting farmers' ability to implement new strategies (Belay et al., 2017). Additionally, agroecological variations shape the adaptation strategies that farmers employ. Given the diverse climate impacts across highland, midland, and lowland zones, adaptation approaches must be tailored to the specific conditions of each agroecological setting (Eshetu et al., 2021).

Farmers' perceptions of climate change further influence their adaptation choices. Those who acknowledge climate variability as a serious threat are more likely to take proactive measures to mitigate its effects (Bryan et al., 2013). Finally, access to accurate climate information is essential for informed decision making. Farmers who receive timely weather forecasts and climate data can better plan their agricultural activities and adopt appropriate adaptation strategies (Roudier et al., 2016).

Table 5. 1 Description of explanatory variables and their hypothesized effects

Explanatory variables	Description and measurement	Variable type	Expected sign
Age	Age of household heads (HH) in years	Continuous	±
Education	1. illiterate, 2. read & write, 3. Primary, 4. secondary	Categorical	+
Family size	Number of HH living in one house	Continuous	±
Income	Total annual income in Ethiopian Birr (ETB)	Continuous	+
Crop failure	1, if HH has experienced crop failure; 0, otherwise	Dummy	+
Extension service	1, if HH has access to the extension service; 0, otherwise	Dummy	+
Access to credit	1, if HH has access to credit; 0, otherwise	Dummy	+
Farm experience	Total number of years that HH spent in farming	Continuous	+
Farm size	Size of farm land owned by HH in hectare	Continuous	+
Agroecology	1. *Dega,* 2. *Woina Dega*, 3. *Kolla*	Categorical	±
Climate perception	1, if HH perceived climate; 0, otherwise	Dummy	+
Recurrent drought	1, if HH is aware of drought occurrence; 0, otherwise	Dummy	+
Climate information	1, if HH has access to climate information; 0, otherwise	Dummy	+

5.3 Results and Discussion

5.3.1 Households' adoption of indigenous adaptation measures

Indigenous adaptation strategies comprise time-tested practices developed over generations to enable communities to cope with environmental change. Based on local knowledge, culture, and lived experience, these strategies are finely tuned to specific climatic conditions, making them locally appropriate, sustainable, and cost-effective. By enhancing adaptive capacity and community resilience, indigenous practices play a vital role in mitigating the adverse impacts of climate variability (Amare, 2018; Ware, 2022).

The study found that farm households employed a diverse set of indigenous adaptation strategies, with clear variations in agroecological zones. The most widely implemented practices in the highlands were traditional irrigation (WAI = 2.23), adjustment of the planting date (WAI = 2.20), and crop diversification (WAI = 2.18), with the availability of perennial rivers substantially encouraging the continued use of traditional irrigation. In the midland zone, farmers relied mainly on planting local crop varieties (WAI = 2.34), adjusting planting dates (WAI = 2.24), and traditional irrigation (WAI = 2.10). On the contrary, lowland farmers predominantly adopted crop diversification (WAI = 2.41), planted local crop varieties (WAI = 2.33) and the application of organic fertilizers (WAI = 2.29) to address climatic stresses. In general, in all agroecological zones, the indigenous strategies most commonly practiced were planting local crop varieties (WAI = 2.22), the diversification of the crop (WAI = 2.15), and adjustment of the planting dates (WAI = 2.14), highlighting the strong dependence on indigenous knowledge systems to improve resilience to climate variability (Table 5.2).

In contrast, strategies such as seasonal migration, reduction of social and religious festivals, and decreased numbers of livestock were the least adopted across all agroecological zones. Their limited use indicates that farmers tend to favor adaptation measures that preserve sociocultural values and economic stability. This calls attention to the need for policies that strengthen indigenous adaptation practices by integrating them into broader climate adaptation frameworks. Enhancing local knowledge systems, improving access to resources for traditional irrigation, and promoting climate-resilient crop varieties can further improve farmers' adaptive capacity. In addition, recognizing agroecology-specific strategies is essential to design targeted interventions that align with the farmers' priorities and the unique environmental conditions of each zone.

Overall, the findings demonstrate that indigenous adaptation strategies in the study area are highly agroecology-specific, reflecting differences in water availability, climatic risk exposure, and livelihood systems. Highland farmers rely more on irrigation and planting-time adjustments due to relatively stable hydrological conditions, while lowland farmers depend more on diversification and soil fertility management in response to higher rainfall variability and moisture stress. These results suggest that indigenous knowledge systems remain central to climate adaptation; however, their effectiveness varies across agroecological contexts and may be constrained under long-term climatic change. Strengthening these systems therefore requires targeted support that integrates local knowledge with appropriate technical and institutional interventions.

A one-way ANOVA analysis revealed significant variations in the mean values of indigenous adaptation strategies in different agroecological zones. Adoption of local crop varieties, traditional irrigation, use of organic fertilizers, crop diversification, and seasonal migration differed significantly at the level of 1% ($p < 0.01$), while reductions in social and religious festivals and livestock numbers showed differences at the level of 5% ($p < 0.05$). On the contrary, changes in planting dates did not show significant variation, indicating that this strategy is commonly and uniformly practiced across all agroecological zones.

Regarding indigenous adaptation strategies, a key informant explained as follows:

Indigenous adaptation strategies, which are low-cost, sustainable, and based on locally available resources, hold significant value, especially in resource-constrained settings. These practices are based on strong community bonds, where knowledge and resources are shared, making social cohesion central to their effectiveness. However, while they are well suited to managing short-term climate variability, they may be less capable of addressing long-term challenges such as rising temperatures and shifting rainfall patterns.

The study's findings align closely with existing empirical evidence on indigenous adaptation strategies. For example, Aboye et al. (2023) reported that migration is among the least frequently adopted strategies in Ethiopia's lowland areas. Nyong et al. (2007) emphasized the effectiveness of traditional practices, such as water conservation, indigenous techniques, and crop diversification, in responding to climate variability. Similarly, Aidoo et al. (2021) identified adjusting planting dates and crop diversification as the most widely adopted strategies among smallholder farmers. Bekuma et al. (2023) also highlighted mixed farming and the reduction of social and religious ceremonies as important adaptation options. Furthermore, Myeni & Moeletsi (2020) found water harvesting is a highly favored strategy, while aligning planting schedules with rainfall patterns has been widely recognized as a critical adaptation measure (Antwi-Agyei & Frimpong, 2021; Chisale et al., 2024). Kom et al. (2023) emphasized the importance of indigenous knowledge in helping rural households overcome climate pressures and make informed adaptation decisions. These findings highlight the need for governments to actively promote and strengthen indigenous adaptation systems. Local agricultural specialists could encourage the integration of traditional knowledge with modern adaptation measures by providing technical assistance, improving resource availability, and promoting climate-resilient farming practices. Designing agroecology-specific interventions is still critical for increasing community resilience and sustaining sustainable agricultural livelihoods.

Table 5. 2 Indigenous adaptation strategies (n=338)

Indigenous adaptation strategies	Agro-ecological zones (WAI)								
	Highland (n=120)		Midland (n=118)		Lowland (n=100)		Total (n=338)		F value
	WAI	Rank	WAI	Rank	WAI	Rank	WAI	Rank	
Planting local crop varieties	1.93	5th	2.34	1st	2.33	2nd	2.22	1st	5.124***
Adjusting planting dates	2.20	2nd	2.24	2nd	2.04	5th	2.14	3rd	1.302Ns
Traditional irrigation	2.23	1st	2.10	3th	1.27	8th	1.86	4th	34.54***
Reducing social & religious festivals	1.52	6th	1.77	7th	1.83	7th	1.67	7th	3.87**
Using organic fertilizers	1.96	4th	1.98	5th	2.29	3th	2.10	5th	21.95***
Reducing no of livestock	1.20	8th	1.95	6th	2.25	4th	1.82	6th	3.42**
Crop diversification	2.18	3rd	2.01	4th	2.41	1st	2.15	2nd	6.64***
Seasonal migration	1.48	7th	1.33	8th	1.99	6th	1.58	8th	12.19***
Grand mean	1.83	-	1.97	-	2.05	-	1.95	-	14.51***

*** and ** indicate significance at the 1% and 5% levels, respectively; WAI=weighted average index; and Ns=not significant.

5.3.2 Households' adoption of introduced adaptation measures

These adaptation strategies refer to modern interventions promoted by governments, NGOs, and development organizations to help communities cope with the impacts of climate change. These approaches often involve technologies, infrastructure, or practices that are not traditionally embedded in local farming systems (Pratap et al., 2024). The survey results showed clear adoption patterns in all agroecological zones. In highland areas, the most widely adopted strategies were the use of inorganic fertilizers (WAI = 2.60), soil and water conservation practices (WAI = 2.38), and improved crop varieties (WAI = 2.32). In the mid-land zone, farmers prioritized primarily inorganic fertilizers (WAI = 2.67), improved mixed agriculture systems (WAI = 2.42), and improved crop varieties (WAI = 2.39). Similarly, in the lowland zone, the dominant strategies included inorganic fertilizers (WAI = 2.66), the use of pesticides and herbicides (WAI = 2.55) and improved crop varieties (WAI = 2.54). The results of a one-way ANOVA indicated that most of the adaptation strategies did not differ significantly between agroecological zones. However, the adoption of pesticides and herbicides showed significant variation at the 1% level ($p < 0.01$), while the improved mixed farming differed significantly at the 5% level ($p < 0.05$) (Table 5.3).

The findings indicated that smallholder farmers in all agroecological zones consistently prioritize the use of inorganic fertilizers and improved crop varieties, while agroforestry is the least adopted adaptation strategy. Low uptake of agroforestry is likely due to limited awareness, inadequate technical support, and perceptions of delayed benefits, despite its well-documented long-term contributions to soil fertility, biodiversity conservation, and climate resilience. On the contrary, the heavy dependence on inorganic fertilizers and pesticides raises serious concerns for soil health and ecosystem stability, as it can lead to nutrient imbalances, land degradation, and loss of biodiversity. These practices are in conflict with the principles of sustainable agricultural adaptation, which seek to strengthen resilience while protecting environmental integrity.

Addressing these challenges requires a multifaceted approach that combines indigenous knowledge, agroecological techniques, and integrated soil fertility management. Promoting practices such as organic fertilizers, crop rotation, and Integrated Pest Management (IPM) can help reduce the dependence on synthetic inputs while preserving production. Local agricultural specialists play an important role in improving climate-smart agriculture and sustainable land management (SLM) by providing targeted incentives, technical support and extension services, which promote long-term agricultural sustainability.

FGD and KII results show a clear shift from organic inputs toward greater reliance on inorganic fertilizers, mainly driven by the pursuit of higher and faster yields. However, participants expressed concerns that excessive use of synthetic fertilizers may degrade soil health by disrupting nutrient cycles, reducing long-term fertility, and causing nutrient imbalance, which could negatively affect crop productivity and produce quality. They also highlighted potential environmental risks, including nutrient leaching into water bodies, with implications for water pollution, aquatic ecosystems, and human health. Overall, the findings point to the need for a more balanced fertilizer management approach to sustain soil productivity and environmental quality over time.

Overall, the findings indicate that introduced adaptation strategies in the study area are characterized by relatively uniform adoption across agroecological zones, reflecting the strong influence of external extension services and input supply systems rather than agroecological differentiation. The dominance of inorganic fertilizers and improved crop varieties suggests a shift toward input-intensive agriculture driven primarily by short-term yield objectives. However, the low adoption of agroforestry and increasing reliance on chemical inputs raise concerns about long-term soil fertility, ecosystem stability, and environmental sustainability. These results highlight a fundamental trade-off between productivity-oriented adaptation and environmentally sustainable farming systems. Strengthening adaptation therefore requires a more balanced approach that integrates introduced technologies with ecological principles and local knowledge systems to ensure both productivity and long-term resilience.

The findings of this study are consistent with previous research on agricultural adaptation strategies. Berck et al. (2018) and Jawo et al. (2023) reported widespread adoption of improved agricultural practices among smallholder farmers. Gbemavo et al. (2022) underlined the relevance of water management practices, including traditional irrigation and water collection, and Gohar & Cashman (2016) argued for the integration of climate-related technology alongside capacity-building activities. Furthermore, Kandel et al. (2023) and Ullah et al. (2023) highlighted the adoption of agroforestry in mountainous regions, while Aidoo et al. (2021) emphasized the importance of weather forecasting and resilient crop varieties for effective adaptation. Kom et al. (2023) found that smallholder farmers commonly used chemical fertilizers, pesticides, and soil conservation practices, further suggesting a preference for modern adaptation methods over traditional ones.

Table 5. 3 Introduced adaptation strategies (n=338)

Introduced adaptation strategies	Agro-ecological zones (WAI)								F-value
	Highland (n=120)		Midland (n=118)		Lowland (n=100)		Total (n=338)		
	WAI	Rank	WAI	Rank	WAI	Rank	WAI	Rank	
Soil and water conservation	2.38	2nd	2.24	5th	2.11	4th	2.26	4th	2.00Ns
Improved crop varieties	2.32	3rd	2.39	3rd	2.54	3rd	2.41	2nd	1.606 Ns
Inorganic fertilizers	2.60	1st	2.67	1st	2.66	1st	2.64	1st	.260Ns
Pesticides and herbicides	2.13	5th	2.26	4th	2.55	2nd	2.28	3rd	6.05***
Improved mixed farming	2.27	4th	2.42	2nd	2.10	5th	2.25	5th	3.06**
Agro-forestry	1.33	6th	1.50	6th	1.61	6th	1.47	6th	1.28Ns
Grand mean	2.17	-	2.25	-	2.26	-	2.23	-	2.38 Ns

*** and ** indicate significance at the 1% and 5% levels, respectively; WAI=weighted average index; and Ns=not significant.

5.3.3 Barriers to adaptation strategies

This study utilized the Problem Confrontation Index (PCI) to identify and rank the key barriers that impede the implementation of adaptation strategies in response to climate variability. Similar approaches have been employed in previous studies to assess constraints on adaptation measures (Gemeda et al., 2023; Masud et al., 2017; Popoola et al., 2020). The analysis highlighted that the limited size of the farm (PCI = 694), inadequate access to climate information (PCI = 641), the poor soil fertility (PCI = 639), the insufficient irrigation infrastructure (PCI = 623), and the increase in the costs of agricultural inputs (PCI = 610) represented the most significant challenges (Table 5.4). Of these, limited farm size, restricted access to meteorological data, and soil degradation emerged as primary barriers, whereas lack of credit facilities and low literacy levels were identified as less critical constraints. These findings underscore the need for a comprehensive approach that improves land use efficiency, improves access to climate information, restores soil health, expands irrigation infrastructure, and strengthens financial support to improve farmers' adaptive capacity.

During focus group discussions, farmers highlighted the major challenges in accessing reliable climate information. One participant explained: 'We often hear about weather changes from friends or the radio, but we need accurate forecasts to plan planting and harvesting.' Soil degradation was also identified as a critical concern, particularly in highland areas. As one farmer remarked: 'Our soil has become less fertile, and despite using fertilizer, we can't achieve the yields we need' while another added, "Our soil does not respond like it used to," underscoring the difficulty of adapting to changing conditions. These insights underscore the urgent need for accurate climate information and effective soil management strategies to improve farmers' ability to adapt to climate variability.

The findings of this study are consistent with previous research that highlights key barriers to climate adaptation among smallholder farmers. Gemeda et al. (2023) and Eshetu et al. (2021) identified irrigation deficiencies, high agricultural input costs, and soil infertility as major obstacles, while Pickson & He (2021) pointed to unpredictable weather, limited land size, and insufficient labor as critical constraints. Similarly, Likinaw et al. (2023) emphasized that restricted irrigation potential and financial limitations hinder the adoption of irrigation-based adaptation strategies. Megersa et al. (2022) also reported that small farm sizes, economic constraints, erratic weather patterns, and limited access to climate forecasts pose significant challenges for farmers. Collectively, these studies reinforce the multifaceted nature of barriers affecting smallholder adaptation efforts.

Table 5. 2 Constraints of adaptation strategies (n=338)

Constraints	The extent of problem confrontation				PCI	Rank
	No problem (0)	Less problem (1)	Moderately Problem (2)	Highly Problem (3)		
Low literacy	122	96	64	56	392	9
Poor access to climate information	43	71	102	122	641	2
Lack of knowledge to adaptation	52	78	93	115	609	6
Lack of credit services	130	85	79	44	375	10
Lack of irrigation facilities	34	55	83	134	623	4
Poor institutional support	54	68	116	100	600	7
High cost of farm inputs	36	92	112	98	610	5
Limited farm size	21	82	93	142	694	1
Lack of agricultural subsidies	140	70	34	94	420	8
Infertile soil	50	61	103	124	639	3

5.3.4. Determinants of indigenous adaptation strategies

The Multinomial Logit (MNL) model was applied to examine the factors associated with farmers' choice of indigenous adaptation strategies. Diagnostic tests indicate that the model is statistically appropriate for analysis, as the variance inflation factor (VIF) and contingency coefficient (CC) results show no evidence of multicollinearity among explanatory variables. In addition, the highly significant likelihood ratio test ($p < 0.01$) confirms that the explanatory variables jointly provide meaningful explanatory power for variation in adaptation choices (Table 5.5).

The results show that household age is associated with differences in adaptation behavior. Older farmers are more likely to report the use of strategies such as traditional irrigation, planting date adjustments, organic fertilizer application, livestock reduction, and crop diversification. This pattern may reflect accumulated farming experience and long-term exposure to climate variability (Anum et al., 2022; Gebru et al., 2020; Marie et al., 2020). In contrast, younger farmers tend to report a broader set of adaptation practices, which may be linked to differences in access to education, information, and willingness to experiment with new technologies (Ali et al., 2021; Asfaw et al., 2019; Hirpha et al., 2020).

Education level shows an overall positive association with several adaptation choices. Higher education is associated with greater reported use of planting date adjustment, livestock management changes, and crop diversification ($p < 0.05$–0.01). This suggests that education may enhance farmers' ability to interpret climate-related information and evaluate different response options. However, education is negatively associated with reliance on traditional irrigation and organic fertilizer use, indicating a possible shift away from some indigenous practices toward more input-oriented approaches. Other studies also report mixed associations depending on awareness and environmental orientation (Abebe & Debebe, 2019; Salam et al., 2021; Teshome et al., 2021b).

Household size shows mixed associations with adaptation choices. Larger households are less likely to report planting date adjustments, which may reflect coordination constraints in household labor allocation, while they are more likely to use organic fertilizers, possibly due to greater availability of family labor (Getahun et al., 2021; Hirpha et al., 2020; Wodaje et al., 2020). This suggests that household labor can function both as a constraint and as a resource depending on the type of strategy considered.

Household income is associated with a wider set of reported adaptation strategies. Higher-income households are more likely to report irrigation use, crop diversification, livestock adjustment, and planting date changes. This pattern suggests that financial capacity may enable broader adaptation options. At the same time, higher income is associated with lower reliance on local crop varieties, indicating a possible shift toward improved or market-oriented crops (Adimassu & Kessler, 2016; Asayehegn et al., 2017; Bojago & Abrham, 2023).

Households reporting crop failure experience show higher likelihood of adopting strategies such as irrigation and crop diversification. This may reflect adaptive responses following production shocks. At the same time, such households report lower reliance on local crop varieties and organic fertilizers, suggesting a shift in strategy preference following adverse experiences (Addis & Abirdew, 2021; Darge et al., 2023; Gemeda et al., 2023).

Access to extension services is associated with differences in reported adaptation behavior. Households with extension access are more likely to report crop diversification, planting date adjustments, organic fertilizer use, and use of local crop varieties. This suggests that extension contact may be linked with greater awareness and exposure to different adaptation options (Derso et al., 2022; Gatdet, 2022).

Similarly, access to credit shows mixed associations with adaptation choices. Credit access is associated with lower reliance on some indigenous coping strategies, such as local crop varieties, planting date adjustments, livestock reduction, and social coping mechanisms, while being positively associated with crop diversification. This may indicate a shift toward more investment-oriented adaptation options among credit-constrained and credit-access households (Darge et al., 2023; Mutunga et al., 2018; Saguye, 2016).

Farming experience is associated with specific adaptation choices. More experienced farmers are more likely to report the use of local crop varieties, possibly reflecting accumulated knowledge and familiarity with traditional practices, while they are less likely to report crop diversification (Aidoo et al., 2021; Rahman et al., 2023). However, evidence in the literature is mixed, as experience may also be associated with adoption of selected modern practices such as crop rotation and weather-based decisions (Trinh et al., 2018).

Farm size is positively associated with the use of several strategies, including local crop varieties, organic fertilizers, and crop diversification. This suggests that larger landholding may be linked with greater flexibility in allocating land across multiple practices and spreading production risk (Alemayehu et al., 2022a; Amare & Simane, 2017; Gudina & Alemu, 2024).

Agroecological zone is also associated with differences in reported adaptation choices. Households in highland areas are more likely to report use of local crop varieties and livestock reduction, while those in midland areas are more likely to report irrigation and crop diversification. These patterns reflect differences in environmental conditions and production constraints across agroecological settings (Amare & Simane, 2017; Eshetu et al., 2021; Megabia et al., 2022; Mossie & Chanie, 2024).

Climate perception shows mixed associations with adaptation choices. In some cases, climate perception is negatively associated with certain indigenous strategies, suggesting that awareness alone may not translate into action without enabling conditions such as resources or institutional support (Aidoo et al., 2021; Getahun et al., 2021).

In contrast, drought experience is more consistently associated with the reporting of multiple adaptation strategies, including irrigation, crop diversification, planting date adjustment, and organic fertilizer use. This suggests that direct exposure to climate shocks may be more strongly associated with behavioral responses than perception alone (Alemu et al., 2019; Darge et al., 2023; Khanal et al., 2018; Aboye et al., 2023).

Finally, access to climate information is associated with broader reported use of adaptation strategies, including crop diversification, planting date adjustment, organic fertilizer use, and use of local crop varieties. It is also associated with more flexible farm and livestock management practices, indicating its role in supporting informed decision-making (Darge et al., 2023; Gemeda et al., 2023; Getahun et al., 2021; Kifle et al., 2022; Owusu et al., 2021).

Overall, the findings indicate that farmers' adoption of indigenous adaptation strategies is shaped by a complex interaction of human capital, resource endowments, institutional access, and exposure to climate stressors. While demographic factors such as age and education influence knowledge and decision-making capacity, economic resources such as income and landholding size determine the feasibility of implementing adaptation measures. Institutional factors, particularly access to extension services and climate information, play a critical role in enhancing awareness and facilitating adoption of diversified strategies. However, the results also suggest that perception alone is insufficient to drive adaptation decisions unless it is supported by adequate resources and institutional support. Moreover, direct exposure to climate shocks such as drought appears to be a stronger trigger of adaptation behavior than perceived gradual climate change. These findings underscore that adaptation is not a purely behavioral response but a structurally constrained process shaped by both socioeconomic capacity and environmental stress.

Table 5. 3 Determinants of indigenous adaptation strategies (n=338)

Explanatory variables	Indigenous adaptation strategies						
	PLCV	APD	TI	RSRF	UOF	RNL	CD
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Age	.840	2.333***	1.376*	.625	3.237***	1.640***	.965*
Education	.990**	.890	-2.326***	1.277***	-1.738**	-.872	1.572***
Family size	-.345	-1.323*	-.461	-.944	1.257**	-.661	.544
Income	-1.934***	2.110***	2.548***	-.133	-.032	.889*	1.394**
Crop failure	-4.350***	-.592	2.548*	.534	-2.814**	-1.087	3.477**
Extension service	2.162**	1.922***	-.225	1.246	3.872**	-.724	4.624***
Credit access	-3.574***	-2.857***	-.544	-3.023***	1.310	-2.085**	1.984*
Farm experience	.715*	.499	-.205	-.033	-.620	-.173	-1.512***
Farm size	1.136**	.354	-.081	.711	.670*	.235	1.707***
AEZs (Highland)	1.215	2.889***	1.580	1.248	1.558	3.118***	.616
Midland	-1.375	.548	2.018*	-.842	-2.972**	.724	3.325***
Climate perception	1.246	2.945	-3.574**	-3.214*	-3.939**	1.872	-4.841***
Recurrent drought	4.994***	3.755**	5.610***	3.051	6.428***	.364	1.213
Climate information	2.862**	3.864***	2.543	-1.635	3.346***	2.682*	6.243***
Reference category: Seasonal migration							
No of observation=338				Prob >chi^2=0.000			
LR Chi^2 (84) =627.019				Pseudo R^2= .844			
Log likelihood= −738.736							

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; PLCV—planting local crop varieties; APD—adjusting planting dates; TI—traditional irrigation; RSRF—reducing social and religious festivals; UOF—using organic fertilizers; RNL—reducing the number of livestock; CD—crop diversification; Coeff—coefficient; AEZs—agroecological zones

5.3.5 Determinants of introduced adaptation strategies

The determinants of adaptation strategies were analyzed using a multinomial logit (MNL) model. Diagnostic tests based on VIF and CC indicate no evidence of multicollinearity among explanatory variables. The model also demonstrates strong explanatory power, as shown by the highly significant likelihood ratio statistic (LR $\chi^2 = 329.844$, $p < 0.01$). In addition, the Cox and Snell pseudo-R^2 value of 0.623 suggests that the included variables jointly explain a substantial share of variation in reported adaptation choices, indicating a reasonably well-fitting model (Table 5.6).

The results show that household age is associated with differences in adaptation choices. Older farmers are less likely to report the use of inorganic fertilizers ($p < 0.01$), but more likely to report pesticide and herbicide use ($p < 0.05$). This pattern suggests differentiated adaptation behavior across age groups, which may reflect differences in experience, risk preferences, and openness to new practices (Teshome et al., 2021b; Asrat & Simane, 2018; Destaw & Fenta, 2021; Fekadu & Belay, 2025; Fisher et al., 2015).

Education is positively associated with several adaptation choices, particularly improved crop varieties, inorganic fertilizers, and mixed farming systems ($p < 0.01$–0.05). This indicates that more educated farmers tend to report greater engagement with modern agricultural practices, which may be linked to improved access to information and better capacity to interpret climate-related risks (Ahmed & Fatema, 2023; Gemeda et al., 2023; Getahun et al., 2021; Molla et al., 2023).

Household size shows a positive association with labor-intensive strategies such as soil and water conservation and mixed farming systems. This suggests that households with more available labor tend to report greater use of physically demanding practices (Erekalo & Yadda, 2023; Fekadu & Belay, 2025; Hirpha et al., 2020).

Household income is positively associated with the reported adoption of improved crop varieties, inorganic fertilizers, and mixed farming systems. This indicates that better-resourced households tend to report greater use of input-intensive adaptation options, which may reflect financial capacity constraints (Adimassu & Kessler, 2016; Asayehegn et al., 2017; Darge et al., 2023).

Experience of crop failure is positively associated with the use of soil and water conservation practices, improved crop varieties, and mixed farming systems. This suggests that households experiencing production shocks are more likely to report shifts toward risk-reducing and resilience-oriented practices (Addis & Abirdew, 2021; Mossie & Chanie, 2024; Onyeneke, 2021).

Access to extension services is associated with higher reported use of soil and water conservation, improved crop varieties, pesticide and herbicide use, and mixed farming systems. This indicates that households with extension contact tend to report broader awareness and use of available adaptation options (Adams & Jumpah, 2021; Aryal et al., 2018; Darge et al., 2023).

Similarly, access to credit is positively associated with improved crop varieties, inorganic fertilizers, pesticide and herbicide use, and mixed farming systems, while its association with soil and water conservation is not statistically significant. This suggests that credit access is more closely linked with input-based adaptation strategies (Myeni & Moeletsi, 2020; Trinh et al., 2018).

Farming experience shows a negative association with the reported use of inorganic fertilizers and soil and water conservation practices. This may reflect stronger reliance on established practices among more experienced farmers or constraints related to labor-intensive technologies (Kandel et al., 2023), although contrasting evidence exists in the literature (Diallo et al., 2020; Sadiq et al., 2019; Trinh et al., 2018).

Farm size is positively associated with the reported use of pesticides and inorganic fertilizers, suggesting that larger landholders tend to report greater use of input-intensive strategies, possibly due to economies of scale and resource availability (Abera & Tesema, 2019; Destaw & Fenta, 2021), although mixed findings have been reported elsewhere (Amare & Simane, 2017).

Agroecological zone is associated with differences in adaptation behavior. Highland households are less likely to report improved crop varieties, pesticides, and mixed farming systems but more likely to report inorganic fertilizer use. In contrast, midland households show higher reported use of soil and water conservation and mixed farming systems, reflecting differing environmental pressures across zones (Aryal et al., 2020; Eshetu et al., 2021; Kandel et al., 2023).

Climate perception is associated with most adaptation strategies, except pesticide and herbicide use. This suggests that awareness of climate variability is linked with greater reporting of preventive and resource-conserving practices such as soil conservation and crop diversification (Adeagbo et al., 2021; Tessema & Simane, 2021).

Drought experience shows a positive association with improved crop varieties, soil and water conservation, inorganic fertilizer use, and mixed farming systems. This indicates that households exposed to drought events tend to report stronger engagement with resilience-oriented strategies (Dasmani et al., 2020; Mulwa et al., 2017; Onyeneke, 2021).

Finally, access to climate information is positively associated with nearly all adaptation strategies, including improved crop varieties, soil and water conservation, inorganic fertilizers, and crop diversification. This highlights the importance of information access in shaping awareness and reported adaptation behavior (Dang et al., 2019; Mutunga et al., 2018; Ndamani & Watanabe, 2016).

Focus group discussions complement these findings by indicating that farmers mainly rely on radio and television for short-term weather updates, with limited access to seasonal forecasts and early warning systems. Participants also reported that incomplete or unreliable climate information, combined with limited access to inputs, credit, and technical support, constrains effective adaptation planning and implementation.

Overall, the findings indicate that farmers' adaptation decisions in the study area are shaped by a complex interaction of socioeconomic capacity, institutional access, agroecological conditions, and exposure to climatic shocks. While human capital variables such as education and experience influence awareness and decision-making capacity, economic resources such as income and farm size determine the feasibility of adopting input-intensive strategies. Institutional factors, particularly access to extension services and climate information, play a central role in expanding awareness and facilitating diversification of adaptation practices. However, the results also suggest that perception alone is insufficient to drive adaptation behavior unless it is supported by adequate resources and institutional backing. In contrast, direct exposure to climatic shocks such as drought emerges as a stronger trigger of behavioral change than gradual climate perception. These findings highlight that adaptation in smallholder farming systems is not merely a cognitive process, but a structurally constrained outcome shaped by both vulnerability and capacity dimensions.

Table 5. 4 Determinants of introduced adaptation strategies (n=338)

	Introduced adaptation strategies				
Explanatory variables	SWC	UICV	AIF	APH	AIMF
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Age	.037	.240	-1.080***	1.036**	.144
Education	.586	1.918***	.960*	.899	1.758***
Family size	.722*	-.915**	.264	-.936**	1.252***
Income	.517	.891**	1.302***	.391	1.250***
Crop failure	1.286*	2.114***	-.071	1.203	2.276***
Extension service	2.563***	3.725***	.326**	1.463	2.782***
Credit access	.408	1.971***	1.078*	2.110***	1.836***
Farm experience	-.652***	-.287	-1.015***	.058	-.392
Farm size	.110	.106	.361**	1.596***	.285
AEZs (Highland)	-.994	-2.456***	1.490**	-3.045***	-1.419*
Midland	.299***	.001	.988	-.456	.362**
Climate perception	1.333**	1.286*	1.670**	.225	1.147*
Recurrent drought	.948*	1.320**	1.580***	.876	1.578**
Climate information	2.678***	1.342**	1.469***	-.842	1.957**
No of observation=338		Reference category: Agroforestry			
LR Chi^2 (60) =329.844		Prob >chi^2=0.000			
Loglikelihood=-855.093		Pseudo R^2= .623			

***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively; SWC—soil and water conservation; UICV—using improved crop varieties; AIF—application of inorganic fertilizers—application of pesticides and herbicides; AIMF—application of improved mixed farming; Coeff—coefficient; AEZs—agroecological zones

5.4. Conclusion

This study examined the adaptation strategies employed by smallholder farmers, the constraints affecting their implementation, and the determinants shaping adaptation choices across agroecological zones in the Ayehu watershed. The findings reveal that farmers rely on a diversified portfolio of both indigenous and introduced adaptation strategies to respond to climate variability. Indigenous practices, including the use of local crop varieties, crop diversification, and adjustment of planting dates, remain central to farmers' coping mechanisms, while introduced measures such as inorganic fertilizers, improved crop varieties, and soil and water conservation practices are increasingly integrated into production systems.

Adaptation behavior is strongly conditioned by agroecological differences, with clear variations observed across highland, midland, and lowland areas, reflecting disparities in climate exposure, resource endowments, and livelihood contexts. These spatial differences underscore the highly place-specific nature of adaptation, indicating that uniform policy interventions are unlikely to be effective and must instead be tailored to local agroecological realities.

Despite these efforts, farmers continue to face persistent structural and environmental constraints, including biophysical limitations (declining soil fertility), institutional barriers (limited access to climate information and irrigation infrastructure), and economic constraints (small landholdings and high input costs), all of which collectively limit the effectiveness and sustainability of adaptation strategies.

The multinomial logit results further demonstrate that adaptation choices are influenced by an interplay of socioeconomic, institutional, and climatic factors such as education, income, access to extension services, credit availability, climate perception, drought experience, access to climate information, and agroecological setting, with extension services and climate information emerging as particularly influential across multiple adaptation options.

Overall, the study shows that smallholder adaptation in the study area is a hybrid and constrained process shaped by both indigenous knowledge systems and introduced technologies. It is not driven by perception alone, but by the interaction of household capacity, institutional access, and environmental stress. Improving adaptation therefore requires moving beyond fragmented interventions toward an integrated, agroecology-specific approach that strengthens climate information systems, expands access to credit and irrigation, and enhances extension services in a way that directly responds to observed spatial heterogeneity and household constraints.

CHAPTER SIX
SYNTHESIS, CONCLUSIONS, AND RECOMMENDATION

6.1. Synthesis

The findings of this study highlighted a strong and interconnected relationship between climate variability, agricultural impacts, farmers' perceptions of these changes, and the adaptation strategies adopted by smallholder farmers in the Ayehu Watershed of the Upper Blue Nile Basin. Historical climate records and future projections showed that the watershed is slowly moving toward a climate regime that is warmer and more variable, with higher minimum and maximum temperatures and less regular rainfall. During the past three decades, annual rainfall has shown a slight decline trend accompanied by pronounced interannual variability, creating considerable uncertainty for water resource management and undermining the reliability of rainfed agriculture that supports rural livelihoods. Seasonal rainfall dynamics further intensified this vulnerability. A decline in *Belg* rainfall increases the risk of early-season drought, which can disrupt crop establishment and early growth stages. On the contrary, increased *Kiremit* rainfall increases the likelihood of flooding, soil erosion, and waterlogging during the main cropping period. At the same time, the observed warming trend, particularly the more rapid increase in minimum temperature, may reduce frost occurrence but also increase evapotranspiration and crop water demand, thus exacerbating heat and moisture stress for temperature-sensitive crops such as maize, wheat and vegetables. Consequently, these climatic changes have contributed to the decline in the yields of major cereal crops in the watershed's diverse agroecological zones of the watershed. Future projections under the CMIP6 scenarios further reinforce these trends, indicating continued warming and increasingly uncertain rainfall patterns. Under high-emission pathways, rainfall variability and the frequency of extreme precipitation events are expected to intensify, presenting serious obstacles to agricultural sustainability and underscoring the urgent need for effective, locally adapted, climate-resilient farming strategies.

These climate dynamics are closely linked to farmers' perceptions, which reflect both environmental realities and socioeconomic contexts. Lowland farmers, exposed to more extreme temperatures and recurrent droughts, reported greater awareness of rainfall and temperature variability, while highland farmers, experiencing more stable conditions, displayed lower sensitivity. Perceptions were also influenced by demographic factors such as age, education, farming experience, and access to extension services or climate information.

Furthermore, farmers' climate perceptions were more aligned with the timing, intensity, and distribution of rainfall than total annual rainfall, suggesting that experiential knowledge and direct observation of seasonal events play a critical role in shaping awareness. In addition, participation in off-farm activities or irrigation can reduce perceived exposure, indicating that both environmental exposure and livelihood strategies modulate climate sensitivity. This interaction between perception and exposure indicates the value of integrating local knowledge with meteorological data for a context-specific understanding of climate risks, which is essential for designing effective adaptation interventions.

In response to these pressures, farmers employed a diverse mix of indigenous and introduced adaptation strategies, carefully tailored to their local agroecological conditions, resource availability, and household characteristics. Indigenous practices, such as planting local crop varieties, diversifying crops, and adjusting planting dates, remain central to building resilience, particularly among older and more experienced farmers. The introduced interventions such as improved crop varieties, inorganic fertilizers, soil and water conservation measures, irrigation and mixed farming systems complemented traditional approaches and enhanced adaptive capacity when supported by access to credit, extension services, and timely climate information. Adoption patterns varied between agroecological zones due to differences in climate exposure, soil fertility, water availability, and household resources. For example, lowland farmers prioritized crop diversification and the use of local crop varieties to address the challenges posed by high temperatures and drought stress. Midland households concentrated on adjusting their planting schedules and diversifying crops in response to irregular rainfall patterns. On the contrary, highland farmers relied more on traditional irrigation methods and mixed cropping systems to mitigate risks related to water shortages and frost. Despite these strategies, small landholdings, declining soil fertility, high input costs, and limited access to reliable climate information constrained the full potential for adaptation. These findings underscore the need for integrated and context-specific support systems that combine indigenous knowledge with modern agricultural technologies. This approach is essential for enhancing resilience, sustain crop productivity, and protecting livelihoods in the face of increasing climate variability.

6.2. Conclusion

Understanding long-term climate dynamics is fundamental for evaluating their implications on agriculture and water resources. This study provides an integrated assessment of observed climate trends, future climate projections, crop productivity responses, farmers' perceptions, and adaptation practices in the Ayehu Watershed. By combining these components, the study generates new knowledge on how climate variability is unfolding, how it is perceived, and how it is shaping agricultural decision-making in a rain-fed smallholder system.

The analysis of observed climatic records and future climate scenarios consistently shows that the watershed is undergoing a structural shift toward a warmer and more variable climate. Temperature has increased across seasons, while rainfall exhibits greater variability, including declining reliability of early-season rainfall and increasing intensity during peak rainfall periods. Future projections reinforce this pattern, indicating continued warming under all emission pathways and uncertain rainfall behavior ranging from reduced to more extreme precipitation under high-emission scenarios. These findings establish a clear trajectory of increasing climatic risk characterized by both drought and flood pressures.

These climate changes are already influencing agricultural productivity in the watershed. Crop yield responses indicate that production is becoming increasingly sensitive to inter-annual climate variability rather than average climatic conditions. Moisture stress during crop establishment and excessive rainfall during peak growing periods jointly contribute to yield instability. This demonstrates a direct linkage between observed and projected climate dynamics and agricultural performance, highlighting climate variability as a dominant driver of production uncertainty.

A key contribution of this study is the evaluation of consistency between observed climate trends and farmers' perceptions. The results show that farmers generally perceive long-term warming and a decline in overall rainfall, indicating a reasonable alignment with observed climatic evidence. However, important inconsistencies are also evident, particularly in relation to seasonal rainfall patterns. Farmers tend to misperceive Kiremit rainfall trends, while more accurately recognizing broader rainfall declines. This indicates that climate perception is partly grounded in lived experience but is also shaped by seasonal memory, livelihood dependence, and information access.

Farmers' climate perceptions significantly influence their adaptation behavior. The econometric analysis identifies that perception of climate risk, access to extension services, climate information, credit availability, income level, and agroecological location are key determinants of adaptation decisions. These factors operate interactively, showing that adaptation is not driven by climate exposure alone but is strongly mediated by institutional and socioeconomic conditions.

In response to increasing climate stress, farmers adopt a hybrid set of adaptation strategies combining indigenous practices and introduced technologies. Indigenous strategies remain widely used due to their affordability and accessibility, while modern inputs are adopted where resources and institutional support allow. However, the effectiveness of these adaptation measures is constrained by structural barriers, including small landholdings, limited irrigation access, declining soil fertility, high input costs, and weak climate information services. These constraints highlight that adaptation capacity is fundamentally shaped by resource endowment and institutional support rather than awareness alone.

Spatially, the study demonstrates strong agroecological differentiation in climate impacts and vulnerability. Highland areas exhibit relatively more stable climatic conditions, while midland and lowland zones experience higher temperature stress and rainfall variability. As a result, midland and lowland areas emerge as vulnerability hotspots, where climate risks are more pronounced and adaptation constraints are more severe. This spatial heterogeneity underscores the importance of location-specific adaptation planning.

Overall, the study makes several key scientific contributions. It integrates observed climate trends with future climate projections to provide a comprehensive understanding of climate dynamics in the watershed. It establishes a clear link between climate variability and crop productivity, showing how climatic changes translate into agricultural instability. It evaluates the consistency between meteorological evidence and farmers' perceptions, identifying both alignment and misinterpretation in seasonal rainfall understanding. It further identifies the socioeconomic, institutional, and environmental determinants of perception and adaptation behavior. Finally, it provides agroecology-specific adaptation insights, demonstrating that vulnerability and adaptive capacity vary significantly across elevation zones.

These findings have broader implications beyond the Ayehu Watershed. They are relevant to the Upper Blue Nile Basin, Ethiopian highlands, and other rain-fed agricultural systems in sub-Saharan Africa facing similar climatic pressures. The results highlight that climate adaptation planning should move beyond uniform recommendations and instead adopt agroecology-sensitive and context-specific strategies. Strengthening climate information services, improving access to credit and extension support, and enhancing locally appropriate adaptation pathways are essential for building resilience in smallholder farming systems under increasing climate uncertainty.

6.3. Recommendation

Smallholder farmers in the Ayehu watershed face increasing risks due to shifting rainfall and temperature patterns, with declining *Belg* rainfall causing early season drought and rising *Kiremit* rainfall creating excess water during the main cropping season. At the same time, increasing minimum and maximum temperatures exacerbate heat stress, deplete soil moisture, and increase irrigation demands. To address these multifaceted challenges, local agricultural experts and extension services should implement climate-smart, targeted adaptation strategies that are tailored to specific areas. These strategies include promoting drought- and flood-tolerant crop varieties, expanding small-scale irrigation and water harvesting infrastructures, strengthening soil and water conservation practices, and integrating agroforestry to reduce heat stress and improve soil moisture retention. By coordinating these measures, stakeholders can maintain agricultural productivity, safeguard water resources, and enhance the resilience of rural livelihoods in the watershed amid ongoing and projected climatic variability.

The pronounced variability in rainfall and temperature across agroecological zones poses major challenges to agricultural production. Declining *Belg* and *Bega* rainfall increases the risks of drought in midland and lowland areas, while rising *Kiremit* rainfall in high-land and midland zones amplifies the probability of flooding, soil erosion, and waterlogging. At the same time, elevated temperatures in the lowland and midland regions could intensify heat stress and crop vulnerability, although stable minimum temperatures may provide some long-term yield benefits. To mitigate these challenges, regional agricultural offices and *woreda* agricultural offices must implement targeted, context-specific adaptation measures, including drought- and flood-tolerant crop varieties, improved soil and water conservation, and improved drainage and small-scale irrigation systems. In addition, national and regional meteorological agencies must ensure timely delivery of localized climate information, while research institutions focus on developing pest and nutrient management strategies tailored to each agroecology. Cooperatives and local governments must further enhance farmers' access to input, credit and risk-reduction programs so that collectively these interventions reinforce resilience, protect livelihoods and sustain agricultural productivity in all zones.

The study revealed that smallholder farmers' perceptions of climate variability differ between agroecological zones: lowland farmers are primarily concerned with drought and water scarcity, midland farmers emphasize crop yield reductions and flooding, and highland farmers focus on pests, diseases, and declining soil fertility. In response, local agricultural extension agents should provide tailored training and capacity building programs that address these zone-specific challenges. At the same time, national and regional meteorological agencies must improve the delivery of timely, accessible, and user-friendly climate information. Research institutions should work collaboratively with agricultural communities to integrate indigenous knowledge with scientific forecasts and develop resilient cropping systems suited to each zone. In addition, cooperatives and local governments should expand access to affordable inputs, promote small-scale irrigation, and strengthen soil fertility management, thus improving adaptive capacity and safeguarding farmers' livelihoods.

Farmers in the study area used a blend of indigenous and introduced adaptation methods; however, their efforts are limited by small landholdings, unreliable weather information, declining soil fertility, limited irrigation infrastructure, and the rising cost of agricultural inputs. To overcome these challenges, a comprehensive and well-coordinated strategy is essential. To begin with, strengthening local extension services will broaden farmer training in climate-resilient practices. Furthermore, the establishment of community-based climate information centres will provide timely and accessible forecasts in local languages. In addition, promoting diversified site-specific cropping systems, such as drought-tolerant varieties in lowland areas and frost-tolerant crops in highland zones, will better align production with changing climatic conditions. Likewise, improving access to affordable input through cooperatives and targeted subsidy programmes will help ease financial pressures. Additionally, scaling up watershed management and expanding small-scale irrigation schemes will strengthen soil and water conservation efforts. Taken together, these interventions will significantly improve the adaptive capacity, mitigate climate-related risks, and promote sustainable agricultural productivity in the watershed.

Finally, future research should investigate how changes in land use, ecosystem services, and water–energy–food nexus interactions under climate variability influence agricultural sustainability. Integrating crop modeling and simulation with innovative adaptation strategies, such as climate-smart irrigation and precision agriculture, will be essential to identify resilient production pathways.

REFERENCES

Abbas, A., Rossi, S., & Huang, B. (2024). Plant metabolic responses and adaptation mechanisms to elevated night temperature associated with global warming. *Grass Research*, *4*(1). https://doi.org/10.48130/grares-0024-0013

Abbas, Q., Han, J., Bakhsh, K., Ullah, R., Kousar, R., Adeel, A., & Akhtar, A. (2022). Adaptation to climate change risks among dairy farmers in Punjab, Pakistan. *Land use policy*, *119*, 106184. https://doi.org/10.1016/j.landusepol.2022.106184

Abebe, G., & Debebe, S. (2019). Factors affecting use of organic fertilizer among smallholder farmers in Sekela district of Amhara region, Northwestern Ethiopia. *Cogent Food & Agriculture*, *5*(1), 1669398. https://doi.org/10.1080/23311932.2019.1669398

Abegaz, W. B., & Abera, E. A. (2020). Temperature and rainfall trends in north eastern Ethiopia. *J Climatol Weather Forecast*, *8*, 262. https://doi.org/10.19080/IJESNR.2020.25.556163

Abegaz, W. B., & Mekoya, A. (2020). Rainfall variability and trends over Central Ethiopia. *Rema*, *10*(39.58), 2054. https://doi.org/10.19080/IJESNR.2020.24.556144

Abeje, A., & Alemayehu, M. (2019). Impacts of Climate Change on Crop Production and Its Adaptation and Mitigation Strategies in Ethiopia. *Journal of Agriculture and Environmental Sciences*, *4*(2).

Abera, Dessie, M., Addis, H. K., & Asmamaw, D. K. (2025). Modeling Maize Production and Water Productivity Under Deficit Irrigation and Mulching as Sustainable Agricultural Water Management Strategies in Semiarid Areas. *Sustainability*, *17*(4), 1347. https://doi.org/10.3390/su17041347

Abera, K., Crespo, O., Seid, J., & Mequanent, F. (2018). Simulating the impact of climate change on maize production in Ethiopia, East Africa. *Environmental Systems Research*, *7*(1), 1-12. https://doi.org/10.1186/s40068-018-0107-z

Abera, N., & Tesema, D. (2019). Perceptions and practices of climate change adaptation and mitigation strategies among farmers in the Konta Special District, Ethiopia. *Environmental & Socio-economic Studies*, *7*(4), 1-16. https://doi.org/10.2478/environ-2019-0019

Abid, M., Scheffran, J., Schneider, U. A., & Elahi, E. (2019). Farmer perceptions of climate change, observed trends and adaptation of agriculture in Pakistan. *Environmental management*, *63*(1), 110-123. https://doi.org/10.1007/s00267-018-1113-7

Aboye, A. B., Kinsella, J., & Leza, T. (2022). Major climatic changes experienced by farm households: Evidence from the lowlands of Southern Ethiopia. *Advancements in Agricultural Development*, *3*(1), 87-102. https://doi.org/10.37433/aad.v3i1.163

Aboye, A. B., Kinsella, J., & Mega, T. L. (2023). Farm households' adaptive strategies in response to climate change in lowlands of southern Ethiopia. *International Journal of Climate Change Strategies and Management*, *15*(5), 579-598. https://doi.org/10.1108/IJCCSM-05-2023-0064

Abrha, M. G. (2015). Local climate trends and farmers' perceptions in Southern Tigray, Northern Ethiopia. *International Journal of Environment and Sustainability*, *4*(3). https://doi.org/10.24102/ijes.v4i3.563. https://doi.org/10.24102/ijes.v4i3.563

Adams, A., & Jumpah, E. T. (2021). Agricultural technologies adoption and smallholder farmers' welfare: Evidence from Northern Ghana. *Cogent Economics & Finance*, *9*(1), 2006905. https://doi.org/10.1080/23322039.2021.2006905

Adane, A., & Asmerom, B. (2025). Analysis of spatiotemporal distribution, variability, and trends of rainfall in Wollo area, Northeastern Ethiopia. *PloS one*, *20*(1), e0312889. https://doi.org/10.1371/journal.pone.0312889

Addis, Y., & Abirdew, S. (2021). Smallholder farmers' perception of climate change and adaptation strategy choices in Central Ethiopia. *International Journal of Climate Change Strategies and Management*, *13*(4/5), 463-482. https://doi.org/10.1108/IJCCSM-09-2020-0096

Adeagbo, O., Ojo, T., & Adetoro, A. (2021). Understanding the determinants of climate change adaptation strategies among smallholder maize farmers in South-west, Nigeria. *Heliyon*, *7*(2). https://doi.org/10.1016/j.heliyon.2021.e06231

Ademe, D., Zaitchik, B. F., Tesfaye, K., Simane, B., Alemayehu, G., & Adgo, E. (2020). Climate trends and variability at adaptation scale: Patterns and perceptions in an agricultural region of the Ethiopian Highlands. *Weather and Climate Extremes*, *29*, 100263. https://doi.org/10.1016/j.wace.2020.100263

Adeniyi, P. A. (2016). Climate change induced hunger and poverty in Africa. *J Global Biosci*, *5*(3), 3711-3724.

Adger, W. N., Brown, I., & Surminski, S. (2018). Advances in risk assessment for climate change adaptation policy. In (Vol. 376, pp. 20180106): The Royal Society Publishing. https://doi.org/10.1162/GLEP_a_00051

Adimassu, Z., & Kessler, A. (2016). Factors affecting farmers' coping and adaptation strategies to perceived trends of declining rainfall and crop productivity in the central Rift valley of Ethiopia. *Environmental Systems Research*, *5*(1), 1-16. https://doi.org/10.1186/s40068-016-0065-2

Adimassu, Z., Tamene, L. D., Abera, W., Tesfaye, K., & Solomon, D. (2021). Climate smart interventions and indicators in Ethiopia: Expert's knowledge and literature review. *AICCRA reports*.

Adlina, M., & Oktari, R. (2024). Farmers' perception and strategies for mitigating and adapting to climate change impacts in the agricultural sector. IOP Conference Series: Earth and Environmental Science. https://doi.org/10.1088/1755-1315/1356/1/012051

Adnan, N., Rehman, H. M., & Alam, M. N. (2025). Exploring agricultural innovation: an empirical investigation of factors influencing the adoption and non-adoption of smart fertilizer technology among farmers in developing countries. *Agriculture & Food Security*, *14*(1), 11. https://doi.org/10.1186/s40066-025-00529-0

Aduko, J., Kuorsoh, P. K., & Boasu, B. Y. (2026). Effects of climate change information on adaptation strategies among smallholder crop farmers in Ghanaian rural communities. *Discover Agriculture*, *4*(1), 18. https://doi.org/10.1007/s44279-026-00485-8

Adunya, T., & Benti, F. (2020). The impacts of climate-induced agricultural drought on four cereal crops: a case study in Bako Tibe District. *Oromia National Regional state, Ethiopia*. https://doi.org/10.20961/carakatani.v35i1.35749

Afework, A., Minale, A. S., Teketay, D., & Terefe, B. (2023). Spatio-temporal dynamics of Acacia decurrens plantations in Awi Zone highlands, northwest Ethiopia. *Papers in Applied Geography*, *9*(4), 442-463. https://doi.org/10.1080/23754931.2023.2243956

Agbo, E. P., Nkajoe, U., Edet, C. O., & Ali, N. (2023). Identification of trends of key parameters affecting vegetation over Nigeria's vegetation zones using innovative trend analysis. *Environmental Earth Sciences*, *82*(20), 464. https://doi.org/10.1007/s12665-023-11141-5

Ahmad, M., Jamil, M., Ullah, S., & Ali, M. (2024). Examine the Effects of Climate Change on Forage Quality and its Subsequent Impact on Milk Yield and Composition. *Indus Journal of Bioscience Research*, *2*(02), 1485-1492. https://doi.org/10.70749/ijbr.v2i02.431

Ahmad, M. M., Yaseen, M., & Saqib, S. E. (2022). Climate change impacts of drought on the livelihood of dryland smallholders: Implications of adaptation challenges. *International Journal of Disaster Risk Reduction*, *80*, 103210. https://doi.org/10.1016/j.ijdrr.2022.103210

Ahmed, K., Shahid, S., Chung, E.-S., Wang, X.-j., & Harun, S. B. (2019). Climate change uncertainties in seasonal drought severity-area-frequency curves: Case of arid region of Pakistan. *Journal of Hydrology*, *570*, 473-485. https://doi.org/10.1016/j.jhydrol.2019.01.019

Ahmed, S., & Fatema, N. (2023). Factors and practices: farmers' adaptation to climate change in Bangladesh. *Journal of Water and Climate Change*, *14*(1), 123-141. https://doi.org/10.2166/wcc.2022.216

Aidoo, D. C., Boateng, S. D., Freeman, C. K., & Anaglo, J. N. (2021). The effect of smallholder maize farmers' perceptions of climate change on their adaptation strategies: The case of two agro-ecological zones in Ghana. *Heliyon*, *7*(11). https://doi.org/10.1016/j.heliyon.2021.e08307

Al-Shamarti, H. K. (2016). The variation of annual precipitation and precipitation concentration index of Iraq. *Journal of Applied Physics*, *8*(4), 36-44. https://doi.org/10.9790/4861-0804033644

Alaminie, A. A., Tilahun, S. A., Legesse, S. A., Zimale, F. A., Tarkegn, G. B., & Jury, M. R. (2021). Evaluation of Past and Future Climate Trends under CMIP6 Scenarios for the UBNB (Abay), Ethiopia. *Water*, *13*(15), 2110. https://doi.org/10.3390/w13152110

Albore, A., Zenebe, A., Tesfay, G., & Abadi, N. (2024). Lowland smallholders' livelihood vulnerability to Climate change-induced hazards in Southern Ethiopia. *Environmental Challenges*, *15*, 100897. https://doi.org/10.1016/j.envc.2024.100897

Alemayehu, A., & Bewket, W. (2016). Local climate variability and crop production in the central highlands of Ethiopia. *Environ. Dev.* 19, 36–48. In. https://doi.org/10.1016/j.envdev.2016.06.002

Alemayehu, A., & Bewket, W. (2017a). Local spatiotemporal variability and trends in rainfall and temperature in the central highlands of Ethiopia. *Geografiska Annaler: Series A, Physical Geography*, *99*(2), 85-101. https://doi.org/10.1080/04353676.2017.1289460

Alemayehu, A., & Bewket, W. (2017b). Smallholder farmers' coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia. *Local Environment*, *22*(7), 825-839. https://doi.org/10.1080/13549839.2017.1290058

Alemayehu, A., Maru, M., Bewket, W., & Assen, M. (2020). Spatiotemporal variability and trends in rainfall and temperature in Alwero watershed, western Ethiopia. *Environmental Systems Research*, *9*(1), 1-15. https://doi.org/10.1186/s40068-020-00184-3

Alemayehu, S., Ayalew, Z., Sileshi, M., & Zeleke, F. (2024). The impact of climate smart agriculture practices on the technical efficiency of wheat farmers in northwestern Ethiopia. *Environment, Development and Sustainability*, 1-23. https://doi.org/10.1007/s10668-024-05288-9

Alemayehu, Z. Y., Minale, A. S., & Legesse, S. A. (2022a). Determinants of smallholder farmers' adaptation strategies to climate variability in Suha watershed, Upper Blue Nile basin, Northwest Ethiopia. *Arabian Journal of Geosciences*, *15*(23), 1725. https://doi.org/10.1007/s12517-022-11004-6

Alemayehu, Z. Y., Minale, A. S., & Legesse, S. A. (2022b). Spatiotemporal rainfall and temperature variability in Suha watershed, Upper Blue Nile Basin, Northwest Ethiopia. *Environmental Monitoring and Assessment*, *194*(8), 538. https://doi.org/10.1007/s10661-022-10165-x

Alemayehu, Z. Y., Minale, A. S., & Legesse, S. A. (2023). Vulnerability of local farmers' livelihood to climate variability across different agro ecology zone in Suha watershed, Upper Blue Nile basin, Ethiopia. *Climate and Development*, *16*(1), 36-53. https://doi.org/10.1080/17565529.2023.2178253

Alemu, M. D., Kebede, A., & Moges, A. (2019). Farmers' perception of soil erosion and adoption of soil conservation technologies at Geshy Sub-Catchment, Gojeb River Catchment, Ethiopia. *Agricultural Sciences*, *10*(1), 46-65. https://doi.org/10.4236/as.2019.101005

Alemu, M. M., & Bawoke, G. T. (2020). Analysis of spatial variability and temporal trends of rainfall in Amhara region, Ethiopia. *Journal of Water and Climate Change*, *11*(4), 1505-1520. https://doi.org/10.2166/wcc.2019.084

Ali, M. A., & Kamraju, M. (2023). Climate Change and Natural Resources. In *Natural Resources and Society: Understanding the Complex Relationship Between Humans and the Environment* (pp. 143-158). Springer. https://doi.org/10.1007/978-3-031-46720-2_10

Ali, M. A., & Kamraju, M. (2025). Understanding the Landscape of Climate Governance. In *Global Climate Governance: Strategies for Effective Management* (pp. 1-23). Springer. https://doi.org/10.1007/978-981-96-2727-1_1

Ali, M. F., & Rose, S. (2021). Farmers' perception and adaptations to climate change: Findings from three agro-ecological zones of Punjab, Pakistan. *Environmental Science and Pollution Research*, *28*(12), 14844-14853. https://doi.org/10.1007/s11356-020-11472-x

Ali, S., Ghosh, B. C., Osmani, A. G., Hossain, E., & Fogarassy, C. (2021). Farmers' climate change adaptation strategies for reducing the risk of rice production: Evidence from rajshahi district in Bangladesh. *Agronomy*, *11*(3), 600. https://doi.org/10.3390/agronomy11030600

Almalki, S. (2016). Integrating Quantitative and Qualitative Data in Mixed Methods Research--Challenges and Benefits. *Journal of education and learning*, *5*(3), 288-296. https://doi.org/10.5539/jel.v5n3p288

Almazroui, M., Ashfaq, M., Islam, M. N., Rashid, I. U., Kamil, S., Abid, M. A., O'Brien, E., Ismail, M., Reboita, M. S., & Sörensson, A. A. (2021). Assessment of CMIP6 performance and projected temperature and precipitation changes over South America. *Earth Systems and Environment*, *5*(2), 155-183. https://doi.org/10.1007/s41748-021-00233-6

Almazroui, M., Islam, M. N., Saeed, S., Saeed, F., & Ismail, M. (2020). Future changes in climate over the Arabian Peninsula based on CMIP6 multimodel simulations. *Earth Systems and Environment*, *4*, 611-630. https://doi.org/10.1007/s41748-020-00183-5

Almazroui, M., & Şen, Z. (2020). Trend analyses methodologies in hydro-meteorological records. *Earth Systems and Environment*, *4*(4), 713-738. https://doi.org/10.1007/s41748-020-00190-6

Altieri, M. A., Nicholls, C. I., Henao, A., & Lana, M. A. (2015). Agroecology and the design of climate change-resilient farming systems: MA Altieri et al. *Agronomy for sustainable development*, *35*(3), 869-890. https://doi.org/10.1007/s13593-015-0285-2

Alves, L. M., Fowler, H., da Costa Barreto, N. D. J., & Llopart, M. (2021). Climate change and climate variability. In *Precipitation* (pp. 53-68). Elsevier. https://doi.org/10.1016/B978-0-12-822699-5.00003-3

Amare, A., & Simane, B. (2017). Determinants of smallholder farmers' decision to adopt adaptation options to climate change and variability in the Muger Sub basin of the Upper Blue Nile basin of Ethiopia. *Agriculture & Food Security*, *6*(1), 1-20. https://doi.org/10.1186/s40066-017-0144-2

Amare, Z. Y. (2018). Indigenous knowledge of rural communities for combating climate change impacts in west central Ethiopia. *Journal of Agricultural Extension*, *22*(1), 181-195. https://doi.org/10.4314/jae.v22i1.16

Anibaldi, R., Rundle-Thiele, S., David, P., & Roemer, C. (2021). Theoretical underpinnings in research investigating barriers for implementing environmentally sustainable farming practices: Insights from a systematic literature review. *Land*, *10*(4), 386. https://doi.org/10.3390/land10040386

Aniye, H. W. Y., Bekele, T., & Worku, W. (2024). Perception of smallholder farmers about climate change and its impacts on crop production across agroecological zones of the Gassera District, Southeastern Ethiopia. *Scientific Reports*, *14*(1), 27632. https://doi.org/10.1038/s41598-024-75778-3.

Ankrah, J., Monteiro, A., & Madureira, H. (2023). Extreme temperature and rainfall events and future climate change projections in the coastal savannah agroecological zone of Ghana. *Atmosphere*, *14*(2), 386. https://doi.org/10.3390/atmos14020386

Antwi-Agyei, P., & Frimpong, H. (2021). Evidence of climate change coping and adaptation practices by smallholder farmers in northern Ghana. *Sustainability*, *13*(3), 1308. https://doi.org/10.3390/su13031308

Anum, R., Ankrah, D. A., & Anaglo, J. N. (2022). Influence of demographic characteristics and social network on peri-urban smallholder farmers adaptation strategies-evidence from southern Ghana. *Cogent Food & Agriculture*, *8*(1), 2130969. https://doi.org/10.1080/23311932.2022.2130969

Anzum, H. M. N., Chakraborty, T. K., & Bosu, H. (2023). Farmer's perception and factors influencing adoption of adaptation measures to cope with climate change: an evidence from coastal Bangladesh: *Environment and Natural Resources Journal*, *21*(2), 113-126. https://doi.org/10.32526/ennrj/21/202200186

Arfasa, G. F., Sekyere, E. O., & Doke, D. A. (2024). Temperature and precipitation trend analysis using the CMIP6 model in the Upper East region of Ghana. *All Earth*, *36*(1), 1-14. https://doi.org/10.1080/27669645.2023.2290966

Arora, G., & Feng, H. (2024). Assessing systematic biases in farmers' local weather change perceptions. *Scientific Reports*, *14*(1), 26641. https://doi.org/10.1038/s41598-024-76327-8

Arora, N. K., & Mishra, I. (2023). Responsible consumption and production: a roadmap to sustainable development. *Environmental Sustainability*, *6*(1), 1-6. https://doi.org/10.1007/s42398-024-00308-w

Aryal, J. P., Rahut, D. B., Maharjan, S., & Erenstein, O. (2018). Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. Natural Resources Forum. https://doi.org/10.1111/1477-8947.12152

Aryal, J. P., Sapkota, T. B., Rahut, D. B., Krupnik, T. J., Shahrin, S., Jat, M. L., & Stirling, C. M. (2020). Major climate risks and adaptation strategies of smallholder farmers in coastal Bangladesh. *Environmental Management*, *66*(1), 105-120. https://doi.org/10.1007/s00267-020-01291-8

Asare, P., & Botchway, E. (2019). Comparing smallholder farmers' climate change perception with climate data: the case of Adansi North District of Ghana. *Heliyon*, *5*(12). https://doi.org/10.1016/j.heliyon.2019.e03065

Asayehegn, K., Temple, L., Sanchez, B., & Iglesias, A. (2017). Perception of climate change and farm level adaptation choices in central Kenya. *Cahiers Agricultures*, *26*(2), 1-11. https://doi.org/10.1051/cagri/2017007

Asefa, A., Haile, M., Berhe, M., & Zenebe, A. (2025). Climate smart land management practices for livelihood resilience in Ethiopia: A systematic review. *Heliyon*.

Asfaw, A., Bantider, A., Simane, B., & Hassen, A. (2021). Smallholder farmers' livelihood vulnerability to climate change-induced hazards: agroecology-based comparative analysis in Northcentral Ethiopia (Woleka Sub-basin). *Heliyon*, *7*(4). https://doi.org/10.1016/j.heliyon.2021.e06761

Asfaw, A., Simane, B., Bantider, A., & Hassen, A. (2019). Determinants in the adoption of climate change adaptation strategies: evidence from rainfed-dependent smallholder farmers in north-central Ethiopia (Woleka sub-basin). *Environment, Development and Sustainability*, *21*(5), 2535-2565. https://doi.org/10.1016/j.heliyon.2021.e06761

Asfaw, A., Simane, B., Hassen, A., & Bantider, A. (2018). Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-basin. *Weather and Climate Extremes*, *19*, 29-41. https://doi.org/10.1016/j.wace.2017.12.002

Asfew, M., & Bedemo, A. (2022). Impact of climate change on cereal crops production in Ethiopia. *Advances in Agriculture*, *2022*(1), 2208694. https://doi.org/10.1155/2022/2208694

Asrat, P., & Simane, B. (2017a). Adapting smallholder agriculture to climate change through sustainable land management practices: empirical evidence from North–West Ethiopia. *J Agric Sci Technol A*, *7*(2017), 289-301. https://doi.org/10.17265/2161-6256/2017.05.001

Asrat, P., & Simane, B. (2017b). Characterizing vulnerability of crop-based rural systems to climate change and variability: agro-ecology specific empirical evidence from the Dabus watershed, north-West Ethiopia. *American Journal of Climate Change*, *6*(4), 643-667. https://doi.org/10.4236/ajcc.2017.64033

Asrat, P., & Simane, B. (2018). Farmers' perception of climate change and adaptation strategies in the Dabus watershed, North-West Ethiopia. *Ecological Processes*, *7*(1), 1-13. https://doi.org/10.1186/s13717-018-0118-8

Assan, E., Suvedi, M., Olabisi, L. S., & Bansah, K. J. (2020). Climate change perceptions and challenges to adaptation among smallholder farmers in semi-arid Ghana: A gender analysis. *Journal of Arid Environments*, *182*, 104247. https://doi.org/10.1016/j.jaridenv.2020.104247

Assaye, A., Ketema, M., & Bekele, A. (2020). Smallholder Farmers' adaptation strategies to climate change: the case of Ankesha Guagusa District of Awi Zone, Northwestern Ethiopia. *J Agric Econom Rural Develop*, *6*(2), 760-772.

Asseng, S., Martre, P., Maiorano, A., Rötter, R. P., O'Leary, G. J., Fitzgerald, G. J., ... & Ewert, F. (2019). Climate change impact and adaptation for wheat protein. *Global change biology*, *25*(1), 155-173. https://doi.org/10.1111/gcb.14481

Atube, F., Malinga, G. M., Nyeko, M., Okello, D. M., Alarakol, S. P., & Okello-Uma, I. (2021). Determinants of smallholder farmers' adaptation strategies to the effects of climate change: Evidence from northern Uganda. *Agriculture & Food Security*, *10*(1), 6. https://doi.org/10.1186/s40066-020-00279-1

Awazi, N. P. (2025). Pastoralist Livelihoods in the Face of Climate Change in the Global South: Climate Resilience Frameworks and Prospects. In *Building Resilience: Climate Change and Livelihoods in the Global South* (pp. 85-116). Springer. https://doi.org/10.1007/978-3-031-93791-0_4

Awoke, W., & Agitew, G. (2022). Rural households' perception of climate change in the central and north Gondar zones, northwest Ethiopia. *African Journal of Food, Agriculture, Nutrition and Development*, *22*(8), 21362-21382. https://doi.org/10.18697/ajfand.113.19400

Ayalew, A. D., Wagner, P. D., Sahlu, D., & Fohrer, N. (2022). Land use change and climate dynamics in the Rift Valley Lake Basin, Ethiopia. *Environmental Monitoring and Assessment*, *194*(11), 791. https://doi.org/10.1007/s10661-022-10393-1

Ayalew, A. T. (2023). The synergic effects of climate variability on rainfall distribution over Hare catchment of Ethiopia. *Advances in Meteorology*, *2023*(1), 1175426. https://doi.org/10.1155/2023/1175426

Ayanlade, A., Radeny, M., & Morton, J. F. (2017). Comparing smallholder farmers' perception of climate change with meteorological data: A case study from southwestern Nigeria. *Weather and climate extremes*, *15*, 24-33. https://doi.org/10.1016/j.wace.2016.12.001

Ayugi, B. O., Chung, E.-S., Zhu, H., Ogega, O. M., Babousmail, H., & Ongoma, V. (2023). Projected changes in extreme climate events over Africa under 1.5° C, 2.0° C and 3.0° C global warming levels based on CMIP6 projections. *Atmospheric Research*, *292*, 106872. https://doi.org/10.1016/j.atmosres.2023.106872

Bagagnan, A. R., Ouedraogo, I., & Fonta, W. M. (2019). Perceived climate variability and farm level adaptation in the central river region of the Gambia. *Atmosphere*, *10*(7), 423. https://doi.org/10.3390/atmos10070423

Balcha, E., Menghistu, H. T., Zenebe, A., Teferi, T., & Hadush, B. (2023). Climate-smart agricultural practices: a case of dairy cooperative farmers in Agula and Maychew, Northern Ethiopia. *Carbon Management*, *14*(1), 2271880. https://doi.org/10.1080/17583004.2023.2271880

Batungwanayo, P., Habarugira, V., Vanclooster, M., Ndimubandi, J., F. Koropitan, A., & Nkurunziza, J. d. D. (2023). Confronting climate change and livelihood: smallholder farmers' perceptions and adaptation strategies in northeastern Burundi. *Regional environmental change*, *23*(1), 47.

Bawakyillenuo, S., Yaro, J. A., & Teye, J. (2016). Exploring the autonomous adaptation strategies to climate change and climate variability in selected villages in the rural northern savannah zone of Ghana. *Local Environment*, *21*(3), 361-382. https://doi.org/10.1080/13549839.2014.965671

Bayable, G., Amare, G., Alemu, G., & Gashaw, T. (2021). Spatiotemporal variability and trends of rainfall and its association with Pacific Ocean Sea surface temperature in West Harerge Zone, Eastern Ethiopia. *Environmental Systems Research*, *10*, 1-21. https://doi.org/10.1186/s40068-020-00216-y

Begum, R. A., Raihan, A., Pereira, J. J., Ahmed, F., & Tam, V. W. (2025). Impacts of economic growth, energy use, population, urbanisation, and tourism on CO2 emissions in Malaysia: an empirical analysis of ARDL approach. *Environment, Development and Sustainability*, 1-29. https://doi.org/10.1007/s10668-025-06093-8

Bekele, D., Alamirew, T., Kebede, A., Zeleke, G., & Melese, A. M. (2017). Analysis of rainfall trend and variability for agricultural water management in Awash River Basin, Ethiopia. *Journal of Water and Climate Change*, *8*(1), 127-141. https://doi.org/10.2166/wcc.2016.044

Bekuma Abdisa, T., Mamo Diga, G., & Regassa Tolessa, A. (2022). Impact of climate variability on rain-fed maize and sorghum yield among smallholder farmers. *Cogent Food & Agriculture*, *8*(1), 2057656. https://doi.org/10.1080/23311932.2022.2057656

Bekuma, T., Mamo, G., & Regassa, A. (2023). Indigenous and improved adaptation technologies in response to climate change adaptation and barriers among smallholder farmers in the East Wollega Zone of Oromia, Ethiopia. *Research in Globalization*, *6*, 100110. https://doi.org/10.1016/j.resglo.2022.100110

Belay, A., Demissie, T., Recha, J. W., Oludhe, C., Osano, P. M., Olaka, L. A., Solomon, D., & Berhane, Z. (2021). Analysis of climate variability and trends in Southern Ethiopia. *Climate*, *9*(6), 96.

Belay, A., Oludhe, C., Mirzabaev, A., Recha, J. W., Berhane, Z., Osano, P. M., Demissie, T., Olaka, L. A., & Solomon, D. (2022). Knowledge of climate change and adaptation by smallholder farmers: evidence from southern Ethiopia. *Heliyon*, *8*(12). https://doi.org/10.1016/j.heliyon.2022.e12089

Belay, A., Recha, J. W., Woldeamanuel, T., & Morton, J. F. (2017). Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture & Food Security*, *6*(1), 1-13. https://doi.org/10.1186/s40066-017-0100-1

Belay, H., Melesse, A. M., & Tegegne, G. (2024). Evaluation and comparison of the performances of the CMIP5 and CMIP6 models in reproducing extreme rainfall in the Upper Blue Nile basin of Ethiopia: Belay et al. *Theoretical and Applied Climatology*, *155*(11), 9471-9496. https://doi.org/10.1007/s00704-024-05187-z

Belay, T., & Mengistu, D. A. (2019). Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, *15*, 100249. https://doi.org/10.1016/j.rsase.2019.100249

Belay, T., & Mengistu, D. A. (2024). Modeling hydrological characteristics based on land use/land cover and climate changes in Muga watershed, Abay River Basin, Ethiopia. *Cogent Food & Agriculture*, *10*(1), 2319935. https://doi.org/10.1080/23311932.2024.2319935

Bendell, J. (2018). A Summary of Some Climate Science in 2018'. *Professor Jem Bendell blog*, *22*.

Benjamin, J., Oyedokun, D. O., Oziegbe, E. V., Oni, J., Ogundare, E. B., Ujah, G. O., & Adebayo, A. (2024). Cereal production in Africa: the threat of current plant pathogens in changing climate-a review. *Discover Agriculture*, *2*(1), 33. https://doi.org/10.1007/s44279-024-00040-3

Bennett, N. J., Blythe, J., Tyler, S., & Ban, N. C. (2016). Communities and change in the anthropocene: understanding social-ecological vulnerability and planning adaptations to multiple interacting exposures. *Regional environmental change*, *16*(4), 907-926. https://doi.org/10.1007/s10113-015-0839-5

Berck, C. S., Berck, P., & Di Falco, S. (2018). *Agricultural adaptation to climate change in Africa*. TAYLOR & FRANCIS Limited. https://doi.org/10.4324/9781315149776

Berg, M., & Lidskog, R. (2018). Deliberative democracy meets democratised science: a deliberative systems approach to global environmental governance. *Environmental Politics*, *27*(1), 1-20. https://doi.org/10.1080/09644016.2017.1371919

Berhanu, A. A., Ayele, Z. B., Dagnew, D. C., Melese, T., Fenta, A. B., & Kassie, K. E. (2024). Smallholder farmers' vulnerability to climate change and variability: Evidence from three agroecologies in the Upper Blue Nile, Ethiopia. *Heliyon*, *10*(7). https://doi.org/10.1016/j.heliyon.2024.e28277

Bernacchi, C. J., Ruiz-Vera, U. M., Siebers, M. H., DeLucia, N. J., & Ort, D. R. (2023). Short-and long-term warming events on photosynthetic physiology, growth, and yields of field grown crops. *Biochemical Journal*, *480*(13), 999-1014. https://doi.org/10.1042/BCJ20220433

Bhattacherjee, A. (2012). *Social science research: Principles, methods, and practices*. University of South Florida.

Bi, D., Dix, M., Marsland, S., O'farrell, S., Sullivan, A., Bodman, R., Law, R., Harman, I., Srbinovsky, J., & Rashid, H. A. (2020). Configuration and spin-up of ACCESS-CM2, the new generation Australian community climate and earth system simulator coupled model. *Journal of Southern Hemisphere Earth Systems Science*, *70*(1), 225-251. https://doi.org/10.1071/ES19040

Bita, C. E., & Gerats, T. (2013). Plant tolerance to high temperature in a changing environment: scientific fundamentals and production of heat stress-tolerant crops. *Frontiers in plant science*, *4*, 273. https://doi.org/10.3389/fpls.2013.00273

Bitana, E. B., Lachore, S. T., & Utallo, A. U. (2023). Vulnerability and responses of rural households to climate variability: agro-climatic-based evidence from southern Ethiopia. *Sustainability and Climate Change*, *16*(4), 286-301. https://doi.org/10.1089/scc.2023.0053

Bojago, E., & Abrham, Y. (2023). Small-scale irrigation (SSI) farming as a climate-smart agriculture (CSA) practice and its influence on livelihood improvement in Offa District, Southern Ethiopia. *Journal of Agriculture and Food Research*, *12*, 100534. https://doi.org/10.1016/j.jafr.2023.100534

Boucher, O., Servonnat, J., Albright, A. L., Aumont, O., Balkanski, Y., Bastrikov, V., Bekki, S., Bonnet, R., Bony, S., & Bopp, L. (2020). Presentation and evaluation of the IPSL-CM6A-LR climate model. *Journal of Advances in Modeling Earth Systems*, *12*(7), e2019MS002010. https://doi.org/10.1029/2019MS002010

Bradley, R. S., & Diaz, H. F. (2021). Late quaternary abrupt climate change in the tropics and sub-tropics: the continental signal of tropical hydroclimatic events (THEs). *Reviews of Geophysics*, *59*(4), e2020RG000732. https://doi.org/10.1029/2020RG000732

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental science & policy*, *12*(4), 413-426. https://doi.org/10.1016/j.envsci.2008.11.002

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. *Journal of Environmental Management*, *114*, 26-35. https://doi.org/10.1016/j.jenvman.2012.10.036

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106-140. https://doi.org/10.1257/pol.20130025

Chae, S. T., & Chung, E.-S. (2024). Significant contribution of bias correction methods to uncertainty in future runoff projections under CMIP6 climate change. *Journal of Hydrology: Regional Studies*, *56*, 101973. https://doi.org/10.1016/j.ejrh.2024.101973

Challinor, A. J., Parkes, B., & Ramirez-Villegas, J. (2015). Crop yield response to climate change varies with cropping intensity. *Global change biology*, *21*(4), 1679-1688. https://doi.org/10.1111/gcb.12808

Chandio, A. A., Ozturk, I., Akram, W., Ahmad, F., & Mirani, A. A. (2020). Empirical analysis of climate change factors affecting cereal yield: evidence from Turkey. *Environmental Science and Pollution Research*, *27*(11), 11944-11957. https://doi.org/10.1007/s11356-020-07739-y

Chemeda, B. A., Wakjira, F. S., & Birhane, E. (2023). Determinants of perception of climate change and adaptation strategies of coffee-based agroforestry farmers in western Ethiopia. *Emerald Open Research*, *1*(6). https://doi.org/10.1108/EOR-06-2023-0010

Chen, Z.-F., Sun, Y., Zhang, X., Li, T., & Yu, J.-H. (2023). Role of anthropogenic forcing and atmospheric circulation in a low-temperature event in February 2022 in eastern China. *Advances in Climate Change Research*, *14*(6), 921-929. https://doi.org/10.1016/j.accre.2023.11.009

Chepkoech, W., Mungai, N. W., Stöber, S., Bett, H. K., & Lotze-Campen, H. (2018). Farmers' perspectives: impact of climate change on African indigenous vegetable production in Kenya. *International Journal of Climate Change Strategies and Management*, *10*(4), 551-579. https://doi.org/10.1108/IJCCSM-07-2017-0160

Cherian, S., Sridhara, S., Manoj, K. N., Gopakkali, P., Ramesh, N., Alrajhi, A. A., Dewidar, A. Z., & Mattar, M. A. (2021). Impact of El Niño Southern Oscillation on rainfall and rice production: a micro-level analysis. *Agronomy*, *11*(6), 1021. https://doi.org/10.3390/agronomy11061021

Cherinet, A., & Mekonnen, Z. (2019). Comparing farmers' perception of climate change and variability with historical climate data: the case of ensaro district, Ethiopia. *International Journal of Environmental Sciences & Natural Resources*, *17*(4), 114-120. https://doi.org/10.19080/IJESNR.2019.17.555966

Cherinet, A., Simane, B., & Asmare, A. M. (2025). Climate Change Adaptation Strategies and Determinants of Adoption Amongst Smallholder Farmers in Jemma Sub-basin, Central Ethiopia. *Journal of Integrated Disaster Risk Management*, *15*. https://doi.org/10.5595/001c.143101

Cheru, U. G. (2024). Climate change, variability, and adaptation in Ethiopia. An analysis from the farmers' perception. *Journal of the Selva Andina Biosphere*, *12*(2), 111-121. https://doi.org/10.36610/j.jsab.2024.120200111

Chevuru, S., de Wit, A., Supit, I., & Hutjes, R. (2023). Copernicus global crop productivity indicators: An evaluation based on regionally reported yields. *Climate Services*, *30*, 100374. https://doi.org/10.1016/j.cliser.2023.100374

Chisale, H. L., Chirwa, P. W., Kamoto, J. F. M., & Babalola, F. D. (2024). Determinants of adaptive capacities and coping strategies to climate change related extreme events by forest dependent communities in Malawi. *Wellbeing, Space and Society*, *6*, 100183. https://doi.org/10.1016/j.wss.2024.100183

Creswell, J. W. (2009). Mapping the field of mixed methods research. In (Vol. 3, pp. 95-108): SAGE publications Sage CA: Los Angeles, CA. https://doi.org/10.1177/1558689808330883

Creswell, J. W. (2021). *A concise introduction to mixed methods research*. SAGE publications.

Crick, F., Gannon, K. E., Diop, M., & Sow, M. (2018). Enabling private sector adaptation to climate change in sub-Saharan Africa. *Wiley Interdisciplinary Reviews: Climate Change*, *9*(2), e505.

CSA. (2016). Central statistical agency (CSA)[Ethiopia] and ICF. *Ethiopia demographic and health survey, Addis Ababa, Ethiopia and Calverton, Maryland, USA*, *1*(1).

Da Silva, R. M., Santos, C. A., Moreira, M., Corte-Real, J., Silva, V. C., & Medeiros, I. C. (2015). Rainfall and river flow trends using Mann–Kendall and Sen's slope estimator statistical tests in the Cobres River basin. *Natural Hazards*, *77*, 1205-1221. https://doi.org/10.1007/s11069-015-1644-7

Dakurah, G., Osbahr, H., & Arnall, A. (2024). Smallholder farmers' cropping decisions in rural North-west Ghana under climate variability and change. *Regional environmental change*, *24*(1), 30. https://doi.org/10.1007/s10113-023-02168-2

Damtew, A., Teferi, E., Ongoma, V., Mumo, R., & Esayas, B. (2022). Spatiotemporal changes in mean and extreme climate: farmers' perception and its agricultural implications in Awash River Basin, Ethiopia. *Climate*, *10*(6), 89. https://doi.org/10.3390/cli10060089

Dang, H. L., Li, E., Nuberg, I., & Bruwer, J. (2019). Factors influencing the adaptation of farmers in response to climate change: A review. *Climate and Development*, *11*(9), 765-774. https://doi.org/10.1080/17565529.2018.1562866

Dantas, L. G., dos Santos, C. A., Santos, C. A., Martins, E. S., & Alves, L. M. (2022). Future changes in temperature and precipitation over northeastern Brazil by CMIP6 model. *Water*, *14*(24), 4118. https://doi.org/10.3390/w14244118

Darge, A., Haji, J., Beyene, F., & Ketema, M. (2023). Smallholder farmers' climate change adaptation strategies in the Ethiopian Rift Valley: The case of home garden agroforestry systems in the Gedeo Zone. *Sustainability*, *15*(11), 8997. https://doi.org/10.3390/su15118997

Das, S., Islam, A. R. M. T., & Kamruzzaman, M. (2023). Assessment of climate change impact on temperature extremes in a tropical region with the climate projections from CMIP6 model. *Climate Dynamics*, *60*(1), 603-622. https://doi.org/10.1007/s00382-022-06416-9

Dasmani, I., Darfor, K. N., & Karakara, A. A.-W. (2020). Farmers' choice of adaptation strategies towards weather variability: Empirical evidence from the three agro-ecological zones in Ghana. *Cogent Social Sciences*, *6*(1), 1751531. https://doi.org/10.1080/23311886.2020.1751531

Dave, K., Kumar, A., Dave, N., Jain, M., Dhanda, P. S., Yadav, A., & Kaushik, P. (2024). Climate change impacts on legume physiology and ecosystem dynamics: a multifaceted perspective. *Sustainability*, *16*(14), 6026. https://doi.org/10.3390/su16146026

Davis, B., Mane, E., Gurbuzer, L. Y., Caivano, G., Piedrahita, N., Schneider, K., Azhar, N., Benali, M., Chaudhary, N., & Rivera, R. (2023). *Estimating global and country-level employment in agrifood systems*. Food & Agriculture Org.
Dawadi, S., Shrestha, S., & Giri, R. A. (2021). Mixed-methods research: A discussion on its types, challenges, and criticisms. *Journal of Practical Studies in Education*, *2*(2), 25-36. https://doi.org/10.46809/jpse.v2i2.20
Debela, D. D., Stellmacher, T., Azadi, H., Kelboro, G., Lebailly, P., & Ghorbani, M. (2020). The impact of industrial investments on land use and smallholder farmers' livelihoods in Ethiopia. *Land use policy*, *99*, 105091. https://doi.org/10.1016/j.landusepol.2020.105091
Demem, M. S. (2023). Impact and adaptation of climate variability and change on small-holders and agriculture in Ethiopia: a review. *Heliyon*, *9*(8). https://doi.org/10.1016/j.heliyon.2023.e18972
Dendir, Z., & Simane, B. (2019). Livelihood vulnerability to climate variability and change in different agroecological zones of Gurage Administrative Zone, Ethiopia. *Progress in Disaster Science*, *3*, 100035. https://doi.org/10.1016/j.pdisas.2019.100035
Dendir, Z., & Simane, B. (2021). Farmers' perceptions about changes in climate variables: Perceived risks and household responses in different agro-ecological communities, Southern Ethiopia. *Climate Services*, *22*, 100236. https://doi.org/10.1016/j.cliser.2021.100236
Déqué, M., Calmanti, S., Christensen, O. B., Aquila, A. D., Maule, C. F., Haensler, A., Nikulin, G., & Teichmann, C. (2017). A multi-model climate response over tropical Africa at+ 2 C. *Climate Services*, *7*, 87-95. https://doi.org/10.1016/j.cliser.2016.06.002
Deressa, T. C., Chalchissa, F. B., & Gemeda, D. O. (2025). Rainfall and temperature variability and trend in the Horro Guduru Wallaga Zone, Northwestern Ethiopia. *Environmental Monitoring and Assessment*, *197*(7), 759. https://doi.org/10.1007/s10661-025-14195-z
Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, *149*(1), 23-31. https://doi.org/10.1017/S0021859610000687
Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global environmental change*, *19*(2), 248-255. https://doi.org/10.1016/j.gloenvcha.2009.01.002
Derso, D., Tolossa, D., & Seyoum, A. (2022). A double hurdle estimation of crop diversification decisions by smallholder wheat farmers in Sinana District, Bale Zone, Ethiopia. *CABI Agriculture and Bioscience*, *3*(1), 25. https://doi.org/10.1186/s43170-022-00098-3
Destaw, F., & Fenta, M. M. (2021). Climate change adaptation strategies and their predictors amongst rural farmers in Ambassel district, Northern Ethiopia. *Jàmbá: Journal of Disaster Risk Studies*, *13*(1), 1-11. https://doi.org/10.4102/jamba.v13i1.974
Dey, S., Abbhishek, K., Saraswathibatla, S., & Das, D. (2025). Assessing farmers' willingness to adopt conservation agricultural practices through an extended theory of planned behavior. *Humanities and Social Sciences Communications*, *12*(1), 1899. https://doi.org/10.1057/s41599-025-06173-0
Diallo, A., Donkor, E., & Owusu, V. (2020). Climate change adaptation strategies, productivity and sustainable food security in southern Mali. *Climatic Change*, *159*(3), 309-327. https://doi.org/10.1007/s10584-020-02684-8
Dibaba, W. T., Miegel, K., & Demissie, T. A. (2019). Evaluation of the CORDEX regional climate models performance in simulating climate conditions of two catchments in Upper Blue Nile Basin. *Dynamics of Atmospheres and Oceans*, *87*, 101104. https://doi.org/10.1016/j.dynatmoce.2019.101104
Djaman, K., O'neill, M., Owen, C. K., Smeal, D., Koudahe, K., West, M., Allen, S., Lombard, K., & Irmak, S. (2018). Crop evapotranspiration, irrigation water requirement and water productivity of maize from meteorological data under semiarid climate. *Water*, *10*(4), 405. https://doi.org/10.3390/w10040405
Dorji, T., Rinchen, K., Morrison-Saunders, A., Blake, D., Banham, V., & Pelden, S. (2024). Understanding how Indigenous knowledge contributes to climate change adaptation and resilience: A systematic literature review. *Environmental management*, *74*(6), 1101-1123. https://doi.org/10.1007/s00267-024-02032-x
Du, Y., Wang, D., Zhu, J., Wang, D., Qi, X., & Cai, J. (2022). Comprehensive assessment of CMIP5 and CMIP6 models in simulating and projecting precipitation over the global land. *International journal of Climatology*, *42*(13), 6859-6875. https://doi.org/10.1002/joc.7616
Dumrul, Y., & Kilicaslan, Z. (2017). Economic impacts of climate change on agriculture: Empirical evidence from ARDL approach for Turkey. *Journal of Business Economics and Finance*, *6*(4), 336-347. https://doi.org/10.17261/Pressacademia.2017.766
Dunne, J. P., Horowitz, L., Adcroft, A., Ginoux, P., Held, I., John, J., Krasting, J. P., Malyshev, S., Naik, V., & Paulot, F. (2020). The GFDL Earth System Model version 4.1 (GFDL-ESM 4.1): Overall coupled model description and simulation characteristics. *Journal of Advances in Modeling Earth Systems*, *12*(11), e2019MS002015. https://doi.org/10.1029/2019MS002032

Ekstrom, J. A., & Moser, S. C. (2014). Identifying and overcoming barriers in urban climate adaptation: Case study findings from the San Francisco Bay Area, California, USA. *Urban climate*, *9*, 54-74. https://doi.org/10.1016/j.uclim.2014.06.002

Ekwueme, B. N. (2021). Quantification of effects of climate change on flood in tropical river basins. *Cogent Engineering*, *8*(1), 1986967. https://doi.org/10.1080/23311916.2021.1986967

Ekwueme, B. N. (2024). Deep neural network modeling of river discharge in a tropical humid watershed. *Earth Science Informatics*, *17*(2), 1161-1177. https://doi.org/10.1007/s12145-023-01219-w

Ekwueme, B. N., & Agunwamba, J. C. (2020). Modeling the influence of meteorological variables on runoff in a tropical watershed. *Civil Engineering Journal*, *6*(12), 2344-2351. https://doi.org/10.28991/cej-2020-03091621

El Kenawy, A. M. (2024). Hydroclimatic extremes in arid and semi-arid regions: status, challenges, and future outlook. In *Hydroclimatic Extremes in the Middle East and North Africa* (pp. 1-22). Elsevier. https://doi.org/10.1016/B978-0-12-824130-1.00012-6

Engda, A., Yimer, F., Mekuyie, M., & Tadesse, M. (2024). Spatiotemporal Analysis of Climate Variability and Trends in West Arsi Zone, South-Central Ethiopia. *Advances in Meteorology*, *2024*(1), 8708922. https://doi.org/10.1155/adme/8708922

Enyew, F. B., Sahlu, D., Tarekegn, G. B., Hama, S., & Debele, S. E. (2024). Performance Evaluation of CMIP6 Climate Model Projections for Precipitation and Temperature in the Upper Blue Nile Basin, Ethiopia. *Climate*, *12*(11), 169. https://doi.org/10.3390/cli12110169

Enyew, F. B., & Wassie, S. B. (2024). Rainfall trends and spatiotemporal patterns of meteorological drought in Menna watershed, northwestern Ethiopia. *Heliyon*, *10*(6). https://doi.org/10.1016/j.heliyon.2024.e27919

Erdaw, M. M. (2023). Contribution, prospects and trends of livestock production in sub-Saharan Africa: a review. *International Journal of Agricultural Sustainability*, *21*(1), 2247776. https://doi.org/10.1080/14735903.2023.2247776

Erekalo, K. T., & Yadda, T. A. (2023). Climate-smart agriculture in Ethiopia: adoption of multiple crop production practices as a sustainable adaptation and mitigation strategies. *World Development Sustainability*, *3*, 100099. https://doi.org/10.1016/j.wds.2023.100099

Erman, M., Sytar, O., Brestic, M., Wasaya, A., Konuşkan, Ö., Kizilgeci, F., & Ikram, M. (2021). Maize adaptability to heat stress under changing climate. *Plant stress physiology*, 163.

Esayas, B., Simane, B., Teferi, E., Ongoma, V., & Tefera, N. (2018). Trends in extreme climate events over three agroecological zones of southern Ethiopia. *Advances in Meteorology*, *2018*(1), 7354157. https://doi.org/10.1155/2018/7354157

Esayas, B., Simane, B., Teferi, E., Ongoma, V., & Tefera, N. (2019). Climate variability and farmers' perception in Southern Ethiopia. *Advances in Meteorology*, *2019*(1), 7341465. https://doi.org/10.1155/2019/7341465

Eshetu, G., Johansson, T., Garedew, W., & Yisahak, T. (2021). Determinants of smallholder farmers' adaptation options to climate change in a coffee-based farming system of Southwest Ethiopia. *Climate and Development*, *13*(4), 318-325. https://doi.org/10.1080/17565529.2020.1772706

Estoque, R. C., Ooba, M., Togawa, T., & Hijioka, Y. (2020). Projected land-use changes in the Shared Socioeconomic Pathways: Insights and implications. *Ambio*, *49*, 1972-1981. https://doi.org/10.1007/s13280-020-01338-4

Etana, D., Snelder, D. J., van Wesenbeeck, C. F., & de Cock Buning, T. (2020). Trends of climate change and variability in three agro-ecological settings in central Ethiopia: contrasts of meteorological data and farmers' perceptions. *Climate*, *8*(11), 121. https://doi.org/10.3390/cli8110121

Etana, D., van Wesenbeeck, C. F., & de Cock Buning, T. (2021). Socio-cultural aspects of farmers' perception of the risk of climate change and variability in Central Ethiopia. *Climate and Development*, *13*(2), 139-151. https://doi.org/10.1080/17565529.2020.1737796

Fagariba, C. J., Song, S., & Soule Baoro, S. K. G. (2018). Climate change adaptation strategies and constraints in Northern Ghana: Evidence of farmers in Sissala West District. *Sustainability*, *10*(5), 1484. https://doi.org/10.3390/su10051484

Fahad, S., Inayat, T., Wang, J., Dong, L., Hu, G., Khan, S., & Khan, A. (2020). Farmers' awareness level and their perceptions of climate change: A case of Khyber Pakhtunkhwa province, Pakistan. *Land use policy*, *96*, 104669. https://doi.org/10.1016/j.landusepol.2020.104669

FAO. (2017). Addressing the gender differentiated investment risks to climate-smart agriculture. *AIMS Agriculture and Food*, *2*(1), 56-74. https://doi.org/10.3934/agrfood.2017.1.56

FAO. (2021). Food and agriculture organization of the United Nations—FAO. In *The Europa directory of international organizations 2021* (pp. 297-305). Routledge. https://doi.org/10.4324/9781003179900-41

Farah, K. H., & Muhumed, U. M. (2024). Evaluation of the Effects of Climate Variability on Water Resources and Agriculture: Insights from Regional Climate Models. *Journal of Engineering Research and Reports*, *26*(9), 66-77. https://doi.org/10.9734/jerr/2024/v26i91264

Farooq, M. S., Uzair, M., Raza, A., Habib, M., Xu, Y., Yousuf, M., Yang, S. H., & Ramzan Khan, M. (2022). Uncovering the research gaps to alleviate the negative impacts of climate change on food security: a review. *Frontiers in plant science*, *13*, 927535. https://doi.org/10.3389/fpls.2022.927535

Fayera, T. (2022). Climate variability and the responses of crop yields to agricultural drought in the East Wollega Zone, Oromia National Regional State, Ethiopia. IOP Conference Series: Earth and Environmental Science. https://doi.org/10.1088/1755-1315/1016/1/012002

Fekadu, G., & Belay, D. (2025). Determinant of farmers' choice of adaptation strategies to climate change in rural areas of Ambo District, Ethiopia. *Journal of Asian and African Studies*, *60*(5), 2758-2777. https://doi.org/10.1177/00219096231225950

Feke, B. E., Terefe, T., Ture, K., & Hunde, D. (2021). Spatiotemporal variability and time series trends of rainfall over northwestern parts of Ethiopia: the case of Horro Guduru Wollega Zone. *Environmental Monitoring and Assessment*, *193*(6), 1-19. https://doi.org/10.1007/s10661-021-09141-8

Feleke, H. G., Amdie, T. A., Rasche, F., Mersha, S. Y., & Brandt, C. (2025). Climate on the Edge: Impacts and Adaptation in Ethiopia's Agriculture. *Sustainability*, *17*(11), 5119. https://doi.org/10.3390/su17115119

Feyissa, T. A., Demissie, T. A., Saathoff, F., & Gebissa, A. (2023). Evaluation of general circulation models CMIP6 performance and future climate change over the omo river basin, Ethiopia. *Sustainability*, *15*(8), 6507. https://doi.org/10.3390/su15086507

Fisher, M., Abate, T., Lunduka, R. W., Asnake, W., Alemayehu, Y., & Madulu, R. B. (2015). Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Climatic Change*, *133*(2), 283-299. https://doi.org/10.1007/s10584-015-1459-2

Foguesatto, C. R., & Machado, J. A. D. (2021). What shapes farmers' perception of climate change? A case study of southern Brazil. *Environment, Development and Sustainability*, *23*, 1525-1538. https://doi.org/10.1007/s10668-020-00634-z

Folke, C., Biggs, R., Norström, A. V., Reyers, B., & Rockström, J. (2016). Social-ecological resilience and biosphere-based sustainability science. *Ecology and society*, *21*(3). http://dx.doi.org/10.5751/ES-08748-210341

Fonjong, L., Matose, F., & Sonnenfeld, D. A. (2024). Climate change in Africa: Impacts, adaptation, and policy responses. In (Vol. 89, pp. 102912): Elsevier. https://doi.org/10.1016/j.gloenvcha.2024.102912

Forster, P. M., Smith, C. J., Walsh, T., Lamb, W. F., Lamboll, R., Hauser, M., ... & Zhai, P. (2023). Indicators of Global Climate Change 2022: annual update of large-scale indicators of the state of the climate system and human influence. *Earth system science data*, *15*(6), 2295-2327. https://doi.org/10.5194/essd-15-2295-202

Fróna, D., Szenderák, J., & Harangi-Rákos, M. (2019). The challenge of feeding the world. *Sustainability*, *11*(20), 5816. https://doi.org/10.3390/su11205816

Gao, X., Sokolov, A., & Schlosser, C. A. (2023). A large ensemble global dataset for climate impact assessments. *Scientific Data*, *10*(1), 801. https://doi.org/10.1038/s41597-023-02708-9

Gao, Y., Su, P., Zhang, A., Wang, R., & Wang, J. a. (2021). Dynamic assessment of global maize exposure to extremely high temperatures. *International Journal of Disaster Risk Science*, *12*(5), 713-730. https://doi.org/10.1007/s13753-021-00360-8

Gashaw, T., Wubaye, G. B., Worqlul, A. W., Dile, Y. T., Mohammed, J. A., Birhan, D. A., Tefera, G. W., van Oel, P. R., Haileslassie, A., & Chukalla, A. D. (2023). Local and regional climate trends and variabilities in Ethiopia: Implications for climate change adaptations. *Environmental Challenges*, *13*, 100794. https://doi.org/10.1016/j.envc.2023.100794

Gashure, S. (2024). Adaptation strategies of smallholder farmers to climate variability and change in Konso, Ethiopia. *Scientific Reports*, *14*(1), 19203. https://doi.org/10.1038/s41598-024-70047-9

Gashure, S., & Wana, D. (2023). Smallholder farmers' perceptions, coping and adaptation strategies to climate variability in the UNESCO designated cultural landscapes of Konso, Ethiopia. *Local Environment*, *28*(10), 1243-1262. https://doi.org/10.1080/13549839.2023.2202379

Gatdet, C. (2022). The Ethiopian agricultural extension services: A mixed perspective. *Cogent Food & Agriculture*, *8*(1), 2132848. https://doi.org/10.1080/23311932.2022.2132848

Gbegbelegbe, S., Chikoye, D., Alene, A., Kyei-Boahen, S., & Chigeza, G. (2024). Strategic Foresight analysis of droughts in southern Africa and implications for food security. *Frontiers in Sustainable Food Systems*, *7*, 1159901. https://doi.org/10.3389/fsufs.2023.1159901

Gbemavo, C. D. S. J., Toffa, J., Tchakpa, C., Loko, Y. L. E., Djedatin, G., Ewedje, E.-E., Orobiyi, A., Sedah, P., & Sabot, F. (2022). Rice farmers' perceptions and response to climate variability, and determinants of adaptation strategies in the Republic of Benin. *International Journal of Climate Change Strategies and Management*, *14*(4), 332-353. https://doi.org/10.1108/IJCCSM-06-2021-0059

Gebisa, B. T., Dibaba, W. T., & Kabeta, A. (2023). Evaluation of historical CMIP6 model simulations and future climate change projections in the Baro River Basin. *Journal of Water and Climate Change*, *14*(8), 2680-2705. https://doi.org/10.2166/wcc.2023.032

Gebre, G. G., Amekawa, Y., & Fikadu, A. A. (2023). Farmers′ use of climate change adaptation strategies and their impacts on food security in Kenya. *Climate Risk Management*, *40*, 100495. https://doi.org/10.1016/j.crm.2023.100495

Gebrechorkos, S. H., Hülsmann, S., & Bernhofer, C. (2019). Regional climate projections for impact assessment studies in East Africa. *Environmental Research Letters*, *14*(4), 044031. https://doi.org/10.1088/1748-9326/ab055a

Gebrehiwot, T., & van der Veen, A. (2021). Farmers' drought experience, risk perceptions, and behavioural intentions for adaptation: Evidence from Ethiopia. *Climate and Development*, *13*(6), 493-502. https://doi.org/10.1080/17565529.2020.1806776

Gebremichael, H. B., Raba, G. A., Beketie, K. T., Feyisa, G. L., & Siyoum, T. (2022). Changes in daily rainfall and temperature extremes of upper Awash Basin, Ethiopia. *Scientific African*, *16*, e01173. https://doi.org/10.1016/j.sciaf.2022.e01173

Gebru, G. W., Ichoku, H. E., & Phil-Eze, P. O. (2020). Determinants of smallholder farmers' adoption of adaptation strategies to climate change in Eastern Tigray National Regional State of Ethiopia. *Heliyon*, *6*(7), e04356. https://doi.org/10.1016/j.heliyon.2020.e04356

Gedefaw, M. (2023). Assessment of changes in climate extremes of temperature over Ethiopia. *Cogent Engineering*, *10*(1), 2178117. https://doi.org/10.1080/23311916.2023.2178117

Geleta, T. D., Dadi, D. K., Funk, C., Garedew, W., Eyelade, D., & Worku, A. (2022). Downscaled climate change projections in urban centers of Southwest Ethiopia using CORDEX Africa simulations. *Climate*, *10*(10), 158. https://doi.org/10.3390/cli10100158

Gemeda, D. O., Korecha, D., & Garedew, W. (2023). Determinants of climate change adaptation strategies and existing barriers in Southwestern parts of Ethiopia. *Climate Services*, *30*, 100376. https://doi.org/10.1016/j.cliser.2023.100376

Getachew, B., & Manjunatha, B. (2021). Climate change projections and trends simulated from the CMIP5 models for the Lake Tana sub-basin, the Upper Blue Nile (Abay) River Basin, Ethiopia. *Environmental Challenges*, *5*, 100385. https://doi.org/10.1016/j.envc.2021.100385

Getachew, B., Manjunatha, B., & Bhat, H. G. (2021). Modeling projected impacts of climate and land use/land cover changes on hydrological responses in the Lake Tana Basin, upper Blue Nile River Basin, Ethiopia. *Journal of Hydrology*, *595*, 125974. https://doi.org/10.1016/j.jhydrol.2021.125974

Getahun, A. B., Ayal, D. Y., Ture, K., & Zeleke, T. T. (2021). Determinants of climate variability adaptation strategies: A case of Itang Special District, Gambella Region, Ethiopia. *Climate Services*, *23*, 100245. https://doi.org/10.1016/j.cliser.2021.100245

Getnet, G. T., Dagnew, A. B., & Ayal, D. Y. (2023). Spatiotemporal variability and trends of rainfall and temperature in the tropical moist montane ecosystem: implications to climate-smart agriculture in Geshy watershed, Southwest Ethiopia. *Climate Services*, *30*, 100384. https://doi.org/10.1016/j.cliser.2023.100384

Ghil, M., & Lucarini, V. (2020). The physics of climate variability and climate change. *Reviews of Modern Physics*, *92*(3), 035002. https://doi.org/10.1103/RevModPhys.92.035002

Ghorbanian, A., Mohammadzadeh, A., & Jamali, S. (2022). Linear and non-linear vegetation trend analysis throughout Iran using two decades of MODIS NDVI imagery. *Remote Sensing*, *14*(15), 3683. https://doi.org/10.3390/rs14153683

Gidden, M. J., Riahi, K., Smith, S. J., Fujimori, S., Luderer, G., Kriegler, E., Van Vuuren, D. P., Van Den Berg, M., Feng, L., & Klein, D. (2019). Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century. *Geoscientific model development*, *12*(4), 1443-1475. https://doi.org/10.5194/gmd-12-1443-2019

Gilewski, P. (2021). Impact of the grid resolution and deterministic interpolation of precipitation on rainfall-runoff modeling in a sparsely gauged mountainous catchment. *Water*, *13*(2), 230. https://doi.org/10.3390/w13020230

Ginbo, T. (2022). Heterogeneous impacts of climate change on crop yields across altitudes in Ethiopia. *Climatic Change*, *170*(1), 12. https://doi.org/10.1007/s10584-022-03306-1

Giraldo, D., Clarkson, G., Dorward, P., Obando, D., & Ramirez-Villegas, J. (2023). The development of a farmer decision-making mind map to inform climate services in Central America. *Frontiers in climate*, *5*, 1235601. https://doi.org/10.3389/fclim.2023.1235601

Gitz, V., Meybeck, A., Lipper, L., Young, C. D., & Braatz, S. (2016). Climate change and food security: risks and responses. *Food and Agriculture Organization of the United Nations (FAO) Report*, *110*, 2-4.

Gohar, A. A., & Cashman, A. (2016). A methodology to assess the impact of climate variability and change on water resources, food security and economic welfare. *Agricultural systems*, *147*, 51-64. https://doi.org/10.1016/j.agsy.2016.05.008

Granata, F., Di Nunno, F. Pathways for Hydrological Resilience: Strategies for Adaptation in a Changing Climate. *Earth Syst Environ* 10, 203–231 (2026). https://doi.org/10.1007/s41748-024-00567-x

Gries, T., Redlin, M., & Ugarte, J. E. (2019). Human-induced climate change: the impact of land-use change. *Theoretical and Applied Climatology*, *135*(3), 1031-1044. https://doi.org/10.1007/s00704-018-2422-8
Grose, M. R., Narsey, S., Delage, F., Dowdy, A. J., Bador, M., Boschat, G., Chung, C., Kajtar, J., Rauniyar, S., & Freund, M. (2020). Insights from CMIP6 for Australia's future climate. *Earth's Future*, *8*(5), e2019EF001469. https://doi.org/10.1029/2019EF001469
Grossi, A., & Dinku, T. (2022). From research to practice: Adapting agriculture to climate today for tomorrow in Ethiopia. *Frontiers in climate*, *4*, 931514. https://doi.org/10.3389/fclim.2022.931514
Gudina, M. H., & Alemu, E. A. (2024). Factors influencing small holder farmers adoption of climate SMART agriculture practices in Welmera Woreda, Central Ethiopia. *Frontiers in climate*, *6*, 1322550. https://doi.org/10.3389/fclim.2024.1322550
Gudmundsson, L., Bremnes, J. B., Haugen, J. E., & Engen-Skaugen, T. (2012). Downscaling RCM precipitation to the station scale using statistical transformations–a comparison of methods. *Hydrology and Earth System Sciences*, *16*(9), 3383-3390. https://doi.org/10.5194/hess-16-3383-2012
Gummadi, S., Rao, K., Seid, J., Legesse, G., Kadiyala, M., Takele, R., Amede, T., & Whitbread, A. (2018). Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980–2010. *Theoretical and Applied Climatology*, *134*(3), 1315-1328. https://doi.org/10.1007/s00704-017-2340-1
Guye, M. H., Legesse, A., & Mohammed, Y. (2023). Existential threats to pastoralism in an arid environment: the fate of Gujii pastoralists in Southern Ethiopia. *Journal of Degraded & Mining Lands Management*, *10*(2). https://doi.org/10.15243/jdmlm.2023.102.4179
Hadgu, G., Fantaye, K., Mamo, G., & Kassa, B. (2015). Farmers' climate change adaptation options and their determinants in Tigray Region, Northern Ethiopia.
Hagger, M. S., Cheung, M. W. L., Ajzen, I., & Hamilton, K. (2022). Perceived behavioral control moderating effects in the theory of planned behavior: A meta-analysis. *Health Psychology*, *41*(2), 155. https://doi.org/10.1037/hea0001153
Hagos, S., Feng, Z., Tai, S. L., & Chen, J. (2023). Regional variability in the environmental controls of precipitation regimes in the tropics. *Journal of Geophysical Research: Atmospheres*, *128*(18), e2023JD038927. https://doi.org/10.1029/2023JD038927
Haider, S., Masood, M. U., Rashid, M., Alshehri, F., Pande, C. B., Katipoğlu, O. M., & Costache, R. (2023). Simulation of the potential impacts of projected climate and land use change on runoff under CMIP6 scenarios. *Water*, *15*(19), 3421. https://doi.org/10.3390/w15193421
Haile, G. G., Tang, Q., Sun, S., Huang, Z., Zhang, X., & Liu, X. (2019). Droughts in East Africa: Causes, impacts and resilience. *Earth-science reviews*, *193*, 146-161. https://doi.org/10.1016/j.earscirev.2019.04.015
Haileslassie, A., Mekuria, W., Schmitter, P., Uhlenbrook, S., & Ludi, E. (2020). Changing agricultural landscapes in Ethiopia: examining application of adaptive management approach. *Sustainability*, *12*(21), 8939. https://doi.org/10.3390/su12218939
Hamed, M. M., Nashwan, M. S., & Shahid, S. (2022). A novel selection method of CMIP6 GCMs for robust climate projection. *Int. J. Climatol*, *42*(8), 4258-4272. https://doi.org/10.1002/joc.7461
Hamer, E. A., Oyedotun, T. D. T., Charles, E., & Moonsammy, S. (2025). Livelihood adaptation to climate-related changes in agroecological zones in developing countries—challenges, prospects, and policy concerns. *Frontiers in climate*, *7*, 1594747. https://doi.org/10.3389/fclim.2025.1594747
Hansen, J., Sato, M., & Ruedy, R. (2011). Climate variability and climate change: The new climate dice. *NASA Goddard Institute for Space Studies, New York*, *2*.
Hasan, M. K., & Kumar, L. (2019). Comparison between meteorological data and farmer perceptions of climate change and vulnerability in relation to adaptation. *Journal of Environmental Management*, *237*, 54-62. https://doi.org/10.1016/j.jenvman.2019.02.028
Hassan, B. A., & Knight, J. (2023). Adaptation to Climate Change and Variability by Farming Households in North-Central Nigeria. *Sustainability*, *15*(23), 16309. https://doi.org/10.1016/j.jenvman.2019.02.028
Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes*, *10*, 4-10. https://doi.org/10.1016/j.wace.2015.08.001
Hayhoe, K., Edmonds, J., Kopp, R., LeGrande, A., Sanderson, B., Wehner, M., & Wuebbles, D. (2017). Climate models, scenarios, and projections.
Hein, Y., Vijitsrikamol, K., Attavanich, W., & Janekarnkij, P. (2019). Do farmers perceive the trends of local climate variability accurately? An analysis of farmers' perceptions and meteorological data in Myanmar. *Climate*, *7*(5), 64. https://doi.org/10.3390/cli7050064
Hirpha, H. H., Mpandeli, S., & Bantider, A. (2020). Determinants of adaptation strategies to climate change among the smallholder farmers in Adama District, Ethiopia. *International Journal of Climate Change Strategies and Management*. https://doi.org/10.1108/IJCCSM-01-2019-0002
Hordofa, A. T., Leta, O. T., Alamirew, T., & Chukalla, A. D. (2021). Spatiotemporal trend analysis of temperature and rainfall over Ziway Lake Basin, Ethiopia. *Hydrology*, *9*(1), 2. https://doi.org/10.3390/hydrology9010002

Howe, P. D., Marlon, J. R., Mildenberger, M., & Shield, B. S. (2019). How will climate change shape climate opinion? *Environmental Research Letters*, *14*(11), 113001. https://doi.org/10.1088/1748-9326/ab466a

Hu, Z.-Z., Kumar, A., Jha, B., & Huang, B. (2020). How much of monthly mean precipitation variability over global land is associated with SST anomalies? *Climate Dynamics*, *54*(1), 701-712. https://doi.org/10.1007/s00382-019-05023-5

Hu, Z., Liu, K., Xu, X., Hu, D., Song, H., Wu, Y., & Wu, J. (2025). Photosynthesis and senescence gene expression drive yield improvements in early season rice under long-term method of fertilization. *Scientific Reports*, *15*(1), 8532. https://doi.org/10.1038/s41598-025-93474-8

Huong, N., Shun Bo, Y., & Fahad, S. (2017). Farmers' perception, awareness and adaptation to climate change: evidence from northwest Vietnam. *International Journal of Climate Change Strategies and Management*, *9*(4), 555-576. https://doi.org/10.1108/IJCCSM-02-2017-0032

Hussein, M. A., & Hmood, M. Y. (2024). Nonstationary time series models using ARDL and NARDL estimation. *Journal of Economics and Administrative Sciences*, *30*(141), 439-456. https://doi.org/10.33095/afbrge60

Ignacio-Reardon, S. J. I., & Luo, J.-j. (2023). Evaluation of the performance of CMIP6 climate models in simulating rainfall over the Philippines. *Atmosphere*, *14*(9), 1459. https://doi.org/10.3390/atmos14091459

Ilame, T. (2025). Multidimensional Scoping Review on Climate Change Vulnerabilities With Adaptation and Mitigation Strategies. *Journal of Climate Resilience & Climate Justice*, *2*, 129-149. https://doi.org/10.1162/crcj_a_00020

Imran, M., Shrestha, R. P., & Datta, A. (2020). Comparing farmers' perceptions of climate change with meteorological data in three irrigated cropping zones of Punjab, Pakistan: M. Imran et al. *Environment, Development and Sustainability*, *22*(3), 2121-2140. https://doi.org/10.1007/s10668-018-0280-2

IPCC. (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. *A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC)*, 25-64.

IPCC. (2014a). *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press.

IPCC. (2014b). *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Ipcc.

IPCC. (2014c). Impacts, adaptation, and vulnerability. *Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, *1132*.

IPCC. (2018). Summary for policymakers. In *Global Warming of 1.5: An IPCC Special Report on the impacts of global warming of 1.5\C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. IPCC.

IPCC. (2021). Climate change 2021: the physical science basis. *Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*, *2*(1), 2391.

IPCC. (2022). IPCC Sixth Assessment Report (AR6): Climate Change 2022-Impacts, Adaptation and Vulnerability: Regional Factsheet Africa.

IPCC. (2023). IPCC, 2023: Climate change 2023: Synthesis report, summary for policymakers. Contribution of working groups i, II and III to the sixth assessment report of the intergovernmental panel on climate change [core writing team, h. Lee and j. Romero (eds.)]. IPCC, geneva, Switzerland.

Jain, S., Srivastava, A., Khadke, L., Chatterjee, U., & Elbeltagi, A. (2024). Global-scale water security and desertification management amidst climate change. *Environmental Science and Pollution Research*, 1-25. https://doi.org/10.1007/s11356-024-34916-0

Javadinejad, S., Eslamian, S., & Ostad-Ali-Askari, K. (2019). Investigation of monthly and seasonal changes of methane gas with respect to climate change using satellite data. *Applied Water Science*, *9*(8), 180. https://doi.org/10.1007/s13201-019-1067-9

Jawo, T., Teutscherová, N., Negash, M., Sahle, K., & Lojka, B. (2023). Smallholder coffee-based farmers' perception and their adaptation strategies of climate change and variability in South-Eastern Ethiopia. *International Journal of Sustainable Development & World Ecology*, 1-15. https://doi.org/10.1080/13504509.2023.2167241

Jha, C. K., & Gupta, V. (2021). Do better agricultural extension and climate information sources enhance adaptive capacity? A micro-level assessment of farm households in rural India. *Ecofeminism and Climate Change*. https://doi.org/10.1108/EFCC-10-2020-0032

Jiang, Y., Lu, B., Liang, M., Wu, Y., Li, Y., Zhao, Z., Liu, G., & Xue, S. (2025). Temperature sensitivity response of soil enzyme activity to simulated climate change at growth stages of winter wheat. *Agronomy*, *15*(1), 106. https://doi.org/10.3390/agronomy15010106

Jin, J., Jian, D., Zhou, X., Chen, Q., & Li, Y. (2025). Impact of El Niño–Southern Oscillation on Global Vegetation. *Atmosphere*, *16*(6), 701. https://doi.org/10.3390/atmos16060701

Jing, P., Wang, D., Zhu, C., & Chen, J. (2016). Plant physiological, morphological and yield-related responses to night temperature changes across different species and plant functional types. *Frontiers in plant science*, *7*, 1774. https://doi.org/10.3389/fpls.2016.01774

Jovchelovitch, S. (2012). Narrative, memory and social representations: A conversation between history and social psychology. *Integrative psychological and behavioral science*, *46*(4), 440-456. https://doi.org/10.1007/s12124-012-9217-8

Jury, M. R., & Funk, C. (2013). Climatic trends over Ethiopia: regional signals and drivers. *International journal of Climatology*, *33*(8), 1924-1935. https://doi.org/10.1002/joc.3560

Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of econometrics*, *7*(1), 67-86. https://doi.org/10.1016/0304-4076(78)90006-4

Kahsay, H. T., Guta, D. D., Birhanu, B. S., & Gidey, T. G. (2019). Farmers' perceptions of climate change trends and adaptation strategies in semiarid highlands of Eastern Tigray, Northern Ethiopia. *Advances in Meteorology*, *2019*. https://doi.org/10.1155/2019/3849210

Kamruzzaman, M., Shahid, S., Islam, A. T., Hwang, S., Cho, J., Zaman, M. A. U., Ahmed, M., Rahman, M. M., & Hossain, M. B. (2021). Comparison of CMIP6 and CMIP5 model performance in simulating historical precipitation and temperature in Bangladesh: a preliminary study. *Theoretical and Applied Climatology*, *145*, 1385-1406. https://doi.org/10.1007/s00704-021-03691-0

Kandel, G. P., Bavorova, M., Ullah, A., Kaechele, H., & Pradhan, P. (2023). Building resilience to climate change: examining the impact of agro-ecological zones and social groups on sustainable development. *Sustainable Development*, *31*(5), 3796-3810. https://doi.org/10.1002/sd.2626

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, *129*(2), 597-652. https://doi.org/10.1093/qje/qju002

Kasie, T. A., Demissie, B. S., Bahry, M. J., Gessesse, G. M., & Wale, L. E. (2020). The impact of the 2015 El Niño-induced drought on household consumption: Evidence from rural Ethiopia. *Climate and Development*, *12*(9), 854-863. https://doi.org/10.1080/17565529.2019.1701400

Kaske, D., Kassahun, T., & Alemu, A. (2022). Study on farmers' perception on climate change: a systematic literature review. https://doi.org/10.33687/ijae.010.03.4111

Kassie, B. T., Hengsdijk, H., Rötter, R., Kahiluoto, H., Asseng, S., & Van Ittersum, M. (2013). Adapting to climate variability and change: experiences from cereal-based farming in the Central Rift and Kobo Valleys, Ethiopia. *Environmental Management*, *52*(5), 1115-1131. https://doi.org/10.1007/s00267-013-0145-2

Kawai, H., Yukimoto, S., Koshiro, T., Oshima, N., Tanaka, T., Yoshimura, H., & Nagasawa, R. (2019). Significant improvement of cloud representation in the global climate model MRI-ESM2. *Geoscientific model development*, *12*(7), 2875-2897. https://doi.org/10.5194/gmd-12-2875-2019

Kelman, I., Gaillard, J.-C., Lewis, J., & Mercer, J. (2016). Learning from the history of disaster vulnerability and resilience research and practice for climate change. *Natural Hazards*, *82*(1), 129-143. https://doi.org/10.1007/s11069-016-2294-0

Kesavavarthini, T., Rajesh, A. N., Venkata Srinivas, C., & Kumar, T. L. (2023). Bias correction of CMIP6 simulations of precipitation over Indian monsoon core region using deep learning algorithms. *International journal of Climatology*, *43*(8), 3749-3767. https://doi.org/10.1002/joc.8056

Ketema, A., & Siddaramaiah, D. G. (2020). Trend and variability of hydrometeorological variables of Tikur Wuha watershed in Ethiopia. *Arabian Journal of Geosciences*, *13*(3), 1-20. https://doi.org/10.1007/s12517-020-5139-9

Khan, A. H., Min, L., Ma, Y., Zeeshan, M., Jin, S., & Zhang, X. (2023). High-temperature stress in crops: male sterility, yield loss and potential remedy approaches. *Plant biotechnology journal*, *21*(4), 680-697. https://doi.org/10.1111/pbi.13946

Khan, N., Shahid, S., Ahmed, K., Ismail, T., Nawaz, N., & Son, M. (2018). Performance assessment of general circulation model in simulating daily precipitation and temperature using multiple gridded datasets. *Water*, *10*(12), 1793. https://doi.org/10.3390/w10121793

Khanal, U., Wilson, C., Hoang, V.-N., & Lee, B. (2018). Farmers' adaptation to climate change, its determinants and impacts on rice yield in Nepal. *Ecological economics*, *144*, 139-147. https://doi.org/10.1016/j.ecolecon.2017.08.006

Khatri, P., Kumar, P., Shakya, K. S., Kirlas, M. C., & Tiwari, K. K. (2024). Understanding the intertwined nature of rising multiple risks in modern agriculture and food system. *Environment, Development and Sustainability*, *26*(9), 24107-24150. https://doi.org/10.1007/s10668-023-03638-7

Kidane, R., Wanner, T., Nursey-Bray, M., Masud-All-Kamal, M., & Atampugre, G. (2022). The role of climatic and non-climatic factors in smallholder farmers' adaptation responses: insights from rural Ethiopia. *Sustainability*, *14*(9), 5715. https://doi.org/10.3390/su14095715

Kiddle, G. L., Bakineti, T., Latai-Niusulu, A., Missack, W., Pedersen Zari, M., Kiddle, R., Chanse, V., Blaschke, P., & Loubser, D. (2021). Nature-based solutions for urban climate change adaptation and wellbeing:

evidence and opportunities from Kiribati, Samoa, and Vanuatu. *Frontiers in Environmental Science*, *9*, 723166. https://doi.org/10.3389/fenvs.2021.723166
Kifle, T., Ayal, D. Y., & Mulugeta, M. (2022). Factors influencing farmers adoption of climate smart agriculture to respond climate variability in Siyadebrina Wayu District, Central highland of Ethiopia. *Climate Services*, *26*, 100290. https://doi.org/10.1016/j.cliser.2022.100290
Kim, J., Han, J., Park, K., & Seok, S. (2022). Improved IDW interpolation application using 3D search neighborhoods: Borehole data-based seismic liquefaction hazard assessment and mapping. *Applied Sciences*, *12*(22), 11652. https://doi.org/10.3390/app122211652
King, E. G., Unks, R. R., & German, L. (2018). Constraints and capacities for novel livelihood adaptation: lessons from agricultural adoption in an African dryland pastoralist system. *Regional Environmental Change*, *18*(5), 1403-1410. https://doi.org/10.1007/s10113-017-1270-x
Kobe, F. T. (2023). Understanding climate change in Ethiopia: impacts and solutions. *International Journal of Big Data Mining for Global Warming*, *5*(02), 2330001. https://doi.org/10.1142/S2630534823300014
Koç, C., Bayazit, Y., & Özgül, S. Y. (2022). Investigation of theoretical hydroelectric potential with GIS-based model in Buyuk Menderes Basin, Turkey. *International Journal of Sustainable Energy*, *41*(11), 2185-2196. https://doi.org/10.1080/14786451.2022.2147525
Kom, Z., Nethengwe, N. S., Mpandeli, S., & Chikoore, H. (2023). Indigenous knowledge indicators employed by farmers for adaptation to climate change in rural South Africa. *Journal of Environmental Planning and Management*, *66*(13), 2778-2793. https://doi.org/10.1080/09640568.2022.2086854
Kone, S., Balde, A., Zahonogo, P., & Sanfo, S. (2024). A systematic review of recent estimations of climate change impact on agriculture and adaptation strategies perspectives in Africa. *Mitigation and Adaptation Strategies for Global Change*, *29*(2), 18. https://doi.org/10.1007/s11027-024-10115-7
Kong, L., Ashraf, U., Cheng, S., Rao, G., Mo, Z., Tian, H., Pan, S., & Tang, X. (2017). Short-term water management at early filling stage improves early-season rice performance under high temperature stress in South China. *European journal of agronomy*, *90*, 117-126. https://doi.org/10.1016/j.eja.2017.07.006
Korteling, J. E., Paradies, G. L., & Sassen-van Meer, J. P. (2023). Cognitive bias and how to improve sustainable decision making. *Frontiers in psychology*, *14*, 1129835. https://doi.org/10.3389/fpsyg.2023.1129835
Kothari, C. R. (2004). *Research methodology*. new Age.
Krishna, A. (2021). Understanding the differences between climate change deniers and believers' knowledge, media use, and trust in related information sources. *Public Relations Review*, *47*(1), 101986. https://doi.org/10.1016/j.pubrev.2020.101986
Kumar, A. (2018). Global warming, climate change and greenhouse gas mitigation. In *Biofuels: greenhouse gas mitigation and global warming: next generation biofuels and role of biotechnology* (pp. 1-16). Springer. https://doi.org/10.1007/978-81-322-3763-1_1
Kumar, L., Chhogyel, N., Gopalakrishnan, T., Hasan, M. K., Jayasinghe, S. L., Kariyawasam, C. S., Kogo, B. K., & Ratnayake, S. (2022). Climate change and future of agri-food production. In *Future Foods* (pp. 49-79). Elsevier. https://doi.org/10.1016/B978-0-323-91001-9.00009-8
Kumar, M. D., Reddy, V. R., Narayanamoorthy, A., Bassi, N., & James, A. (2018). Rainfed areas: poor definition and flawed solutions. *International Journal of Water Resources Development*, *34*(2), 278-291. https://doi.org/10.1080/07900627.2017.1278680
Kumar, P., Sahu, N. C., Kumar, S., & Ansari, M. A. (2021). Impact of climate change on cereal production: evidence from lower-middle-income countries. *Environmental Science and Pollution Research*, *28*(37), 51597-51611. https://doi.org/10.1007/s11356-021-14373-9
Kumar, S., Chatterjee, U., David Raj, A., & Sooryamol, K. (2024). Global warming and climate crisis/extreme events. In *Climate crisis: Adaptive approaches and sustainability* (pp. 3-18). Springer. https://doi.org/10.1007/978-3-031-44397-8_1
Kumsa, D. C., Tesso, A., & Tolera, D. (2024). Deciphering climate variability trends: unveiling the impact on household staple crop productivity in East Wallaga Zone, Ethiopia. *Frontiers in Climate*, *6*, 1490248. https://doi.org/10.3389/fclim.2024.1490248
Kwakye, J. (2023). Understanding agriculturists' perception and adaptation to the current climate patterns in Jaman south municipality, Ghana. *International Journal of Environment and Climate Change*, *13*(10), 2742-2755. https://doi.org/10.9734/ijecc/2023/v13i102939
Lehner, F., & Deser, C. (2023). Origin, importance, and predictive limits of internal climate variability. *Environmental Research: Climate*, *2*(2), 023001. https://doi.org/10.1088/2752-5295/accf30
Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84-87. https://doi.org/10.1038/nature16467
Lewis, K. (2017). Understanding climate as a driver of food insecurity in Ethiopia. *Climatic Change*, *144*, 317-328. https://doi.org/10.1007/s10584-017-2036-7

Li, Z., Ciais, P., Wright, J. S., Wang, Y., Liu, S., Wang, J., Li, L. Z., Lu, H., Huang, X., & Zhu, L. (2023). Increased precipitation over land due to climate feedback of large-scale bioenergy cultivation. *Nature Communications*, *14*(1), 4096. https://doi.org/10.1038/s41467-023-39803-9

Li, Z., Sun, Z., & Wang, C. (2026). Understanding the adaptive behaviors of farmers on the Qinghai-Tibetan Plateau: a mixed-methods study on the mediating role of risk perception and the moderating effects of climate change benefits and self-efficacy. *Humanities and Social Sciences Communications*. https://doi.org/10.1057/s41599-026-06567-8

Lian, X., Piao, S., Chen, A., Huntingford, C., Fu, B., Li, L. Z., Huang, J., Sheffield, J., Berg, A. M., & Keenan, T. F. (2021). Multifaceted characteristics of dryland aridity changes in a warming world. *Nature Reviews Earth & Environment*, *2*(4), 232-250.

Liang, Q., Nittel, S., Whittier, J. C., & De Bruin, S. (2018). Real-time inverse distance weighting interpolation for streaming sensor data. *Transactions in GIS*, *22*(5), 1179-1204. https://doi.org/10.1111/tgis.12458

Likinaw, A., Bewket, W., & Alemayehu, A. (2023). Smallholder farmers' perceptions and adaptation strategies to climate change risks in northwest Ethiopia. *International Journal of Climate Change Strategies and Management*, *15*(5), 599-618. https://doi.org/10.1108/IJCCSM-01-2022-0001

Limantol, A. M., Keith, B. E., Azabre, B. A., & Lennartz, B. (2016). Farmers' perception and adaptation practice to climate variability and change: a case study of the Vea catchment in Ghana. *SpringerPlus*, *5*, 1-38. https://doi.org/10.1186/s40064-016-2433-9

Lobell, D.B., Deines, J.M. & Tommaso, S.D. Changes in the drought sensitivity of US maize yields. *Nat Food* 1, 729–735 (2020). https://doi.org/10.1038/s43016-020-00165-w

Loeb, N. G., Su, W., & Kato, S. (2016). Understanding climate feedbacks and sensitivity using observations of Earth's energy budget. *Current climate change reports*, *2*(4), 170-178. https://doi.org/10.1007/s40641-016-0047-5

Lombe, P., Carvalho, E., & Rosa-Santos, P. (2024). Drought dynamics in sub-Saharan Africa: Impacts and adaptation strategies. *Sustainability*, *16*(22), 9902. https://doi.org/10.3390/su16229902

Londhe, D. S., Katpatal, Y. B., & Bokde, N. D. (2023). Performance assessment of bias correction methods for precipitation and temperature from CMIP5 model simulation. *Applied Sciences*, *13*(16), 9142. https://doi.org/10.3390/app13169142

Magang, D. S., Ojara, M. A., Yunsheng, L., & King'uza, P. H. (2024). Future climate projection across Tanzania under CMIP6 with high-resolution regional climate model. *Scientific Reports*, *14*(1), 12741. https://doi.org/10.1038/s41598-024-63495-w

Mairura, F. S., Musafiri, C. M., Kiboi, M. N., Macharia, J. M., Ng'etich, O. K., Shisanya, C. A., Okeyo, J. M., Mugendi, D. N., Okwuosa, E. A., & Ngetich, F. K. (2021). Determinants of farmers' perceptions of climate variability, mitigation, and adaptation strategies in the central highlands of Kenya. *Weather and Climate Extremes*, *34*, 100374. https://doi.org/10.1016/j.wace.2021.100374

Malhi, Y., Franklin, J., Seddon, N., Solan, M., Turner, M. G., Field, C. B., & Knowlton, N. (2020). Climate change and ecosystems: Threats, opportunities and solutions. In (Vol. 375, pp. 20190104): The Royal Society. https://doi.org/10.1098/rstb.2019.0104

Malik, A., & Kumar, A. (2020). Spatio-temporal trend analysis of rainfall using parametric and non-parametric tests: case study in Uttarakhand, India. *Theoretical and Applied Climatology*, *140*(1), 183-207. https://doi.org/10.1007/s00704-019-03080-8

Mammo, B. T. (2022). Climate Change and its Impact on Agricultural GDP Growth in Ethiopia: A Time Series Analysis. *International Journal of Academic Reserach in Economics and Management Sciences*, *11*(2). https://doi.org/10.6007/IJAREMS/v11-i2/13971

Mamun, A. A., Roy, S., Islam, A. R. M. T., Alam, G. M., Alam, E., Chandra Pal, S., Sattar, M. A., & Mallick, J. (2021). Smallholder farmers' perceived climate-related risk, impact, and their choices of sustainable adaptation strategies. *Sustainability*, *13*(21), 11922. https://doi.org/10.3390/su132111922

Mandal, D., & Roy, T. (2024). Climate change impact on soil erosion and land degradation. In *Climate change impacts on soil-plant-atmosphere continuum* (pp. 139-161). Springer. https://doi.org/10.1007/978-981-99-7935-6_5

Manh, N. T., & Ahmad, M. M. (2021). Indigenous farmers' perception of climate change and the use of local knowledge to adapt to climate variability: A case study of Vietnam. *Journal of International Development*, *33*(7), 1189-1212. https://doi.org/10.1002/jid.3573

Mani, Z. A., & Goniewicz, K. (2023). Adapting disaster preparedness strategies to changing climate patterns in Saudi Arabia: A rapid review. *Sustainability*, *15*(19), 14279. https://doi.org/10.3390/su151914279

Manono, B. O., Khan, S., & Kithaka, K. M. (2025). A Review of the Socio-Economic, Institutional, and Biophysical Factors Influencing Smallholder Farmers' Adoption of Climate Smart Agricultural Practices in Sub-Saharan Africa. *Earth*, *6*(2), 48. https://doi.org/10.3390/earth6020048

Marie, M., Yirga, F., Haile, M., & Tquabo, F. (2020). Farmers' choices and factors affecting adoption of climate change adaptation strategies: evidence from northwestern Ethiopia. *Heliyon*, *6*(4), e03867. https://doi.org/10.1016/j.heliyon.2020.e03867

Markos, D., Worku, W., & Mamo, G. (2023a). Exploring adaptation responses of maize to climate change scenarios in southern central Rift Valley of Ethiopia. *Scientific Reports*, *13*(1), 12949. https://doi.org/10.1038/s41598-023-39795-y

Markos, D., Worku, W., & Mamo, G. (2023b). Spatio-temporal variability and rainfall trend affects seasonal calendar of maize production in southern central Rift Valley of Ethiopia. *PLOS Climate*, *2*(6), e0000218. https://doi.org/10.1371/journal.pclm.0000218

Marshal, W., Chung, J. X., & Mohd Akhir, M. F. B. (2024). Evaluation of CMIP6 Models Performance in Simulating Historical Biogeochemistry across Southern South China Sea. *EGUsphere*, *2024*, 1-24. https://doi.org/10.5194/bg-21-4007-2024

Masrizal, M. (2012). Mixed method research. *Jurnal Kesehatan Masyarakat Andalas*, *6*(2), 53-56.

Masud, M. M., Azam, M. N., Mohiuddin, M., Banna, H., Akhtar, R., Alam, A. F., & Begum, H. (2017). Adaptation barriers and strategies towards climate change: Challenges in the agricultural sector. *Journal of Cleaner Production*, *156*, 698-706. https://doi.org/10.1016/j.jclepro.2017.04.060

Matewos, T. (2019). Climate change-induced impacts on smallholder farmers in selected districts of Sidama, Southern Ethiopia. *Climate*, *7*(5), 70. https://doi.org/10.3390/cli7050070

Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., Brovkin, V., Claussen, M., Crueger, T., & Esch, M. (2019). Developments in the MPI‐M Earth System Model version 1.2 (MPI‐ESM1. 2) and its response to increasing CO2. *Journal of Advances in Modeling Earth Systems*, *11*(4), 998-1038. https://doi.org/10.1029/2018MS001400

Maxwell, S. L., Butt, N., Maron, M., McAlpine, C. A., Chapman, S., Ullmann, A., Segan, D. B., & Watson, J. E. (2019). Conservation implications of ecological responses to extreme weather and climate events. *Diversity and Distributions*, *25*(4), 613-625. https://doi.org/10.1111/ddi.12878

Mazengiya, M. N. (2024). Review on the opportunities and challenges to implement climate smart agriculture practice in Ethiopia. *Discover Agriculture*, *2*(1), 110. https://doi.org/10.1007/s44279-024-00118-y

Mbienda, A. K., Guenang, G., Kaissassou, S., Tanessong, R., Choumbou, P., & Giorgi, F. (2023). Enhancement of RegCM4. 7‐CLM precipitation and temperature by improved bias correction methods over Central Africa. *Meteorological Applications*, *30*(1), e2116. https://doi.org/10.1002/met.2116

Megabia, T. T., Amare, Z. Y., & Asmare, A. M. (2022). Rural household perception and adaptation strategies to climate change and variability: in the case of Libo-kemkem Woreda, Ethiopia. *Environmental Systems Research*, *11*(1), 1-10. https://doi.org/10.1186/s40068-022-00270-8

Megersa, G., Tesfaye, K., Getnet, M., Tana, T., Jaletab, M., & Lakew, B. (2019). Rainfall variability and its implications for wheat and barley production in Central Ethiopia. *Ethiop. J. Crop Sci*, *7*(2), 89-111.

Megersa, G. G., Jaleta, M., Tesfaye, K., Getnet, M., Tana, T., & Lakew, B. (2022). Perceived climate change and determinants of adaptation responses by smallholder farmers in Central Ethiopia. *Sustainability*, *14*(11), 6590. https://doi.org/10.3390/su14116590

Mehta, P. (2024). The impact of climate change on the environment, water resources, and agriculture: a comprehensive review. *Climate, Environment and Agricultural Development: A Sustainable Approach Towards Society*, 189-201. https://doi.org/10.1007/978-981-97-8363-2_12

Mekonen, A. A., & Berlie, A. B. (2020). Spatiotemporal variability and trends of rainfall and temperature in the Northeastern Highlands of Ethiopia. *Modeling Earth Systems and Environment*, *6*(1), 285-300. https://doi.org/10.1007/s40808-019-00678-9

Mekonen, A. A., Berlie, A. B., & Ferede, M. B. (2020). Spatial and temporal drought incidence analysis in the northeastern highlands of Ethiopia. *Geoenvironmental Disasters*, *7*(1), 1-17. https://doi.org/10.1007/s40808-019-00678-9

Mekonnen, Z., Kidemu, M., Abebe, H., Semere, M., Gebreyesus, M., Worku, A., Tesfaye, M., & Chernet, A. (2021). Traditional knowledge and institutions for sustainable climate change adaptation in Ethiopia. *Current research in Environmental sustainability*, *3*, 100080. https://doi.org/10.1186/s40677-020-0146-4

Mekonnen, Z., Woldeamanuel, T., & Kassa, H. (2019). Socio-ecological vulnerability to climate change/variability in central rift valley, Ethiopia. *Advances in Climate Change Research*, *10*(1), 9-20. https://doi.org/10.1016/j.accre.2019.03.002

Mekuria, W., & Mekonnen, K. (2018). Determinants of crop–livestock diversification in the mixed farming systems: evidence from central highlands of Ethiopia. *Agriculture & Food Security*, *7*(1), 1-15. https://doi.org/10.1186/s40066-018-0212-2

Mengistu, A. G., Woldesenbet, T. A., Dile, Y. T., & Bayabil, H. K. (2023). Modeling the impacts of climate change on hydrological processes in the Baro–Akobo River basin, Ethiopia. *Acta Geophysica*, *71*(4), 1915-1935. https://doi.org/10.1007/s11600-022-00956-8

Mengistu, D., Bewket, W., Dosio, A., & Panitz, H.-J. (2021). Climate change impacts on water resources in the upper blue nile (Abay) river basin, ethiopia. *Journal of Hydrology*, *592*, 125614. https://doi.org/10.1016/j.jhydrol.2020.125614

Mengistu, D., Bewket, W., & Lal, R. (2014). Recent spatiotemporal temperature and rainfall variability and trends over the Upper Blue Nile River Basin, Ethiopia. *International journal of Climatology*, *34*(7), 2278-2292. https://doi.org/10.1002/joc.3837

Mera, G. A. (2018). Drought and its impacts in Ethiopia. *Weather and Climate Extremes*, *22*, 24-35. https://doi.org/10.1016/j.wace.2018.10.002

Meressa, A. M., & Bantie, L. (2024). The impacts of climate change on peasant's crop production in major crop producing zones in Ethiopia. *Discover Sustainability*, *5*(1), 443. https://doi.org/10.1007/s43621-024-00628-1

Meshesha, T. M., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Fenta, A. A., Berihun, M. L., Mulu, A., Setargie, T. A., & Kassa, S. B. (2024). Agroecology-based land use/land cover change detection, prediction and its implications for land degradation: a case study in the Upper Blue Nile Basin. *International Soil and Water Conservation Research*, *12*(4), 786-797. https://doi.org/10.1016/j.iswcr.2024.02.002

Mihiretu, A., Okoyo, E. N., & Lemma, T. (2020). Small holder farmers' perception and response mechanisms to climate change: Lesson from Tekeze lowland goat and sorghum livelihood zone, Ethiopia. *Cogent Food & Agriculture*, *6*(1), 1763647. https://doi.org/10.1080/23311932.2020.1763647

Mishra, H. (2025). Environmental degradation and impacts on agricultural production: A challenge to urban sustainability. In *Sustainable urban environment and waste management: Theory and practice* (pp. 53-92). Springer. https://doi.org/10.1007/978-981-96-1140-9_3

Misra, A. K., Agrawal, G., & Yadav, A. (2025). When to perform cloud seeding for maximum agricultural crop yields? A modeling study. *International Journal of Numerical Methods for Heat & Fluid Flow*, *35*(8), 2697-2724. https://doi.org/10.1108/HFF-09-2024-0711

Mo, F., Sun, M., Liu, X.-Y., Wang, J.-Y., Zhang, X.-C., Ma, B., & Xiong, Y.-C. (2016). Phenological responses of spring wheat and maize to changes in crop management and rising temperatures from 1992 to 2013 across the Loess Plateau. *Field Crops Research*, *196*, 337-347. https://doi.org/10.1016/j.fcr.2016.06.024

Moges, D. M., & Bhat, H. G. (2021). Climate change and its implications for rainfed agriculture in Ethiopia. *Journal of Water and Climate Change*, *12*(4), 1229-1244. https://doi.org/10.2166/wcc.2020.058

Mohamed, M. A., El Afandi, G. S., & El-Mahdy, M. E.-S. (2022). Impact of climate change on rainfall variability in the Blue Nile basin. *Alexandria Engineering Journal*, *61*(4), 3265-3275. https://doi.org/10.1016/j.aej.2021.08.056

Mohammed, E. A., Zhi, X., & Abdela, K. A. (2025). Extreme weather patterns in Ethiopia: analyzing extreme temperature and precipitation variability. *Atmosphere*, *16*(2), 133. https://doi.org/10.3390/atmos16020133

Mohammed, Y., Yimer, F., Tadesse, M., & Tesfaye, K. (2018). Variability and trends of rainfall extreme events in north east highlands of Ethiopia. *Int J Hydro*, *2*(5), 594-605. https://doi.org/10.15406/ijh.2018.02.00131

Molla, E., Melka, Y., & Desta, G. (2023). Determinants of farmers' adaptation strategies to climate change impacts in northwestern Ethiopia. *Heliyon*, *9*(8). https://doi.org/10.1016/j.heliyon.2023.e18514

Montagnini, F., & Metzel, R. (2018). The contribution of agroforestry to sustainable development goal 2: end hunger, achieve food security and improved nutrition, and promote sustainable agriculture. In *Integrating landscapes: Agroforestry for biodiversity conservation and food sovereignty* (pp. 11-45). Springer. https://doi.org/10.1007/978-3-319-69371-2_2

Moon, H., Gudmundsson, L., Guillod, B. P., Venugopal, V., & Seneviratne, S. I. (2019). Intercomparison of daily precipitation persistence in multiple global observations and climate models. *Environmental Research Letters*, *14*(10), 105009. https://doi.org/10.1088/1748-9326/ab4169

Moroda, G. T., Tolossa, D., & Semie, N. (2018). Perception and adaptation strategies of rural people against the adverse effects of climate variability: A case study of Boset District, East Shewa, Ethiopia. *Environmental development*, *27*, 2-13. https://doi.org/10.1016/j.envdev.2018.07.005

Moshe, A., & Beza, M. (2024). Temporal Dynamics and Trend Analysis of Areal Rainfall in Muger Subwatershed, Upper Blue Nile, Ethiopia. *Advances in Meteorology*, *2024*(1), 6261501. https://doi.org/10.1155/2024/6261501

Mossie, M., & Chanie, T. (2024). Small-scale farmers perception, adaptation choices to climate change and existing barriers: Evidence from northern Ethiopia. *Climate Services*, *36*, 100517. https://doi.org/10.1016/j.cliser.2024.100517

Moussa, H., & Abboud, M. (2024). The Methodology of Applying Inverse Distance Weighting Interpolation Method in Determining Normal Heights. *Resourceedings*, *4*(1), 01-06. https://doi.org/10.21625/resourceedings.v4i1.1068

Mramba, R. P., & Mapunda, P. E. (2025). Assessing farmers' awareness of climate change impacts and adaptation practices in a semi-arid region in Tanzania. *Discover Sustainability*, *6*(1), 877. https://doi.org/10.1007/s43621-025-01831-4

Mugi-Ngenga, E. W., Kiboi, M. N., Mucheru-Muna, M. W., Mugwe, J. N., Mairura, F. S., Mugendi, D. N., & Ngetich, F. K. (2021). Indigenous and conventional climate-knowledge for enhanced farmers' adaptation to climate variability in the semi-arid agro-ecologies of Kenya. *Environmental Challenges*, *5*, 100355. https://doi.org/10.1016/j.envc.2021.100355

Mulla, S., Ahmed, R., Singh, K., Singh, S. K., Deshmukh, N., & Inamdar, F. K. (2023). Climate change effect on-climate parameters like temperature, rainfall and water resources sectors in India. In *Climate change impacts in India* (pp. 9-59). Springer. https://doi.org/10.1007/978-3-031-42056-6_2

Müller-Plath, G., & Lüdecke, H.-J. (2024). Normalized coefficients of prediction accuracy for comparative forecast verification and modeling. *Research in Statistics*, *2*(1), 2317172. https://doi.org/10.1080/27684520.2024.2317172

Mulugeta, S., Fedler, C., & Ayana, M. (2019). Analysis of long-term trends of annual and seasonal rainfall in the Awash River Basin, Ethiopia. *Water*, *11*(7), 1498. https://doi.org/10.3390/w11071498

Mulwa, C., Marenya, P., & Kassie, M. (2017). Response to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics. *Climate Risk Management*, *16*, 208-221. https://doi.org/10.1016/j.crm.2017.01.002

Muneer, S., Bakhsh, K., Ali, R., Yasin, M. A., & Kamran, M. A. (2024). Farm households' perception and adaptation to climate change in relation of food crop productivity in Pakistan. *Environment, Development and Sustainability*, *26*(5), 11379-11396. https://doi.org/10.1007/s10668-023-03333-7

Murthy, D. S., & Sri, K. K. (2023). Farmers' Perception towards Climate Change and its Effect on Agriculture in Kolar District of Karnataka, India. *International Journal of Environment and Climate Change*, *13*(11), 2676-2683. https://doi.org/10.9734/ijecc/2023/v13i11343

Mustafa, G., Alotaibi, B. A., & Nayak, R. K. (2023). Linking climate change awareness, climate change perceptions and subsequent adaptation options among farmers. *Agronomy*, *13*(3), 758. https://doi.org/10.3390/agronomy13030758

Mutengwa, C. S., Mnkeni, P., & Kondwakwenda, A. (2023). Climate-smart agriculture and food security in Southern Africa: A review of the vulnerability of smallholder agriculture and food security to climate change. *Sustainability*, *15*(4), 2882. https://doi.org/10.3390/su15042882

Mutunga, E. J., Ndungu, C. K., & Muendo, P. (2018). Factors influencing smallholder farmers' adaptation to climate variability in kitui county, Kenya.

Myeni, L., & Moeletsi, M. E. (2020). Factors determining the adoption of strategies used by smallholder farmers to cope with climate variability in the eastern free state, South Africa. *Agriculture*, *10*(9), 410. https://doi.org/10.3390/agriculture10090410

Nasir, J., Zeleke, T., Gidey, E., Assefa, E., Kahsay, S., Birhane, E., & Mhangara, P. (2025). The synergetic effect of drought and land use changes on Ethiopian Rift Valley Northwestern Escarpment livelihood systems. *Discover Environment*, *3*(1), 20. https://doi.org/10.1007/s44274-025-00193-y

Nautiyal, S., Goswami, M., Prakash, S., Khan, Y. I., Shivanna, S., & Baksi, S. (2024). Analysing crop yield variations with respect to climate change in Kodagu District, Western Ghats, India. *Environmental Sustainability*, *7*(3), 349-362. https://doi.org/10.1007/s42398-024-00323-x

Ndamani, F., & Watanabe, T. (2016). Determinants of farmers' adaptation to climate change: A micro level analysis in Ghana. *Scientia Agricola*, *73*, 201-208. https://doi.org/10.1590/0103-9016-2015-0163

Negash, E., Van Schaeybroeck, B., Termonia, P., Van Ginderachter, M., Van Weverberg, K., & Nyssen, J. (2024). Topoclimate and diurnal cycle of summer rain over the Ethiopian highlands in a convection-permitting simulation. *International journal of Climatology*, *44*(2), 406-427. https://doi.org/10.1002/joc.8334

Ngaiza, V. V., Nungula, E. Z., Chappa, L. R., Maitra, S., & Gitari, H. I. (2026). Impacts of soil degradation on the severity of soil-borne diseases and sustainable management strategies: A review. *World Scientific Research*, *13*(1), 7-20. https://doi.org/10.20448/wsr.v13i1.7988

Nguyen, T. P. L., Seddaiu, G., Virdis, S. G. P., Tidore, C., Pasqui, M., & Roggero, P. P. (2016). Perceiving to learn or learning to perceive? Understanding farmers' perceptions and adaptation to climate uncertainties. *Agricultural systems*, *143*, 205-216. https://doi.org/10.1016/j.agsy.2016.01.001

Niles, M. T., Brown, M., & Dynes, R. (2016). Farmer's intended and actual adoption of climate change mitigation and adaptation strategies. *Climatic Change*, *135*(2), 277-295. https://doi.org/10.1007/s10584-015-1558-0

Nwofoke, C., & Bargissa, B. (2024). Climate Change Trends And Its Effects On The Production Of Selected Food Crops: Evidence From Amaro Kelle District Of Southern Ethiopia. *International Journal of Agricultural Science, Research and Technology in Extension and Education Systems (IJASRT in EESs)*, *14*(2), 141-150. https://doi.org/10.9790/2402-1809021323

Nyong, A., Adesina, F., & Osman Elasha, B. (2007). The value of indigenous knowledge in climate change mitigation and adaptation strategies in the African Sahel. *Mitigation and Adaptation Strategies for Global Change*, *12*(5), 787-797. https://doi.org/10.1007/s11027-007-9099-0

O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., & Lowe, J. (2016). The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific model development*, *9*(9), 3461-3482. https://doi.org/10.5194/gmd-9-3461-2016

Ofori, S. A., Cobbina, S. J., & Obiri, S. (2021). Climate change, land, water, and food security: Perspectives From Sub-Saharan Africa. *Frontiers in Sustainable Food Systems*, *5*, 680924. https://doi.org/10.3389/fsufs.2021.680924

Oiganji, E., Igbadun, H., Amaza, P., & Lenka, R. (2025). Innovative technologies for improved water productivity and climate change mitigation, adaptation, and resilience: a review. *Journal of Applied Sciences and Environmental Management*, *29*(1), 123-136. https://doi.org/10.4314/jasem.v29i1.17

Oluwole, O., Ibidapo, O., Arowosola, T., Raji, F., Zandonadi, R. P., Alasqah, I., Lho, L. H., Han, H., & Raposo, A. (2023). Sustainable transformation agenda for enhanced global food and nutrition security: a narrative review. *Frontiers in Nutrition*, *10*, 1226538. https://doi.org/10.3389/fnut.2023.1226538

Omokpariola, D. O., Agbanu-Kumordzi, C., Samuel, T., Kiswii, L., Moses, G. S., & Adelegan, A. M. (2025). Climate change, crop yield, and food security in Sub-Saharan Africa. *Discover Sustainability*, *6*(1), 678. https://doi.org/10.1007/s43621-025-01580-4

Ongoma, V., Chen, H., & Gao, C. (2018). Projected changes in mean rainfall and temperature over East Africa based on CMIP5 models. *International journal of Climatology*, *38*(3), 1375-1392. https://doi.org/10.1002/joc.5252

Onyeneke, R. U. (2021). Does climate change adaptation lead to increased productivity of rice production? Lessons from Ebonyi State, Nigeria. *Renewable Agriculture and Food Systems*, *36*(1), 54-68. https://doi.org/10.1017/S1742170519000486

Orke, Y. A., & Li, M.-H. (2021). Hydroclimatic variability in the bilate watershed, Ethiopia. *Climate*, *9*(6), 98. https://doi.org/10.3390/cli9060098

Osman, M. A., Onono, J. O., Olaka, L. A., Elhag, M. M., & Abdel-Rahman, E. M. (2021). Climate variability and change affect crops yield under rainfed conditions: A case study in Gedaref State, Sudan. *Agronomy*, *11*(9), 1680. https://doi.org/10.3390/agronomy11091680

Ouertani, E., Erraach, Y., Arfa, L., De-Magistris, T., Ornelas Herrera, S. I., & Kallas, Z. (2025). Beekeepers' intentions to adopt resilience strategies for climate change: a comparative and integrated approach using the theory of planned behavior and protection motivation theory. *Frontiers in Climate*, *7*, 1604488. https://doi.org/10.3389/fclim.2025.1604488

Owusu, V., Ma, W., Emuah, D., & Renwick, A. (2021). Perceptions and vulnerability of farming households to climate change in three agro-ecological zones of Ghana. *Journal of Cleaner Production*, *293*, 126154. https://doi.org/10.1016/j.jclepro.2021.126154

Ozelkan, E., Bagis, S., Ozelkan, E. C., Ustundag, B. B., Yucel, M., & Ormeci, C. (2015). Spatial interpolation of climatic variables using land surface temperature and modified inverse distance weighting. *International Journal of Remote Sensing*, *36*(4), 1000-1025. https://doi.org/10.1080/01431161.2015.1007248

Pandey, R., Jha, S. K., Alatalo, J. M., Archie, K. M., & Gupta, A. K. (2017). Sustainable livelihood framework-based indicators for assessing climate change vulnerability and adaptation for Himalayan communities. *Ecological indicators*, *79*, 338-346. https://doi.org/10.1016/j.ecolind.2017.03.047

Panya, K., & Nyarwath, O. (2022). Demystifying philosophies and paradigms underpinning scientific research. *The Strategic Journal of Business & Change Management*, *9*(4), 1367-1382. https://doi.org/10.61426/sjbcm.v9i4.2498

Park, T., Hashimoto, H., Wang, W., Thrasher, B., Michaelis, A. R., Lee, T., Brosnan, I. G., & Nemani, R. R. (2023). What does global land climate look like at 2° C warming? *Earth's Future*, *11*(5), e2022EF003330. https://doi.org/10.1029/2022EF003330

Paudel, P. (2024). Examining paradigmatic shifts: Unveiling the philosophical foundations shaping social research methodologies. *Journal of the University of Ruhuna*, *12*(1). https://doi.org/10.4038/jur.v12i1.8033

Paul, C. J., & Weinthal, E. (2019). The development of Ethiopia's Climate Resilient Green Economy 2011–2014: implications for rural adaptation. *Climate and Development*, *11*(3), 193-202. https://doi.org/10.1080/17565529.2018.1442802

Perlwitz, J., Knutson, T., & Kossin, J. (2017). Large-scale circulation and climate variability.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326. https://doi.org/10.1002/jae.616

Pickson, R. B., & He, G. (2021). Smallholder farmers' perceptions, adaptation constraints, and determinants of adaptive capacity to climate change in Chengdu. *SAGE Open*, *11*(3), 21582440211032638. https://doi.org/10.1177/21582440211032638

Pickson, R. B., He, G., Ntiamoah, E. B., & Li, C. (2020). Cereal production in the presence of climate change in China. *Environmental Science and Pollution Research*, *27*(36), 45802-45813. https://doi.org/10.1177/21582440211032638

Ployhart, R. E., & Ward, A.-K. (2011). The "quick start guide" for conducting and publishing longitudinal research. *Journal of Business and Psychology*, *26*(4), 413-422. https://doi.org/10.1007/s10869-011-9209-6

Poggi, G. M., Aloisi, I., Corneti, S., Esposito, E., Naldi, M., Fiori, J., Piana, S., & Ventura, F. (2022). Climate change effects on bread wheat phenology and grain quality: A case study in the north of Italy. *Frontiers in plant science*, *13*, 936991. https://doi.org/10.3389/fpls.2022.936991

Poortinga, W., Whitmarsh, L., Steg, L., Böhm, G., & Fisher, S. (2019). Climate change perceptions and their individual-level determinants: A cross-European analysis. *Global environmental change*, *55*, 25-35. https://doi.org/10.1016/j.gloenvcha.2019.01.007

Popoola, O. O., Yusuf, S. F. G., & Monde, N. (2020). Information sources and constraints to climate change adaptation amongst smallholder farmers in Amathole District Municipality, Eastern Cape Province, South Africa. *Sustainability*, *12*(14), 5846. https://doi.org/10.3390/su12145846

Pratap, D., Tamuly, G., Ganavi, N., Anbarasan, S., Pandey, A. K., Singh, A., & Iberaheem, M. (2024). Climate change and global agriculture: Addressing challenges and adaptation strategies. *J. Exp. Agric. Int*, *46*(6), 799-806. https://doi.org/10.9734/jeai/2024/v46i62533

Praveena, K., & Malaisamy, A. (2024). Climatic shifts and agricultural strategies: A thorough review on impact of climate change on food security and crop productivity. *Int J Environ Clim Change*, *14*(1), 817-831. https://doi.org/10.9734/ijecc/2024/v14i13900

Purwanti, T. S., Syafrial, S., Huang, W. C., Hartono, B., Rahman, M. S., & Putritamara, J. A. (2023). Understanding farmers' adaptation to climate change: A protection motivation theory application. *Cogent Social Sciences*, *9*(2), 2282210. https://doi.org/10.1080/23311886.2023.2282210

Qange, S., Mdoda, L., Nontu, Y., Mabitsela, M. M., & Gidi, L. S. (2025). Evaluating the impact of adopting conservation agriculture on farm returns of smallholder vegetable farmers in the Eastern Cape Province: implication for extension services. *Frontiers in Sustainable Food Systems*, *9*, 1605561. https://doi.org/10.3389/fsufs.2025.1605561

Qin, D., Ding, Y., Zhai, P., Song, L., Luo, Y., & Jiang, K. (2023). Adaptation and mitigation: measures, actions and effects. In *The Change of Climate and Ecological Environment in China 2021: Synthesis Report* (pp. 129-164). Springer. https://doi.org/10.1007/978-981-99-4487-3_4

Qin, P., Xu, H., Liu, M., Liu, L., Xiao, C., Mallakpour, I., Naeini, M. R., Hsu, K., & Sorooshian, S. (2022). Projected impacts of climate change on major dams in the Upper Yangtze River Basin. *Climatic Change*, *170*(1), 8. https://doi.org/10.1007/s10584-021-03303-w

Radwan, N., Halder, B., Ahmed, M. F., Refadah, S. S., Khan, M. Y. A., Scholz, M., Sammen, S. S., & Pande, C. B. (2025). Seasonal Precipitation and Anomaly Analysis in Middle East Asian Countries Using Google Earth Engine. *Water*, *17*(10), 1475. https://doi.org/10.3390/w17101475

Rahman, M. M., Chowdhury, M. M. I., Al Amran, M. I. U., Malik, K., Abubakar, I. R., Aina, Y. A., Hasan, M. A., Rahman, M. S., & Rahman, S. M. (2024). Impacts of climate change on food system security and sustainability in Bangladesh. *Journal of Water and Climate Change*, *15*(5), 2162-2187. https://doi.org/10.2166/wcc.2024.631

Rahman, M. S., Zulfiqar, F., Ullah, H., Himanshu, S. K., & Datta, A. (2023). Farmers' perceptions, determinants of adoption, and impact on food security: case of climate change adaptation measures in coastal Bangladesh. *Climate Policy*, *23*(10), 1257-1270. https://doi.org/10.1080/14693062.2023.2212638

Rana, M. (2025). Climate risk and resilience: evaluating their impact on sustainable development in South Asia. *Theoretical and Applied Climatology*, *156*(6), 319. https://doi.org/10.1007/s00704-025-05531-x

Rapholo, M. T., & Diko, L. (2020). Are smallholder farmers' perceptions of climate variability supported by climatological evidence? Case study of a semi-arid region in South Africa. *International Journal of Climate Change Strategies and Management*, *12*(5), 571-585. https://doi.org/10.1108/IJCCSM-01-2020-0007

Raza, A., Razzaq, A., Mehmood, S. S., Zou, X., Zhang, X., Lv, Y., & Xu, J. (2019). Impact of climate change on crops adaptation and strategies to tackle its outcome: A review. *Plants*, *8*(2), 34. https://doi.org/10.3390/plants8020034

Raza, A., Safdar, M., Adnan Shahid, M., Shabir, G., Khil, A., Hussain, S., Khan, M., Aziz, S. U. R., Azam, S., & Sattar, J. (2024). Climate change impacts on crop productivity and food security: an overview. *Transforming agricultural management for a sustainable future: Climate change and machine learning perspectives*, 163-186. https://doi.org/10.1007/978-3-031-63430-7_8

Ray, D. K., West, P. C., Clark, M., Gerber, J. S., Prishchepov, A. V., & Chatterjee, S. (2019). Climate change has likely already affected global food production. *PloS one*, *14*(5), e0217148. https://doi.org/10.1371/journal.pone.0217148

Rezaei, E. E., Webber, H., Asseng, S., Boote, K., Durand, J. L., Ewert, F., ... & MacCarthy, D. S. (2023). Climate change impacts on crop yields. *nature reviews earth & environment*, *4*(12), 831-846. https://doi.org/10.1038/s43017-023-00491-0

Ricart, S., Gandolfi, C., & Castelletti, A. (2025). What drives farmers' behavior under climate change? Decoding risk awareness, perceived impacts, and adaptive capacity in northern Italy. *Heliyon*, *11*(1). https://doi.org/10.1016/j.heliyon.2024.e41328

Rizzo, G., Migliore, G., Schifani, G., & Vecchio, R. (2024). Key factors influencing farmers' adoption of sustainable innovations: a systematic literature review and research agenda. *Organic Agriculture*, *14*(1), 57-84. https://doi.org/10.1007/s13165-023-00440-7

Rosenzweig, M. R., & Udry, C. (2020). External validity in a stochastic world: Evidence from low-income countries. *The Review of Economic Studies*, *87*(1), 343-381. https://doi.org/10.1093/restud/rdz021

Roudier, P., Alhassane, A., Baron, C., Louvet, S., & Sultan, B. (2016). Assessing the benefits of weather and seasonal forecasts to millet growers in Niger. *Agricultural and forest meteorology*, *223*, 168-180. https://doi.org/10.1016/j.agrformet.2016.04.010

Rowhani, P., Lobell, D. B., Linderman, M., & Ramankutty, N. (2011). Climate variability and crop production in Tanzania. *Agricultural and forest meteorology*, *151*(4), 449-460. https://doi.org/10.1016/j.agrformet.2010.12.002

Sadiq, M. A., Kuwornu, J. K., Al-Hassan, R. M., & Alhassan, S. I. (2019). Assessing maize farmers' adaptation strategies to climate change and variability in Ghana. *Agriculture*, *9*(5), 90. https://doi.org/10.3390/agriculture9050090

Sagar, A. K., Chakraborty, A., & Srivastava, R. K. (2025). Global Atmospheric Trends and Climate Change: A Comprehensive Analysis of Greenhouse Gases and Temperature (2003–2020). In *Mitigation and Adaptation Strategies Against Climate Change in Natural Systems* (pp. 301-320). Springer. https://doi.org/10.1007/978-3-031-75968-0_16

Saguye, T. S. (2016). Determinants of smallholder farmers' adoption of climate change and variability adaptation strategies: evidence from Geze Gofa District, Gamo Gofa Zone, Southern Ethiopia. *Gamo Gofa Zone, Southern Ethiopia*.

Sahilu, M., Tekalign, S., Mohammed, Y., Sishaw, T., Kedir, H., & Asfaw, S. (2024). Spatiotemporal trends and variability of rainfall across agro-ecologies in East Guji Zone, Southeast Ethiopia. *PLOS Climate*, *3*(3), e0000361. https://doi.org/10.1371/journal.pclm.0000361

Sahoo, D., & Moharaj, P. (2024). Assessing agricultural vulnerability to climate change through dynamic indexing approach. *Environmental Science and Pollution Research*, *31*(42), 55000-55021. https://doi.org/10.1007/s11356-024-34738-0

Salam, M. A., Sarker, M. N. I., & Sharmin, S. (2021). Do organic fertilizer impact on yield and efficiency of rice farms? Empirical evidence from Bangladesh. *Heliyon*, *7*(8). https://doi.org/10.1016/j.heliyon.2021.e07731

Salameh, A. A. (2024). Using the precipitation concentration index for characterizing the rainfall distribution in the Levant. *Journal of Water and Climate Change*, *15*(4), 1945-1960. https://doi.org/10.2166/wcc.2024.037

Salerno, J., Bailey, K., Diem, J., Konecky, B., Bridges, R., Namusisi, S., Bitariho, R., Palace, M., & Hartter, J. (2022). Smallholder knowledge of local climate conditions predicts positive on-farm outcomes. *Weather, Climate, and Society*, *14*(3), 671-680. https://doi.org/10.1175/WCAS-D-21-0131.1

Sandal, S., Ethier, I., Onu, U., Fung, W., Bajpai, D., Bilchut, W. H., Bagasha, P., De Chiara, L., Hafiz, E., & Smyth, B. (2024). Climate change, kidney health, and environmentally sustainable kidney care: a multinational survey of health care professionals. *Journal of the American Society of Nephrology*, *35*(8), 1084-1094. https://doi.org/10.1681/ASN.0000000000000402

Sang, Y.-F., Wang, Z., & Liu, C. (2014). Comparison of the MK test and EMD method for trend identification in hydrological time series. *Journal of Hydrology*, *510*, 293-298. https://doi.org/10.1016/j.jhydrol.2013.12.039

Sayers, P. B., Yuanyuan, L., Moncrieff, C., Jianqiang, L., Tickner, D., Gang, L., & Speed, R. (2017). Strategic drought risk management: eight 'golden rules' to guide a sound approach. *International Journal of River Basin Management*, *15*(2), 239-255. https://doi.org/10.1080/15715124.2017.1280812

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), 15594-15598. https://doi.org/10.1073/pnas.0906865106

Seo, S. N. (2014). Evaluation of the Agro-Ecological Zone methods for the study of climate change with micro farming decisions in sub-Saharan Africa. *European Journal of Agronomy*, *52*, 157-165. https://doi.org/10.1016/j.eja.2013.09.014

Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M., & Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: from physical changes to their

social repercussions. *Regional environmental change*, *17*, 1585-1600. https://doi.org/10.1007/s10113-015-0910-2
Serraj, R., Krishnan, L., & Pingali, P. (2019). Agriculture and food systems to 2050: a synthesis. *Agriculture & food systems to*, *2050*, 3-45. https://doi.org/10.1142/9789813278356_0001
Sertse, S. F., Khan, N. A., Shah, A. A., Liu, Y., & Naqvi, S. A. A. (2021). Farm households' perceptions and adaptation strategies to climate change risks and their determinants: Evidence from Raya Azebo district, Ethiopia. *International Journal of Disaster Risk Reduction*, *60*, 102255. https://doi.org/10.1016/j.ijdrr.2021.102255
Shah, M., Thakkar, A., & Shastri, H. (2024). Comparative analysis of bias correction techniques for future climate assessment using CMIP6 hydrological variables for the Indian subcontinent. *Acta Geophysica*, 1-17. https://doi.org/10.1007/s11600-024-01378-4
Shamim, T., Bhat, M.S., Alam, A. *et al.* Impact of El Nino Southern Oscillation, Indian Ocean Dipole and North Atlantic Oscillation on the drought scenarios in the Upper Indus Basin. *Theor Appl Climatol* 156, 234 (2025). https://doi.org/10.1007/s00704-025-05459-2.
Sharma, P. J., Patel, P., & Jothiprakash, V. (2020). Hydroclimatic teleconnections of large-scale oceanic-atmospheric circulations on hydrometeorological extremes of Tapi Basin, India. *Atmospheric Research*, *235*, 104791. https://doi.org/10.1016/j.atmosres.2019.104791
Shawul, A. A., & Chakma, S. (2020). Trend of extreme precipitation indices and analysis of long-term climate variability in the Upper Awash basin, Ethiopia. *Theoretical and Applied Climatology*, *140*(1), 635-652. https://doi.org/10.1007/s00704-020-03112-8
Shifaw, E., Sha, J., Li, X., Bao, Z., Ji, J., Ji, Z., Kassaye, A. Y., Lai, S., & Yang, Y. (2024). Ecosystem services dynamics and their influencing factors: Synergies/tradeoffs interactions and implications, the case of upper Blue Nile basin, Ethiopia. *Science of the Total Environment*, *938*, 173524. https://doi.org/10.1016/j.scitotenv.2024.173524
Shiru, M. S., & Chung, E.-S. (2021). Performance evaluation of CMIP6 global climate models for selecting models for climate projection over Nigeria. *Theoretical and Applied Climatology*, *146*(1), 599-615. https://doi.org/10.1007/s00704-021-03746-2
Shumetie, A., & Alemayehu Yismaw, M. (2018). Effect of climate variability on crop income and indigenous adaptation strategies of households. *International Journal of Climate Change Strategies and Management*, *10*(4), 580-595. https://doi.org/10.1108/IJCCSM-04-2016-0039
Sida, T. S., Desalegn, T., Abate, G. T., & Amede, T. (2025). Feeding a fast− growing population by 2050 through accelerated agricultural transformation: potential avenues for Ethiopia. *Pathways to African Food Security*, 35. https://doi.org/10.4324/9781032649696-5
Simane, B., Kapwata, T., Naidoo, N., Cissé, G., Wright, C. Y., & Berhane, K. (2025). Ensuring Africa's Food Security by 2050: the role of population growth, climate-resilient strategies, and putative pathways to resilience. *Foods*, *14*(2), 262. https://doi.org/10.3390/foods14020262
Simane, B., Zaitchik, B. F., & Foltz, J. D. (2016). Agroecosystem specific climate vulnerability analysis: application of the livelihood vulnerability index to a tropical highland region. *Mitigation and Adaptation Strategies for Global Change*, *21*(1), 39-65. hhttps://doi.org/10.1007/s11027-014-9568-1
Simotwo, H. K., Mikalitsa, S. M., & Wambua, B. N. (2018). Climate change adaptive capacity and smallholder farming in Trans-Mara East sub-County, Kenya. *Geoenvironmental Disasters*, *5*, 1-14. https://doi.org/10.1186/s40677-018-0096-2
Singh, A., Arora, K., & Babu, S. C. (2024). Examining the impact of climate change on cereal production in India: Empirical evidence from ARDL modelling approach. *Heliyon*, *10*(18). https://doi.org/10.1016/j.heliyon.2024.e36403
Singh, B. K., Delgado-Baquerizo, M., Egidi, E., Guirado, E., Leach, J. E., Liu, H., & Trivedi, P. (2023). Climate change impacts on plant pathogens, food security and paths forward. *Nature Reviews Microbiology*, *21*(10), 640-656. https://doi.org/10.1038/s41579-023-00900-7
Singh, C., Dorward, P., & Osbahr, H. (2016). Developing a holistic approach to the analysis of farmer decision-making: Implications for adaptation policy and practice in developing countries. *Land use policy*, *59*, 329-343. https://doi.org/10.1016/j.landusepol.2016.06.041
Singh, R., Devi, G., Parmar, D., & Mishra, S. (2017). Impact of rainfall and temperature on the yield of major crops in Gujarat state of India: a panel data analysis (1980-2011). *Curr J Appl Sci Technol*, *24*(5), 1-9. https://doi.org/10.9734/CJAST/2017/35163
Singh, S. (2020). Farmers' perception of climate change and adaptation decisions: A micro-level evidence from Bundelkhand Region, India. *Ecological Indicators*, *116*, 106475. https://doi.org/10.1016/j.ecolind.2020.106475
Singha, C., Sahoo, S., Govind, A., Pradhan, B., Alrawashdeh, S., Hamdi Aljohani, T., Almohamad, H., Md Towfiqul Islam, A. R., & Abdo, H. G. (2024). Impacts of hydroclimate change on climate-resilient

agriculture at the river basin management. *Journal of Water and Climate Change*, *15*(1), 209-232. https://doi.org/10.2166/wcc.2023.656

Sinore, T., & Wang, F. (2024). Impact of climate change on agriculture and adaptation strategies in Ethiopia: A meta-analysis. *Heliyon*, *10*(4). https://doi.org/10.1016/j.heliyon.2024.e26103

Sisay, T., Tesfaye, K., Ketema, M., Dechassa, N., & Getnet, M. (2023). Climate-smart agriculture technologies and determinants of farmers' adoption decisions in the Great Rift Valley of Ethiopia. *Sustainability*, *15*(4), 3471. https://doi.org/10.3390/su15043471

Skendžić, S., Zovko, M., Živković, I. P., Lešić, V., & Lemić, D. (2021). The impact of climate change on agricultural insect pests. *Insects*, *12*(5), 440. https://doi.org/10.3390/insects12050440

Sohail, M. T., Elkaeed, E. B., Irfan, M., Acevedo-Duque, Á., & Mustafa, S. (2022). Determining farmers' awareness about climate change mitigation and wastewater irrigation: a pathway toward green and sustainable development. *Frontiers in Environmental Science*, *10*. https://doi.org/10.3389/fenvs.2022.900193

Solaja, S., Kolawole, A., Awe, T., Oriade, O., Ayojimi, W., Ojo, I., Nayan, G., Adedayo, R., Etta-Oyong, S., & Olasehinde, F. (2024). Assessment of smallholder rice farmers' adaptation strategies to climate change in Kebbi state, Nigeria. *Heliyon*, *10*(15). https://doi.org/10.1016/j.heliyon.2024.e35384

Song, Y. H., Chung, E. S., & Shahid, S. (2021). Spatiotemporal differences and uncertainties in projections of precipitation and temperature in South Korea from CMIP6 and CMIP5 general circulation model s. *International journal of Climatology*, *41*(13), 5899-5919. https://doi.org/10.1002/joc.7159

Song, H., & Zhu, Z. (2025). Farmers' adaptive behaviors to climate change and their influencing factors: evidence from the Guanzhong Region of Shaanxi, China. *Frontiers in Sustainable Food Systems*, *9*, 1648301. https://doi.org/10.3389/fsufs.2025.1648301

Spinoni, J., Barbosa, P., Cherlet, M., Forzieri, G., McCormick, N., Naumann, G., Vogt, J. V., & Dosio, A. (2021). How will the progressive global increase of arid areas affect population and land-use in the 21st century? *Global and Planetary Change*, *205*, 103597. https://doi.org/10.1016/j.gloplacha.2021.103597

Spiridonov, V., Ćurić, M., & Novkovski, N. (2025). Introduction: Understanding Earth's Complex Systems. In *Atmospheric Perspectives: Unveiling Earth's Environmental Challenges* (pp. 1-8). Springer. https://doi.org/10.1007/978-3-031-86757-6_1

Stouffer, R. J., Eyring, V., Meehl, G. A., Bony, S., Senior, C., Stevens, B., & Taylor, K. (2017). CMIP5 scientific gaps and recommendations for CMIP6. *Bulletin of the American Meteorological Society*, *98*(1), 95-105. https://doi.org/10.1175/BAMS-D-15-00013.1

Sultan, B., & Gaetani, M. (2016). Agriculture in West Africa in the twenty-first century: climate change and impacts scenarios, and potential for adaptation. *Frontiers in plant science*, *7*, 1262. https://doi.org/10.3389/fpls.2016.01262

Suryabhagavan, K. (2017). GIS-based climate variability and drought characterization in Ethiopia over three decades. *Weather and Climate Extremes*, *15*, 11-23. https://doi.org/10.1016/j.wace.2016.11.005

Swami, D., & Parthasarathy, D. (2021). Dynamics of exposure, sensitivity, adaptive capacity and agricultural vulnerability at district scale for Maharashtra, India. *Ecological Indicators*, *121*, 107206. https://doi.org/10.1016/j.ecolind.2020.107206

Swart, N. C., Cole, J. N., Kharin, V. V., Lazare, M., Scinocca, J. F., Gillett, N. P., Anstey, J., Arora, V., Christian, J. R., & Hanna, S. (2019). The Canadian earth system model version 5 (CanESM5. 0.3). *Geoscientific model development*, *12*(11), 4823-4873. https://doi.org/10.5194/gmd-12-4823-2019

Takele, A., Abelieneh, A., & Wondimagegnhu, B. A. (2023). Determinants of adoption of land management practices among farmers in Western Lake Tana and Beles River watersheds (Ethiopia) as a climate change adaptation strategy. *Cogent Food & Agriculture*, *9*(1), 2170951. https://doi.org/10.1080/23311932.2023.2170951

Takele, G. S., Gebrie, G. S., Gebremariam, A. G., & Engida, A. N. (2022). Future climate change and impacts on water resources in the Upper Blue Nile basin. *Journal of Water and Climate Change*, *13*(2), 908-925. https://doi.org/10.2166/wcc.2021.235

Talebian, S., Carlsen, H., Johnson, O., Volkholz, J., & Kwamboka, E. (2021). Assessing future cross-border climate impacts using shared socioeconomic pathways. *Climate Risk Management*, *32*, 100311. https://doi.org/10.1016/j.crm.2021.100311

Tan, X., Wu, Y., Liu, B., & Chen, S. (2020). Inconsistent changes in global precipitation seasonality in seven precipitation datasets. *Climate Dynamics*, *54*(5), 3091-3108. https://doi.org/10.1007/s00382-020-05158-w

Tanimu, B., Bello, A.-A. D., Abdullahi, S. A., Ajibike, M. A., Yaseen, Z. M., Kamruzzaman, M., bin Muhammad, M. K. I., & Shahid, S. (2024). Comparison of conventional and machine learning methods for bias correcting CMIP6 rainfall and temperature in Nigeria. *Theoretical and Applied Climatology*, *155*(6), 4423-4452. https://doi.org/10.1007/s00704-024-04888-9

Tariku, T. B., Gan, K. E., Tan, X., Gan, T. Y., Shi, H., & Tilmant, A. (2021). Global warming impact to River Basin of Blue Nile and the optimum operation of its multi-reservoir system for hydropower production and irrigation. *Science of the Total Environment*, *767*, 144863. https://doi.org/10.1016/j.scitotenv.2020.144863
Tashakkori, A., & Teddlie, C. (2021). *Sage handbook of mixed methods in social & behavioral research*. SAGE publications.
Tatebe, H., Ogura, T., Nitta, T., Komuro, Y., Ogochi, K., Takemura, T., Sudo, K., Sekiguchi, M., Abe, M., & Saito, F. (2019). Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6. *Geoscientific model development*, *12*(7), 2727-2765. https://doi.org/10.5194/gmd-12-2727-2019
Taye, M., Simane, B., Zaitchik, B. F., Selassie, Y. G., & Setegn, S. (2019). Rainfall variability across the agro-climatic zones of a tropical highland: The case of the jema watershed, northwestern ethiopia. *Environments*, *6*(11), 118. https://doi.org/10.3390/environments6110118
Taye, M. T., Dyer, E., Charles, K. J., & Hirons, L. C. (2021). Potential predictability of the Ethiopian summer rains: understanding local variations and their implications for water management decisions. *Science of the Total Environment*, *755*, 142604. https://doi.org/10.1016/j.scitotenv.2020.142604
Tegegn, M. G., Berlie, A. B., & Utallo, A. U. (2024). Spatiotemporal variability and trends of intra-seasonal rainfall and temperature in the drought-prone districts of Northwestern Ethiopia. *Discover Sustainability*, *5*(1), 230. https://doi.org/10.1007/s43621-024-00445-6
Teku, D., & Eshetu, S. (2024). Impact of climatic variabilities and extreme incidences on the physical environment, public health, and people's livelihoods in Ethiopia. *Frontiers in climate*, *6*, 1435138. https://doi.org/10.3389/fclim.2024.1435138
Tena, T. M., Mudenda, F., Nguvulu, A., Mwaanga, P., & Gathenya, J. M. (2021). Analysis of river tributaries' streamflow contribution using WEAP model: a case of the Ngwerere and Kanakatampa Tributaries to the Chongwe River in Zambia. *Journal of Water Resource and Protection*, *13*(4), 309-323. https://doi.org/10.4236/jwarp.2021.134019
Tesema, T. G., Robi, N. D., Tsehai, K. K., Abebe, Y. A., & Liben, F. M. (2025). Assessing Rainfall and Temperature Trends in Central Ethiopia: Implications for Agricultural Resilience and Future Climate Projections. *Sustainability*, *17*(15), 7077. https://doi.org/10.3390/su17157077
Tesfahunegn, G. B., & Gebru, T. A. (2021). Climate change effects on agricultural production: insights for adaptation strategy from the context of smallholder farmers in Dura catchment, northern Ethiopia. *GeoJournal*, *86*(1), 417-430. https://doi.org/https://doi.org/10.1007/s10708-019-10077-3. https://doi.org/10.1007/s10708-019-10077-3
Tesfahunegn, G. B., Mekonen, K., & Tekle, A. (2016). Farmers' perception on causes, indicators and determinants of climate change in northern Ethiopia: Implication for developing adaptation strategies. *Applied Geography*, *73*, 1-12. https://doi.org/10.1016/j.apgeog.2016.05.009
Tesfamariam, B. G., Gessesse, B., & Melgani, F. (2019). Characterizing the spatiotemporal distribution of meteorological drought as a response to climate variability: The case of rift valley lakes basin of Ethiopia. *Weather and Climate Extremes*, *26*, 100237. https://doi.org/10.1016/j.wace.2019.100237
Tesfaye, L., Alemayehu, S., Jalango, D., Karanja, S., Magambo, G., Ghosh, A., Vyas, S., Nowak, A., Wamicwe, P., & Newman, R. (2023). Climate-smart agriculture investment plan for Ethiopia.
Tesfaye, S., Taye, G., Birhane, E., & van der Zee, S. E. (2019). Observed and model simulated twenty-first century hydro-climatic change of Northern Ethiopia. *Journal of Hydrology: Regional Studies*, *22*, 100595. https://doi.org/10.1016/j.ejrh.2019.100595
Teshome, A., & Zhang, J. (2019). Increase of extreme drought over Ethiopia under climate warming. *Advances in Meteorology*, *2019*, 1-18. https://doi.org/10.1155/2019/5235429
Teshome, H., Tesfaye, K., Dechassa, N., Tana, T., & Huber, M. (2021a). Analysis of past and projected trends of rainfall and temperature parameters in Eastern and Western Hararghe zones, Ethiopia. *Atmosphere*, *13*(1), 67. https://doi.org/10.3390/atmos13010067
Teshome, H., Tesfaye, K., Dechassa, N., Tana, T., & Huber, M. (2021b). Smallholder farmers' perceptions of climate change and adaptation practices for maize production in Eastern Ethiopia. *Sustainability*, *13*(17), 9622. https://doi.org/10.3390/su13179622
Tessema, M. W., Atnafe, A. D., Tora, S. E., Bantider, A., & Shure, E. (2025). Trend analysis of climate change and effect of climate-smart agricultural practices: the case of Humbo Woreda, Wolaita Zone, South Ethiopia. *Frontiers in Climate*, *7*, 1456328. https://doi.org/10.3389/fclim.2025.1456328
Tessema, I., & Simane, B. (2019). Vulnerability analysis of smallholder farmers to climate variability and change: an agro-ecological system-based approach in the Fincha'a sub-basin of the upper Blue Nile Basin of Ethiopia. *Ecological Processes*, *8*(1), 1-18. https://doi.org/10.1186/s13717-019-0159-7

Tessema, I., & Simane, B. (2021). Smallholder Farmers' perception and adaptation to climate variability and change in Fincha sub-basin of the Upper Blue Nile River Basin of Ethiopia. *GeoJournal*, *86*(4), 1767-1783. https://doi.org/10.1007/s10708-020-10159-7

Tessema, N., Kebede, A., & Yadeta, D. (2021). Modelling the effects of climate change on streamflow using climate and hydrological models: the case of the Kesem sub-basin of the Awash River basin, Ethiopia. *International Journal of River Basin Management*, *19*(4), 469-480. https://doi.org/10.1080/15715124.2020.1755301

Teyso, T., & Anjulo, A. (2016). Spatio-temporal variability and trends of rainfall and temperature over Gamo Gofa Zone, Ethiopia. *Journal of Scientific Research and Reports*, *12*(2), 1-11. https://doi.org/10.9734/JSRR/2016/28667

Thornton, P. K., Ericksen, P. J., Herrero, M., & Challinor, A. J. (2014). Climate variability and vulnerability to climate change: a review. *Global change biology*, *20*(11), 3313-3328. https://doi.org/10.1111/gcb.12581

Tilahun, K. (2006). Analysis of rainfall climate and evapo-transpiration in arid and semi-arid regions of Ethiopia using data over the last half a century. *Journal of Arid Environments*, *64*(3), 474-487. https://doi.org/10.1016/j.jaridenv.2005.06.013

Tirfeessa, T., Gemechu, A., & Zemedu, L. (2025). The impact of climate variability on chickpea production in the central highlands of ethiopia using auto regressive distributive lag model. *Discover Agriculture*, *3*(1), 73. https://doi.org/10.1007/s44279-025-00200-z

Tofu, D. A., & Mengistu, M. (2023). Observed time series trend analysis of climate variability and smallholder adoption of new agricultural technologies in west Shewa, Ethiopia. *Scientific African*, *19*, e01448. https://doi.org/10.1016/j.sciaf.2022.e01448

Tofu, D. A., Woldeamanuel, T., & Haile, F. (2022). Smallholder farmers' vulnerability and adaptation to climate change induced shocks: The case of Northern Ethiopia highlands. *Journal of Agriculture and Food Research*, *8*, 100312. https://doi.org/10.1016/j.jafr.2022.100312

Tofu, D. A., & Wolka, K. (2023). Climate change induced a progressive shift of livelihood from cereal towards Khat (Chata edulis) production in eastern Ethiopia. *Heliyon*, *9*(1). https://doi.org/10.1016/j.sciaf.2022.e01448

Tombe, T. B. (2016). Climate change education for climate resilient green economy (CRGE) of Ethiopia. *International Journal of African and Asian Studies*, *20*, 89-105.

Trinh, T. Q., Rañola Jr, R. F., Camacho, L. D., & Simelton, E. (2018). Determinants of farmers' adaptation to climate change in agricultural production in the central region of Vietnam. *Land use policy*, *70*, 224-231. https://doi.org/10.1016/j.landusepol.2017.10.023

Ullah, A., Mishra, A. K., & Bavorova, M. (2023). Agroforestry adoption decision in green growth initiative programs: Key lessons from the billion trees afforestation project (BTAP). *Environmental Management*, *71*(5), 950-964. https://doi.org/10.1007/s00267-023-01797-x

Usmail, A. J., Maja, M. M., & Lakew, A. A. (2023). Farmers' perceptions of climate variability and adaptation strategies in the rural areas of Dire Dawa administration, eastern Ethiopia. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e15868

Vahmani, P., Jones, A. D., & Li, D. (2022). Will anthropogenic warming increase evapotranspiration? Examining irrigation water demand implications of climate change in California. *Earth's Future*, *10*(1), e2021EF002221. https://doi.org/10.1029/2021EF002221

Valli, M., Sree, K. S., & Krishna, I. V. M. (2013). Analysis of precipitation concentration index and rainfall prediction in various agro-climatic zones of Andhra Pradesh, India. *Int Res J Environ Sci*, *2*(5), 53-61.

Vasudevan, A., Rani, P. J., Raja, N., Nedumaran, G., Arokiasamy, A. R. A., & Qian, C. (2025). Fintech for sustainable agriculture: insights from Tamil Nadu, India. *Frontiers in Sustainable Food Systems*, *9*, 1614553. https://doi.org/10.3389/fsufs.2025.1614553

Vermeulen, S. J., Campbell, B. M., & Ingram, J. S. (2012). Climate change and food systems. *Annual review of environment and resources*, *37*, 195-222. https://doi.org/10.1146/annurev-environ-020411-130608

Vialard, J., Jin, F. F., Mcphaden, M. J., Fedorov, A., Cai, W., An, S. I., Dommenget, D., Fang, X., Stuecker, M., & Wang, C. (2025). The El Niño Southern Oscillation (ENSO) recharge oscillator conceptual model: Achievements and future prospects. *Reviews of Geophysics*, *63*(1), e2024RG000843. https://doi.org/10.1029/2024RG000843

Von Loeper, W., Musango, J., Brent, A., & Drimie, S. (2016). Analysing challenges facing smallholder farmers and conservation agriculture in South Africa: A system dynamics approach. *South African Journal of Economic and Management Sciences*, *19*(5), 747-773. https://doi.org/10.4102/sajems.v19i5.1588

Waaswa, A., Oywaya Nkurumwa, A., Mwangi Kibe, A., & Ng'eno Kipkemoi, J. (2024). Adapting agriculture to climate change: Institutional determinants of adoption of climate-smart agriculture among smallholder farmers in Kenya. *Cogent Food & Agriculture*, *10*(1), 2294547. https://doi.org/10.1080/23311932.2023.2294547

Wagener, T., Reinecke, R., & Pianosi, F. (2022). On the evaluation of climate change impact models. *Wiley Interdisciplinary Reviews: Climate Change*, *13*(3), e772. https://doi.org/10.1002/wcc.772

Wagesho, N., Goel, N., & Jain, M. (2013). Temporal and spatial variability of annual and seasonal rainfall over Ethiopia. *Hydrological Sciences Journal*, *58*(2), 354-373. https://doi.org/10.1080/02626667.2012.754543

Wahelo, T. T., Mengistu, D. A., & Merawi, T. M. (2025). Spatiotemporal Climate Variability and Its Impact on Local Community Livelihoods: A Focus on Crop Production in Metekel Zone, Northwest Ethiopia. *Journal of Agriculture and Food Research*, 102159. https://doi.org/10.1016/j.jafr.2025.102159

Wakweya, R. B. (2025). Impacts of climate change on crop production and food security in Ethiopia. *Discover Sustainability*, *6*(1), 158. https://doi.org/10.1007/s43621-025-00830-9

Wang, F., Shao, W., Yu, H., Kan, G., He, X., Zhang, D., Ren, M., & Wang, G. (2020). Re-evaluation of the power of the Mann-Kendall test for detecting monotonic trends in hydrometeorological time series. *Frontiers in Earth Science*, *8*, 14. https://doi.org/10.3389/feart.2020.00014

Wang, M., Beal, D. J., Chan, D., Newman, D. A., Vancouver, J. B., & Vandenberg, R. J. (2017). Longitudinal research: A panel discussion on conceptual issues, research design, and statistical techniques. *Work, Aging and Retirement*, *3*(1), 1-24. https://doi.org/10.1093/workar/waw033

Ware, G. B. (2022). Climate change adaptation and mitigation measures in Ethiopia. *Int. J. Agric. Food Sci.*, *4*, 40-46. https://doi.org/10.33545/2664844X.2022.v4.i2a.97

Ware, M. B., Matewos, T., Guye, M., Legesse, A., & Mohammed, Y. (2023). Spatiotemporal variability and trend of rainfall and temperature in Sidama Regional State, Ethiopia. *Theoretical and Applied Climatology*, *153*(1), 213-226. https://doi.org/10.1007/s00704-023-04463-8

Warsame, A. A., Sheik-Ali, I. A., Ali, A. O., & Sarkodie, S. A. (2021). Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. *Environmental Science and Pollution Research*, *28*(16), 19838-19850. https://doi.org/10.1007/s11356-020-11739-3

Weldegerima, T. M., Zeleke, T. T., Birhanu, B. S., Zaitchik, B. F., & Fetene, Z. A. (2018). Analysis of rainfall trends and its relationship with SST signals in the Lake Tana Basin, Ethiopia. *Advances in Meteorology*, *2018*, 1-10. https://doi.org/10.1155/2018/5869010

Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P. (2019). Observed impacts of anthropogenic climate change on wildfire in California. *Earth's Future*, *7*(8), 892-910. https://doi.org/10.1029/2019EF001210

Wodaje, G. G., Eshetu, Z., & Argaw, M. (2020). Local perceptions and adaptation to climate variability and change: In the Bilate watershed. *African Journal of Environmental Science and Technology*, *14*(11), 374-384. https://doi.org/10.5897/AJEST2020.2854

Worku, G., Teferi, E., Bantider, A., Dile, Y. T., & Taye, M. T. (2018). Evaluation of regional climate models performance in simulating rainfall climatology of Jemma sub-basin, Upper Blue Nile Basin, Ethiopia. *Dynamics of Atmospheres and Oceans*, *83*, 53-63. https://doi.org/10.1016/j.dynatmoce.2018.06.002

Wubaye, G. B., Gashaw, T., Worqlul, A. W., Dile, Y. T., Taye, M. T., Haileslassie, A., Zaitchik, B., Birhan, D. A., Adgo, E., & Mohammed, J. A. (2023). Trends in rainfall and temperature extremes in Ethiopia: station and agro-ecological zone levels of analysis. *Atmosphere*, *14*(3), 483. https://doi.org/10.3390/atmos14030483

Yadav, D., Babu, S., Yadav, D. K., Kumawat, A., Singh, D., Yadav, A. K., Rathore, S. S., Singh, R., Joshi, N., & Yadav, R. K. (2024). Cropping system intensification: implications on food security and environmental sustainability in India. *Anthropocene Science*, *3*(1), 1-22. https://doi.org/10.1007/s44177-024-00078-4

Yaméogo, T. B., Fonta, W. M., & Wünscher, T. (2018). Can social capital influence smallholder farmers' climate-change adaptation decisions? Evidence from three semi-arid communities in Burkina Faso, West Africa. *Social Sciences*, *7*(3), 33. https://doi.org/10.3390/socsci7030033

Yeleliere, E., Antwi-Agyei, P., & Guodaar, L. (2023). Farmers response to climate variability and change in rainfed farming systems: Insight from lived experiences of farmers. *Heliyon*, *9*(9). https://doi.org/10.1016/j.heliyon.2023.e19656

Yılmaz, B., Aras, E., & Nacar, S. (2024). A CMIP6-ensemble-based evaluation of precipitation and temperature projections. *Theoretical and Applied Climatology*, *155*(8), 7377-7401. https://doi.org/10.1007/s00704-024-05066-7

Yimer, S. M., Bouanani, A., Kumar, N., Tischbein, B., & Borgemeister, C. (2022). Assessment of climate models performance and associated uncertainties in rainfall projection from CORDEX over the Eastern Nile Basin, Ethiopia. *Climate*, *10*(7), 95. https://doi.org/10.3390/cli10070095

Zegeye, H. (2018). Climate change in Ethiopia: impacts, mitigation and adaptation. *International Journal of Research in Environmental Studies*, *5*(1), 18-35.

Zeleke, A., Tesfaye, K., Tadesse, T., Alem, T., Ademe, D., & Adgo, E. (2023). Spatiotemporal analysis of rainfall and temperature variability and trends for climate resilient maize farming system in major agroecology zones of northwest Ethiopia. *International Journal of Agricultural Sustainability*, *21*(1), 2255450. https://doi.org/10.1080/14735903.2023.2255450

Zhang, L.-X., Xiao-Long, C., & Xiao-Ge, X. (2019). Short commentary on CMIP6 scenario model intercomparison project (ScenarioMIP). *Advances in Climate Change Research*, *15*(5), 519.

Zhang, W., Zhao, Y., Li, L., Xu, X., Yang, L., Luo, Z., Wang, B., Ma, S., Fan, Y., & Huang, Z. (2021). The effects of short-term exposure to low temperatures during the booting stage on starch synthesis and yields in wheat grain. *Frontiers in plant science*, *12*, 684784. https://doi.org/10.3389/fpls.2021.684784

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., ... & Asseng, S. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of sciences*, *114*(35), 9326-9331. https://doi.org/10.1073/pnas.1701762114

Zhu, X., Miao, P., Zhu, H., Li, W., Liang, X., Wang, L., Chen, Z., & Zhou, J. (2024). Extreme precipitation accelerates nitrate leaching in the intensive agricultural region with thick unsaturated zones. *Science of the Total Environment*, *918*, 170789. https://doi.org/10.1016/j.scitotenv.2024.170789

APPENDICES
BAHIR DAR UNIVERSITY
FACULTY OF SOCIAL SCIENCES
DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDY

Appendixes 1: Survey questionnaire

Introduction

This survey questionnaire is designed with the aim to collect data and analyze the impact of climate variability on smallholder farmers' productivity and adaptation strategies across the agro-ecological zones of Ayehu watershed. The Survey also aims to investigate different adaptation strategies employed by smallholder farmers at different agro-ecological zones of the watershed to climate variability. Your responses to each item of the questionnaire are highly valuable & crucial for the success of this study. Therefore, you are kindly requested to give genuine & accurate information for each of the questions outlined below. The information collected from you will serve only for the academic purpose and it will be kept confidential. Thus, please feel free to convey the required information honestly.

Thank you in advanced for your time and participation.

Instruction: i). Circle the appropriate responses for close ended questions
ii). Complete appropriate answer for open-ended questions
iii). Do not write your name in the question paper

Part I: General information of the respondents

i. Region_______ Zone________________ *Woreda*____________ *Kebele*___________
Code of respondent________________Agro-ecological zone_____________________

Part II: Household's demographic characteristics

1. Sex 1=Male 2=Female
2. Age of the household head (in year) _______in years.
3. Marital Status 1=Single 2=Married 3=divorced 4=Widowed
4. Educational status 1= Illiterate 2=Can read and write 3=Primary school
4=Secondary and above 5=If other specify____________________________
5. Family size (in number) ________________

Households' perception to climate variability

6. Have you observed any changes in the mean of climate variables (temperature and rainfall) in the last 30 years? 1=Yes 2=No

Likert scale measurement of smallholder farmers' perception to climate variability

No	changes in mean climate variables	Scale of agreement				
		1	2	3	4	5
1	There is a decrease in the amount of rainfall					
2	There is an increase in the amount and duration of rainfall					
3	There is an increase in temperature					
4	There is a decrease in temperature					
5	Rainfall comes on time					
	Rainfall comes late					
6	There is enough rain at the beginning of rainy season					
7	Rainfall couldn't support full period of crop growth					
8	There is an early cessation of rainfall					
9	Rainfall stops on time					

10	Rainfall intensity increased					
11	Crop diseases and pests increase as a result of climate variability					
12	There is an irregularity of rainfall					
13	Rainfall intensity decreased					

Note: 1=Strongly agree, 2=agree, 3=neutral, 4=Disagree, 5=Strongly disagree

7. Is the current climate condition the same as it was 20 years ago in your locality?
1=Yes 2=No

8. What changes have been occurred in daily temperature in the past 20 years?
1=Increase 2=Decrease 3=No change/constant 4=I don't know 5=Other, please specify____

9. What changes have been occurred in rainfall in the past 20 years?
1=Increase 2=Decrease 3=No change 4=Change in the seasons of rainfall 5=Increase in the frequency of drought 6= I don't know 7=If other specify_______________________

10. What are the local indicators that show the variability in rainfall through time in your locality?
1= Changes in cropping season
2=Changes in crop types
3=Changes in productivity
4=Other, please specify______________________

11. In terms of the frequency of drought, what trends have you observed in the last 30 years? 1=Increasing trend 2=Decreasing trend 3=Not changed 4=Not known
In terms of the frequency of flood, what trends have you observed? 1=Increasing trend 2=Decreasing trend 3=Not changed 4=Not know.

12. What do you think are the causes for climate variability in your locality?
1=Natural phenomena 2=land use change 3=Deforestation 4=wrath of God 5=Not known

13. Which local indicators do you use to evaluate the temperature trends in the area?
1. Prevalence of human and animal diseases, which were not familiar to the area (E.g., Malaria).
2. Invasion of new plant and animal species
3. Change of communities clothing styles
4. If other specify________________________________

14. What is your perception towards climate variability of your locality?
1=There is climate variability 2=The climate has not changed (it is the same as it was 30 years ago) 3=The climate has totally changed 4= I have no idea

15. If your response to question number----is 'the climate has changed/there is variability, what are the local indicators for the change? (Multiple responses are possible) 1=Increase in temperature 2=Unpredictability of rainfall 3=Recurrent drought 4=Hail storms 5=Decrease in the volume of rivers
6=If other specify______________________________________.

16. Is there a change in timing of rainfall? 1=Yes 2=No

17. If your response to question number 26 is yes, how do you characterize it?
1=Comes early and goes late 2=Comes late and goes early 3=Comes on time and goes early 4=Comes late and goes early

18. If your answer for question number 17 comes late and goes early, what changes have you observed in crop production?
1=Decrease in crop yield 3=No change in crop yield
2=Increase in crop yield 4= Decrease of long cycle crops

5. If other specify________________________________

19. What did you notice about the trends of livestock production in your locality?
1=Increasing 2=Decreasing 3=Not changed

20. If your answer for question number---is decreased, what do you think is the reason?
1=Livestock disease 2=shortage of water
3=Shortage of grazing land and forage 4=high temperature 5=If other please specify_____________

21. What do you think about the causes of climate variability in your locality?
1=Land degradation 2=Deforestation 3=Population growth 4=Land use land cover changes 5=Absence of sustainable farming system

22. What is/are the impacts of climate variability on crop production? 1= Reduction of water source 2=Reduction of crop yield 3=Loss of soil fertility 4=Prevalence of pests and diseases

23. What types of crops are grown in your farmland?

Types of crops grown	Responses	
	Yes	No
Teff		
Wheat		
Maize		
Sorghum		
Barley		
Bean		

24. What types of livestock do you have?

Types of livestock	Responses	
	Yes	No
Horse		
Cow		
Sheep		
Goat		
Donkey		
Mule		

Part II: Impact of climate variability on crop production

25. What are the main causes for the decline of crop production in your locality? (Multiple responses are possible)
1=Scarcity of farmland 2=Decline of soil fertility 3=Pests and diseases 4=Crop diseases 5=Climate variability 6=Non-use of fertilizers

26. How do you describe the trends of crop production in the last ten years?
1=Increase 2=Decrease 3=Not changed

27. If your response for question number 26 is decrease, what are the main causes for decline of crop production? 1=Climate variability 2=Pests 3= Crop diseases 4=Land scarcity
5=Lack of fertilizers 6=multiple responses are possible

28. Which type of climate variability have you observed over the last two decades? 1. Erratic rainfall 2. late onset 3. early cessation 4. change in growing period

29. How you explain the trend of rainfall in the last two decades? 1. increase 2. Decrease 3. uniform 4. If other please specify______________________________

Smallholder farmers adaptation strategies against climate variability

30. Which adaptation strategies do you use for soil and water conservation practices in order to minimize the challenges of climate variability?

No	Soil and water conservation practices	Yes	No	If no, please specify the reason
1	Planting trees			
2	Contour ploughing			
3	Soil and stone bunds			
4	Terracing			
5	Crop rotation			
6	Checkdams			
7	Intercropping			

31. Adaptation strategies used to overcome the impact of climate variability on crop production

No	Adaptation strategies	Yes	No
	Crop		
1	Crop diversification		
2	Planting eucalyptus/*Acacia Decurrens*		
3	Growing drought tolerant crop varieties		
4	Adjusting crop planting calendar		
5	Growing early matured crop varieties		
	Livestock		
6	Livestock diversification		
7	Breeding improved livestock species		
8	Minimizing the number of livestock		
9	Change the types of livestock kept		
10	Improving livestock forage		
	Off-farm activities		
11	Trading grains and pulses		
12	Sale of charcoal/firewood		
13	Sale of products of hand craft (weaving, pottery, metal)		

14	Sale of local drinks (*Areki, Tella…*)		

32. What indigenous adaptation strategies do you employ when rainfall and temperature related hazard occurs? 1. Crop diversification 2. Using of agrochemicals 3. Planting cash crops 4. Irrigation farming
33. Which type of physical soil and water conservation practices do you use? 1. Constructing soil bunds 2. Constructing Stone bunds 3. Diverting flood to farm 4. Terracing 5. Contour ploughing
34. Which type of biological soil and water conservation practices do you use? 1. Planting trees/ agro forestry 2. Crop rotation 3. Mixed cropping 4. If other please specify_______________
35. What are the major constraints which hindered the effective implementation of adaptation strategies?

No	Constraints of adaptation strategies	Rank (order of severity)
1	Low literacy	
2	Poor access to meteorological information	
3	Lack of knowledge about appropriate adaptation options	
4	Lack of credit services	
5	Lack of irrigation facilities	
6	Poor institutional support	
7	High cost of farm inputs	
8	Lack of finance and technical support	
9	Lack of modern agricultural inputs	
10	Reliance on single rain season	

Determinants of adaptation strategies

Socio-economic factors

36. Do you have your own farm land? 1=Yes 2=No

If your answer for question number---- is yes, describe its size in hectare or *Timad*?

- ✓ Cultivated land ________________
- ✓ Grass and woodland_____________
- ✓ Forest land __________________
- ✓ Homestead___________________
- ✓ Irrigated Land________________
- ✓ Total _______________________

Has your farm land size decreased or increased since you started farming? 1=Increased 2= Decreased 3=No change

37. How far is your farmland from homestead? ______in Km/Meter

What are the production and the area in the last five years?

Year	Crop	Production in quintal	Area (ha)
2023			
2022			
2021			

2020			
2019			

38. What would you say about cultivated land productivity in the last five years?
1= Increased 2=Decreased 3=No change observed
39. If your answer for question number 38 is increased, what are the reasons for any increase in your cultivated land productivity?
1=Increased soil fertility 2=Strong extension service (improved seed supply, agrochemical use, organic fertilizer) 3=Suitable weather conditions 4=Soil and water conservation practices 5= Other, please specify______________________________________
40. Again, if your response for question number---is decreased, what are the reasons for any decrease of your cultivated land productivity?
1=Land degradation 2= Lack of timely input supply 3=Lack of oxen 4=Rainfall variability 5=Drought 6=Pests and Crop diseases 7=Other, please specify_____________________
41. What is the fertility status of your cultivated land?
1. Not fertile 2. Somewhat fertile 3. fertile 4. Highly fertile
42. Do you have land use right/ownership certificate? 1. Yes 2. No
43. If your answer for question number 42 is yes, has this motivated you to increase the use of SWC mechanisms? 1. Yes 2. No
44. Do you have access to climate information? 1=Yes 2=No
45. If your response for question number 44 is yes, what is/are the source of information on climate variables? 1=Media 2=Own experience 3=Development agents 4=fellow farmers
Institutional factors
46. Is there any agricultural extension service in your locality? 1=Yes 2=No
47. Does the presence of extension services help you to improve productivity and production? 1=Yes 2=No
48. How often do you meet and get advice from the extension agent? 1=weekly 2=Once in two weeks, 3=Once in three weeks, 4=Once in a month 5. If other specify__________________
49. What types of advices did you receive from extension agents? (Multiple response is possible)
1=Improved crop production systems 2= Improved livestock production 3=soil and water conservation 4=Irrigation use 5=Natural resource management 6= planting and harvesting time 7=Crop diversification 8=If other specify____.

50. Do you get important information related to agriculture and market from this information center/source? 1=Yes 2= No
51. What is your source for climate related information? 1. Radio 2. Television 3. Newspaper and magazine 4. Agriculture experts 5. Neighbours 6. Other, please specify
____.
52. Have you participated in skill-upgrading training to improve your knowledge regarding adaptation strategies to climate variability? 1=Yes 2=No
53. If your response for question number 52 is yes, did the training that you gain help for farming productivity?
1. Very little 2. Little 3. Moderate 4. Significant 5. Very significant
54. Have you been engaged in off-farm/non-farm activities? 1= Yes 2=No
55. If your response for question number 54 is yes, mention some of the major sources of off-farm/non-farm activities____
____.
56. Do you have access to credit from any sources? 1=Yes 2=No

57. If your response for question number 56 is yes, what is/ are the sources of credit? Multiple responses are possible
1=Saving and credit institutions 2=Micro finance institutions 3=Cooperatives 4=Banks
5=Relatives 6=Neighbours

Part 2. Checklists for FGD discussants

1. How are the trends of the rainfall and the temperature during the past 20 to 30 years? Is it increasing, decreasing, coming on time and stopping at the right time?
What are your traditional or local indicators to realize the presence of climate variability?
Have you ever heard climate variability? If yes, from which sources?
3. What are the major consequences that you have ever suffered due to climate variability?
4. What are the major impacts of climate variability on farming productivity?
5. Do you believe that the change in climate will continue in the future?
Do smallholder farmers have awareness towards adaptation measures to climate variability?
6. What indigenous adaptation strategies are employed by smallholder farmers to minimize the adverse impacts of climate variability?
7. What factors affect the choice of different adaptation strategies?
8. What are the major challenges which hindered the implementation of different adaptation strategies?
9. Do you believe the adaptation strategies employed by smallholder farmers similar at different agro-ecological zones? If not, mention major adaptation strategies practiced at different agro-ecological zones? (*Dega, Woina Dega, and Kolla*).
How do you evaluate the roles of development agents in building awareness and mobilizing the community to strengthen their adaptive strategies to climatic variability?
What trainings had been given to stallholder farmers regarding climate variability adaptation strategies?
10. How do temperature and rainfall variability affect crop productivity?
11. Is there a change in the cropping calendar (sowing and harvesting time) as compared to the last 20 years?
Are crops that you cultivate currently similar with the crops that were grown 20 or 30 years ago? If no, what are the reasons for change of crops?
Again, are the livestock you rearing now similar with livestock that were 20 or 30 years ago? If not, what are the reasons for change?
Is there any change of sowing time of dominant crops now when you compare with 20 or 30 years ago? what time of the year do you practice seed sowing currently?
12. What should the government and the community do to avert the impact of climate variability on farming productivity?
13. Have you observed any shift on rainfall characteristics like onset, cessation and length of growing period over the past 20-30 years?

Part 3. Checklists for key informants

1. Describe the rainfall and temperature pattern over the last 20 year.
2. How smallholder farmers perceive about climate variability
3. What are the causes for the decline of crop production?
4. What are the dominant types of crops cultivated and livestock kept in the area
5. What is farm, off-farm, or non-farm activities that smallholder farmers have been engaged to generate cash or other forms of income?
6. How climate variability affects crop and livestock production
7. Can you tell us the sowing time of dominant crops grown some twenty-thirty years back and the time that these crops are sown in recent years?

8. What are the dominant adaptation strategies employed by smallholder farmers across different agro-ecological zones?
9. What are the determinant factors which affect the choice of adaptation strategies by smallholder farmers?
10. What are the major challenges hindering the successful implementations of adaptation strategies by smallholder farmers?
11. What are barriers hindering climate variability adaptation strategies by the smallholder farmers?