Addis Ababa University

School of Graduate Studies

Climate Change, Vulnerability and Adaptation of Rural Households in Northwest Ethiopia

By: Aimro Likinaw Melesse

Addis Ababa University

Addis Ababa, Ethiopia

October, 2023

Climate Change, Vulnerability and Adaptation of Rural Households in Northwest Ethiopia

Aimro Likinaw Melesse

A Dissertation Submitted for the Partial Fulfillment of the Requirement for the Degree of Doctor of Philosophy in Geography and Environmental Studies (Environment and Natural Resources Management)

Addis Ababa University

Addis Ababa, Ethiopia

October, 2023

Declaration

I, the undersigned, declare that this work is my own and original work. It has not been presented at this or any other university. Furthermore, I affirm that I have fully acknowledged all of the resources and materials utilized in the dissertation.

Name: Aimro Likinaw Melesse

Signature: _____

Date: 16/10/2023

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

Advisor

Woldeamlak Bewket (Professor), Signature _____ Date: 16/10/23

Dissertation Approval

Addis Ababa University

College of Social Sciences

Department of Geography and Environmental Studies

This certificate certifies that **Aimro Likinaw Melesse** dissertation titled **"Climate Change, Vulnerability and Adaptation of Rural Households in Northwest Ethiopia"** has been submitted to fulfill the requirements for the degree of Doctor of Philosophy in Geography and Environmental Studies (with a specialization in Environment and Natural Resource Management) and complies with the accepted standards for originality and quality.

Signed by the Examining Committee:

Degefie Tibebe		10/10/23
Chair, Examining Committee	Signature	Date
Melsenner Andrew		16/10/23
External Examiner	Signature	Date
Mulumebet Wolie		16/10/2023
Internal Examiner	Signature	Date
Wondemagegnehu Bewket		16/10/23
Research Advisor	Signature	Date

Acknowledgments

First and foremost, I would like to express my utmost gratitude to the Almighty God for granting me good health and strength, which enabled me to successfully accomplish this research endeavor. I give all glory to Him for eternity. I extend my sincere appreciation and thanks to my esteemed academic supervisors, Prof. Woldeamlak Bewket and Dr. Arragaw Alemayehu, for their unwavering professional guidance, valuable scientific input in this work, and their friendly demeanor throughout the research period.

I would like to acknowledge, with gratitude, the individuals and institutions that have played a pivotal role in the successful completion of this research. Firstly, I am thankful to my home institution, Dilla University, for granting me a study leave to pursue my PhD and for partially financing this study. I also extend my thanks to Addis Ababa University for their financial support. Furthermore, I would like to express my sincere appreciation to the National Meteorological Agency of Ethiopia for providing the rainfall and temperature data of the study area. Special recognition is also due to the experts in natural resources at the district agricultural offices, the staff of the different kebele offices, enumerators, and farmers in the Lay Gayint, Tach Gayint, and Simada districts for their kind cooperation and support during the data collection process.

Lastly, I would like to express my heartfelt thanks to my family for their unwavering support throughout my academic journey. Without their invaluable assistance, I would not have been able to complete this difficult and lengthy undertaking.

Contents

List of Tables

List of Figures

List of Acronyms and abbreviations

a.s.l	above sea level
ANOVA	One-way Analysis of Variance
CCRPI	Climate Change Risk Perception Index
CCRPS	Climate Change Risk Perception Score
CRGE	Climate-Resilient Green Economy
CSA	Central Statistical Agency
CV	Coefficients of Variations
DA	Development Agents
ENACTS	Enhancing National Climate Services
ENSO	El Niño Southern Oscillation
EPCC	Ethiopian Panel on Climate Change
ETCCDI	Expert Team on Climate Change Detection and Indices
FAO	Food and Agriculture Organization
FAR	Fifth Assessment Report
FDRE	Federal Democratic Republic of Ethiopia
FGD	Focus Group Discussions
GDP	Gross Domestic Product
G-ITA	Graphical Innovative Trend Assessment
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
ITA	Innovative Trend Analysis
KII	Key Informant Interviews
LVI	Livelihood Vulnerability Index
MK	Mann-Kendall
MMK	Modified Mann-Kendall
NAP	National Adaptation Plan
NAPA	National Adaptation Programme of Action
ENMA	Ethiopian National Meteorological Agency
NPC	National Planning Commission

PDF	Probability Density Function
PSNP	Productive Safety Nets Program
SDG	Sustainable Development Goals
SeVI	Socio-economic Vulnerability Index
S-ITA	Statistical Innovative Trend Assessment
SRS	Simple Random Sampling
SSE	Sen's Slope Estimator
SSD	Sen's Standard Deviation
UCL/LCL	Upper Class Limit/Lower Class Limit
UNDP	United Nations Development Programme
USAID	United States Agency for International Development
WMO	World Meteorological Organization

Chapter One

1. General Introduction

Arguably, the most urgent global environmental crisis is climate change, affecting a multitude of sectors, including agriculture. This has been discussed in various studies (Abdallah et al. 2019; Belay et al. 2022; Pedersen et al. 2021). The impact of climate is evident through escalating temperatures, irregular rainfall, and occurrences of floods, droughts, and water scarcity, as noted by researchers (Adu et al. 2018; Ramli et al. 2019; Zandalinas et al. 2021). Numerous studies, such as those conducted by Hundera et al. (2019) and Nematchoua et al. (2019) and, have extensively documented the adverse consequences of global climate change across various sectors. Moreover, vulnerability to these changes varies due to factors related to location, sector, and community characteristics, a point emphasized by Das et al. (2020) and Thomas et al. (2019). Highlighting the significance of resource reliance, Hein et al. (2019) and Nematchoua et al. (2019) underscore that individuals heavily dependent on natural resource exploitation for their livelihoods face greater susceptibility to climate change contrasted with individuals who are less reliant.

Africa's economic foundation rests upon agriculture, which also sustains a significant portion of livelihoods spanning the continent (Kogo et al., 2021). The year 2019 witnessed persistent climatic shifts in Africa, marked by escalating temperatures, and occurrences of extreme weather, as reported by the World Meteorological Organization (WMO, 2020). The threat of climate change endures across the continent, as outlined by Austin et al. (2020) and Ojara et al. (2021). The region of East Africa, in particular, confronts the brunt of climatic risks like floods and droughts (Gebrechorkos et al., 2019).

The vulnerability of Africa to climate change stands as a key concern highlighted in both the Fifth Assessment Report (FAR) and the Sixth Assessment Report (SAR) of the Intergovernmental Panel on Climate Change (IPCC, 2014; IPCC, 2022). The report highlights Africa's heightened susceptibility, projecting that within the 2050s, a substantial segment of the population (ranging from 350-600 million) could encounter water stress, predominantly affecting the northern and southern regions. Projections by Bryan et al. (2013) and Connolly and Smit (2016) underscore the severe reality of climate change consequences, estimating notable crop production losses (ranging from 8-22%) for key staples in Africa by 2050.

The issue is further aggravated by the continent's dependence on rainwater-based farming, as highlighted by Baarsch et al. (2020) and Dumenu and Tiamgne (2020). In the realm of global

poverty, Sub-Saharan Africa stands as among the foremost impoverished areas, rendering it exceptionally susceptible to climate patterns (Antwi-Agyei and Stringer, 2021: Kogo et al., 2021). Besides the rising temperatures, climate transformation within sub-Saharan Africa is poised to trigger alterations in rainfall patterns. These shifts encompass heightened occurrences of extreme events, notably droughts, floods, and desertification (Connolly and Smit, 2016; Makate, 2019). East Africa, according to predictions by Tan et al. (2020), is on the edge of confronting both catastrophic droughts and intense wet scenarios. The World Bank's assessment (2016) forecasts severe economic consequences due to climate change. Projections indicate anticipated agricultural losses ranging from 2 to 7 percent of the GDP by 2100, particularly concentrated in portions of the Sahara. In Western and Central Africa, the estimates range between 0.4 and 1.3 percent, whereas Northern and Southern Africa may experience losses reaching up to 2.4 percent.

Ethiopia is characterized by significant variations in precipitation levels, which lead to the existence of dry and semi-dry regions (Eze et al., 2022; Moussa et al., 2021; Negash et al., 2020). Thus, the country is vulnerable to climate variability, primarily due to its reliance on precipitation-dependent agriculture and limited ability to adjust to predicted changes (Amare and Simane, 2017; Asfaw et al., 2021; Asrat and Simane, 2018).

Since the 1960s, Ethiopia has encountered numerous droughts, varying in intensity and duration. The years 1965, 1969, 1973, 1983, 1987, 1989, 1997, 1998, 1999, 2003, 2005, 2008, 2009, 2012, and 2015 have been recognized as particularly severe drought periods (Bisrat and Berhanu, 2019; Gebrehiwot et al., 2011; Masih et al., 2014). Apart from droughts, Ethiopia is also prone to flooding, especially during the Kiremt season in low-lying areas. Riverine floods impact over 250,000 people each year, as well as over 200 essential education and health facilities (Abdella and Mekuanent, 2021; Demissie et al., 2021; Mekonnen et al., 2023). The projected number of people affected by these risks is expected to reach 1 million by 2025 and 1.5 million by 2050. Given the potentially devastating impacts of these natural disasters on the country's population and infrastructure, it is crucial for Ethiopia to develop strategies to manage and mitigate their impacts (Mamo et al., 2019; Weldegebriel and Amphune, 2017).

Ethiopia faces a diverse array of consequences due to severe climatic events and fluctuations in weather patterns, profoundly impacting its farming output. These consequences encompass a range of challenges, including the threat of food insecurity (Hilemelekot et al., 2021), population dislocation (Solomon et al., 2018), deepened poverty (Onyutha, 2019; Seife, 2021), and conflicts (Van Weezel, 2019). The significance of agriculture within Ethiopia's economic

landscape is unmistakable. It serves as a cornerstone, contributing to 52% of the nation's GDP, offering employment to 80% of the populace, and fostering 80% of the country's foreign exchange earnings.

In light of this, it is crucial to develop policies and programs that can support the adaptive capability of farmers. Moreover, identifying farmers' perceptions of climate variability can help policymakers obtain substantial knowledge for localized policy design and implementation perspectives. Behailu et al. (2021) suggest that comparing farmers' insights with meteorological archives is crucial in developing a sustainable policy framework for building climate resilience. In the future, this approach assists in designing sustainable intervention options tailored to location-specific climate variability and its associated impacts. Overall, gaining a deeper insight into farmers' viewpoints and decision-making processes is essential to formulate effective and sustainable practices.

Like other regions in Ethiopia, the districts of Simada, Tach Gayint and Lay Gayint (the present study area), situated within the South Gondar Zone, are extremely susceptible to climate variability. This susceptibility has been emphasized by Getachew (2017). The Zone has been experiencing recurrent natural disasters caused by climate variability, which have had devastating impacts. Smallholder farmers in the area have been recurrently impacted by rainfall scarcity and associated droughts (Atinkut and Mebrat, 2016; Bazezew et al., 2013; Endalew and Sen, 2020). As a result of these climatic challenges, most households in the study area encounter difficulties in attaining food self-sufficiency and heavily depend on the Productive Safety Nets Program (PSNP).

Vulnerability assessment is a vital tool for identifying and targeting communities that are most vulnerable to specific environmental stresses (Adego et al., 2022; Crozier et al., 2019). These assessments enable the implementation of specialized interventions to achieve the specific requirements of susceptible populations, aiding in the development of appropriate interventions (Bedeke et al., 2020; Conway and Schipper, 2011). These interventions can enhance resilience to droughts by reducing exposure and sensitivity or enhance a community's adaptive capability. While national and sectoral vulnerability assessments are important for understanding development priorities, they often overlook local vulnerability. Therefore, to effectively implement adaptation measures, it is crucial to thoroughly understand local communal attributes and evaluate the benefits of individuals who are prone to being impacted. Unfortunately, the current policy agenda for national climate adaptation fails to adequately resolve these issues. Thus, conducting locale-specific assessments of rural household-level

vulnerability, as emphasized by Endalew and Sen (2021), becomes essential in examining practical policy-related questions.

Furthermore, it is imperative to recognize actual managing strategies that can sustain rural livelihoods and contribute to the attainment of SDGs. Notably, enhancing the climate change adaptive capability of susceptible individuals is part of the aims set by the SDGs (UNDP, 2020). Overall, susceptibility evaluation plays a crucial role in identifying and addressing the needs of vulnerable communities affected by climate stress, enabling the design of appropriate interventions to mitigate the impacts of such stress. By implementing these interventions, the coping capability of households to adverse climate impacts in the study area can be enhanced, thereby reducing the overall impact on farmers.

In recognition of the challenges posed by climate variability and change, the Ethiopian government has formulated a series of national policies, programmes, and strategies aimed at both adaptation and mitigation measures. These efforts encompass several significant initiatives: the National Adaptation Programme of Action (NAPA) established in 2007, the Climate Resilience Strategy introduced in 2011, the Climate-Resilient Green Economy (CRGE) Strategy launched in 2015, the National Planning Commission (NPC) founded in 2016, and the Climate Resilient Green Economy: National Adaptation Plan (NAP) developed in 2020. Alongside the governmental endeavors, the country's farmers have also been proactively adjusting to the changing climate conditions.

Over the past decades, farmers have embraced diverse techniques for climate adaptation. These methods encompass the implementation of water harvesting technologies and soil conservation measures. Strategies include the building of stone terraces and soil bunds, the creation of enclosures, modifications to crop calendars, diversification of crops, and active participation in tree-planting initiatives (Asrat and Simane, 2018; Belay et al., 2022; Kahsay et al., 2019). However, despite the variety of localized adaptation responses adopted by farmers and the progress made in policy formulation and execution to encourage adaptation options, the uptake of such options has not met expectations. This is especially true for those adaptation options designed to diminish vulnerability and increase production to boost food security (Bewket et al., 2015; EPCC, 2015; EPCC, 2015). As a result, there remains a need for heightened efforts to motivate farmers towards the implementation of adaptation choices that can strengthen their resilience to climate fluctuations. This, in turn, will lead to improved agricultural output and reinforce food security within Ethiopia.

Numerous studies have investigated into the perspectives and reactions of farmers across diverse Ethiopian regions to the consequences of climate change on their agricultural systems. These inquiries, documented in Abdela (2022), Belay et al. (2022), Hilemelekot et al. (2021), and Zeleke et al. (2022), collectively shed light on local dynamics. Despite this extensive research, a significant gap remains in comprehending the interplay between farmers' perceptions of climate change risks and the strategies they employ to adapt. This gap in knowledge presents a difficult obstacle to formulating policies that effectively tackle climate-related risks while enhancing farmers' awareness, especially among vulnerable demographics. Furthermore, the assessment of Ethiopian farmers' susceptibility to climate variability, explored in various studies including Abeje et al. (2019), Asfaw et al. (2021), Bogale and Erena (2022), Mekonnen and Berlie (2021), and Zeleke et al. (2023), warrants a complex approach.

Vulnerability, as a concept, encompasses multifaceted dimensions such as adaptive capability, sensitivity and exposure. These aspects are complicatedly interconnected with specific locales and evolve over time. Hence, a comprehensive analysis of vulnerability at the household level emerges as essential, offering visions into the current ramifications of climate variability within the study area. Moreover, prevailing literature predominantly focuses on average or mean rainfall distribution in the Ethiopian context, as evidenced by works like Ademe et al. (2020), Asfaw et al. (2018), Gemeda et al. (2021), and Hilemelekot et al. (2021). This, however, leaves a noticeable gap in research, particularly concerning extreme precipitation events. Addressing this gap not only at the national scale but also within the specific study area becomes an imperative pursuit for a holistic understanding of Ethiopia's climate dynamics.

The present study focuses on historical climate analysis, allowing researchers to examine natural climate variability. This analysis is essential for understanding long-term climate trends and distinguishing them from short-term fluctuations. While climate modelling and projections play a crucial role in understanding future climate change, historical climate analysis remains an indispensable component of climate research. Despite their sophistication, climate models are not perfect representations of the real world. This imperfection is particularly evident in tropical highland environments, which pose substantial challenges for climate projections. These challenges arise due to sparse observations, significant local heterogeneity, and inconsistent performance of global climate models (GCMs). Furthermore, these areas are often densely populated, with agriculture-based livelihoods that are sensitive to transient climate extremes not always accounted for in available climate projections.

Within this context, the present study makes a substantial contribution to the existing knowledge by investigating into the perspectives held by smallholder farmers concerning the risks, vulnerabilities, and strategies for adapting to climate variability in the area. The core objective of this research centers on facilitating the effective implementation of measures directed toward diminishing the vulnerability of agricultural communities and amplifying their adaptive capabilities. The insights gathered from this study hold immense potential in guiding policymakers and furnishing them with actionable insights. These insights, in turn, serve as valuable resources for the development and execution of policies that strengthen household resilience against the challenges imposed by climate variability. As a result, this investigation enriches the collective body of knowledge, effectively laying the groundwork for enlightened decision-making that can successfully tackle the adverse impacts of climate variability while concurrently fostering sustainability.

2. Study site description

Geographically, the area (Simada, Lay Gayint and Tach Gayint districts) is situated between 11° 02'–12° 04' N latitude and 38° 10'–38° 43'E longitude, with an area of 4,592.69 km2 (Figure 1.1).

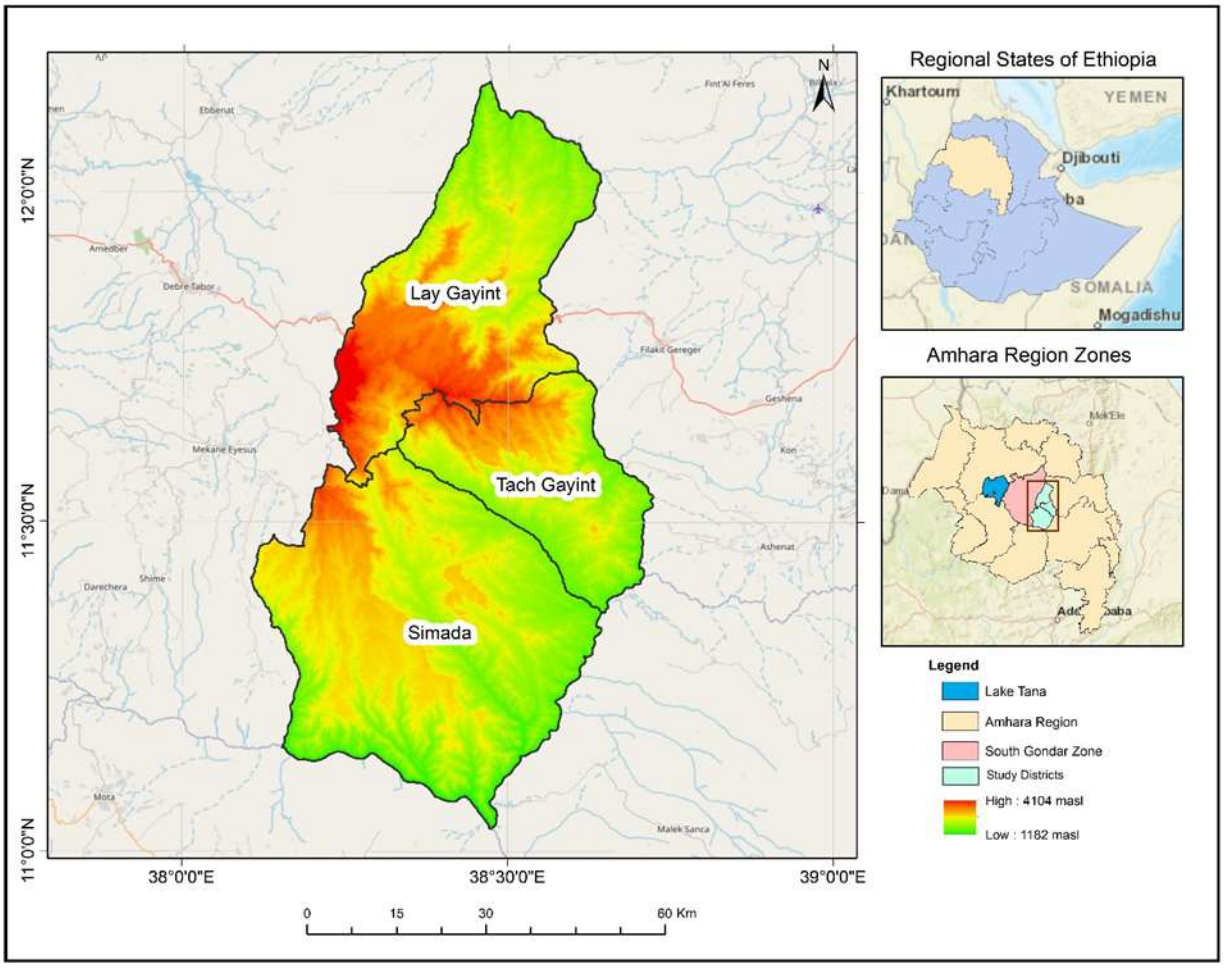

Figure 1. 1 . Location map of the study site

In the context of the simplified agro-ecological classification, the area is divided into three distinct districts. Lay Gayint occupies the *High Dega* agro-ecological zone, situated between elevations of 3200 to 3700 m a.s.l. Tach Gayint and Simada, conversely, are positioned in the *Dega* and *Woyna Dega* zones, respectively. These areas experience varying elevations, varying from 2300 to 3200 m a.s.l for Tach Gayint and 1500 to 2300 m a.s.l for Simada. The rainfall patterns in the study area exhibit a bimodal distribution. From June to mid-September, the primary rainy season known as *Kiremt* prevails, whereas the secondary rainy season, *Belg*, happens from March to May. It is worth noting that the *Belg* season is notably erratic, leading to frequent crop failures and posing significant harvesting challenges. Drawing from climate data provided by the National Meteorological Agency (NMA) of Ethiopia covering 38 years (1981-2018), the mean yearly rainfall in the area amounts to 1040mm. Additionally, the mean annual maximum, minimum, and average temperatures stand at 25°C, 11°C, and 18°C, respectively.

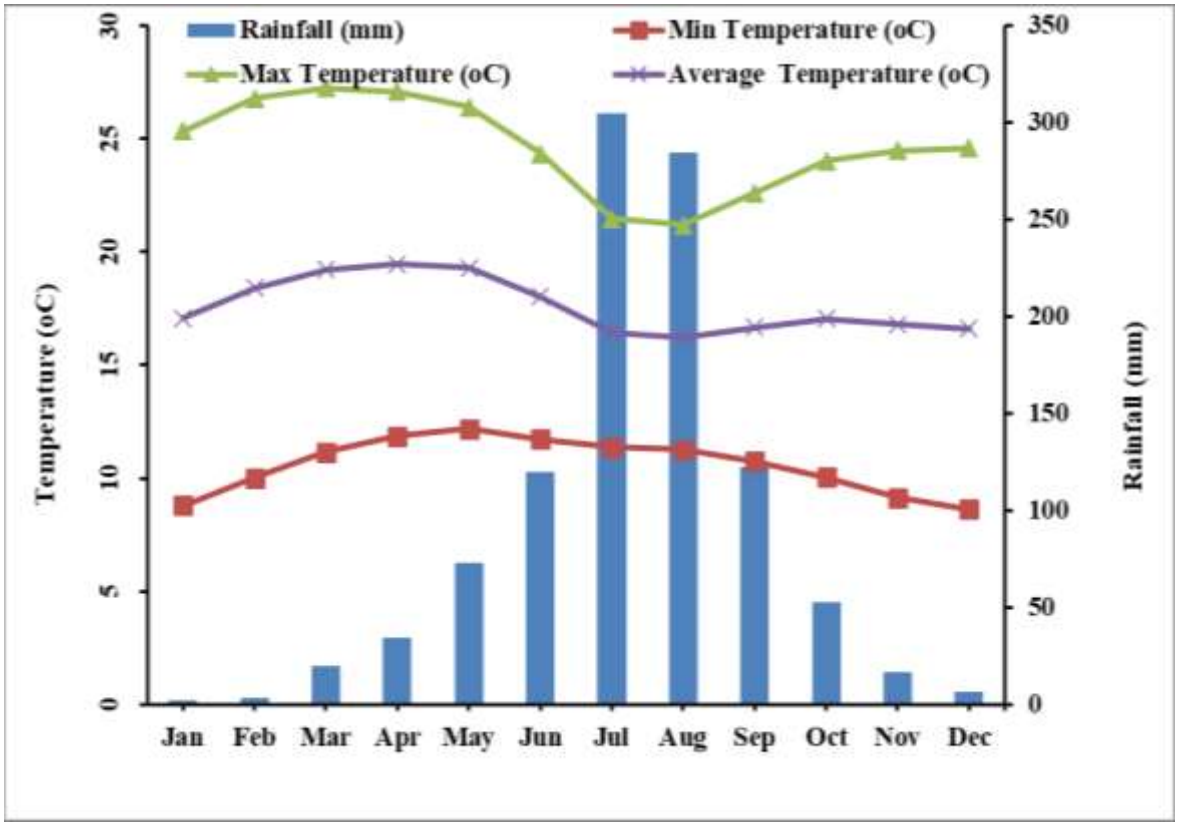

Figure 1. 2. Mean monthly rainfall and mean monthly maximum and minimum temperatures (1981–2018) of the study area.

The study area exhibits a mixed crop-livestock system, characterized by continuous and intensive cropping. The primary cereals cultivated in the region encompass Barley (*Hordium vulgare*), wheat (*Triticum aestivum*), maize (*Zea mays*), and tef (*Eragrostis tef*). Among the livestock reared, cattle, sheep, goats, and equines dominate. Despite this, the contribution of cattle as a source of income is curtailed because of the prevalence of cattle sicknesses (Getachew, 2017). Crop farming faces various challenges stemming from erratic rainfall, inadequate soil fertility, inadequate use of better-quality farming technologies, and small per capita landholding (Ayalew et al., 2012). Over time, the area has undergone significant degradation due to prolonged farming, overgrazing, socio-economic and policy constraints (Getachew, 2017). The population's rapid growth has led to land fragmentation, reducing farm sizes and increasing landlessness, particularly among youth. Consequently, the average farm size has dwindled to less than 1.0 hectare, below the national average of 1.01 hectares. Additionally, essential amenities like electricity and roads are notably lacking, falling below minimum standards and national averages.

Essential rural infrastructure, such as healthcare and water facilities, are also scarce, rendering the area sensitive to climate shocks. The neighboring urban districts fare better in this aspect. Unfortunately, agricultural insurance and credit markets are absent, compounding the challenges faced by rural households. The current state of the area is characterized by food scarcity due to late onset, premature termination, and inadequate *Belg* performance. This aligns with its classification as one of the country's food-insecure regions. Consequently, a significant portion of households cannot secure adequate food and heavily rely on food assistance or support from the Productive Safety Nets Program (PSNP). As per the South Gondar Zone Administration office's records, the PSNP has benefitted five districts, incorporating the study area (Ebnat, Libokemkem Simada, Tach Gayint and Lay Gayint).

3. Research questions

The central research questions addressed in this study are:

1. What is the nature of climate variability and trends in the study area?
2. What are the trends in extreme precipitation indices in the study area?
3. To what extent are farmers' livelihoods vulnerable to climate variability and change in the study area?
4. What are the perceptions and adaptation strategies of smallholder farmers to climate change risks in the study area?

4. Objectives of the research

This research aims to examine climate change, vulnerability and adaptation of rural households in Northwest Ethiopia. To achieve this goal, the study has the following specific objectives to:

1. examine local scale climate variability and trends in a vulnerable rural landscape in the area.
2. analyze trends of extreme precipitation indices in the area using two most commonly used methods: the Mann Kendall and innovative trend analysis methods
3. assess smallholder farmers' vulnerability to climate change in the area; and
4. assess smallholder farmers’ perceptions and adaptation strategies to climate change risks in the area.

5. Scope and limitations of the study

The study aims to understand the unique challenges and risks faced by households in relation to the impacts of climate change in the area. It explores multiple dimensions of vulnerability

and adaptation, including the effects of climate variability on livelihoods, livelihood strategies, resource accessibility, social dynamics, and adaptive capacities of these households. Additionally, the study involves assessing existing adaptation measures and identifying potential strategies to enhance resilience. To evaluate vulnerability and its effects on households, the study utilizes two key tools: the Livelihood Vulnerability Index (LVI) and the Socioeconomic Vulnerability Index (SeVI). These indices play a crucial role in assessing vulnerability and gaining insights into the specific challenges faced by these households. However, the selection of appropriate indicators and the assignment of suitable weights have proven to be challenging aspects of this method. The subjective nature of indicator selection and weight assignment, coupled with the difficulty in testing or validating metrics with varying scales, remains a primary limitation of the indicator method, as highlighted by Endalew and Sen (2021) and Etwire et al. (2013). Furthermore, it is important to acknowledge that the local context significantly influences the formulation and development of indicators. To achieve desirable results, an extensive literature review and consultation with subject matter experts, as conducted in this study, are essential steps in the process.

6. Significance of the Study

To date, the majority of studies have primarily focused on broader scales of analysis, such as national, regional, and district levels, rather than investigating the specific context of individual households at the local level. However, it is crucial to acknowledge that national-level studies may not provide a thorough comprehension of livelihoods and adaptive capacities on a localized scale. To address this knowledge gap, the study specifically focuses on the vulnerability of farmers at the household level. Therefore, this study holds significant importance in understanding the vulnerability of farmers to climate change and variability. By examining the specific context of individual households at the local level, the study can offer valuable perspectives on the unique difficulties and risks confronted by farmers in relation to climate-related impacts. This understanding can contribute to the development of targeted and effective strategies to enhance the resilience and adaptive capacity of farmers. Furthermore, the study can help policymakers, researchers, and practitioners gain a comprehensive understanding of localized vulnerabilities and inform evidence-based decision-making processes concerning adaptation and mitigation measures. Ultimately, the significance of this study lies in its potential to contribute to the development of more tailored and impactful interventions to support farmers in navigating the challenges posed by climate change and variability.

7. Conceptual framework

This study employs the Livelihood Vulnerability Index-Intergovernmental Panel on Climate Change (LVI-IPCC) framework, as introduced by the IPCC in 2001. It stands as a significant approach for assessing vulnerability. In this context, vulnerability indicates the likelihood of experiencing unfavourable outcomes. The LVI-IPCC framework takes into consideration diverse factors contributing to vulnerability, including exposure to climate hazards, sensitivity to those hazards, and adaptive capacity (IPCC, 2014). Exposure denotes the extent to which a system or community faces climate-related hazards. On the other hand, sensitivity pertains to the inherent characteristics of a system that render it more or less susceptible to the impacts of climate change. These characteristics encompass elements like poverty, lack of infrastructure, or dependence on climate-sensitive resources. Adaptive capacity evaluates the ability of a system or community to adapt and respond to the challenges posed by climate change. It takes into consideration factors such as governance structures, resource accessibility, technological capabilities, and social networks, which empower communities to adapt and bolster resilience.

This framework adopts an integrated approach to vulnerability assessment, encompassing both biophysical and socio-economic dimensions. While the biophysical aspect addresses exposure and sensitivity, it doesn't adequately encompass the intricate socio-economic dynamics intrinsic to the system. The socio-economic dimension investigates into adaptive capacity, signifying the ability of households to manage the effects of climate variability. Aspects such as socio-economic status and demographic characteristics play a pivotal role in shaping the adaptive capacities of households. By integrating these distinct dimensions, the LVI-IPCC framework offers a comprehensive and systematic method to quantify and analyze vulnerability. It aids policymakers, researchers, and practitioners in comprehending the complex dynamics of vulnerability and identifying suitable strategies to fortify resilience and diminish vulnerability to climate change impacts. The LVI-IPCC framework has found widespread application in various studies (e.g., Amare and Simane, 2017; Asfaw and Bantider, 2021; Endalew and Sen). Overall, the LVI-IPCC framework plays a pivotal role in enhancing our grasp of vulnerability and guiding activities to cultivate adaptive capacity and resilience in response to climate change.

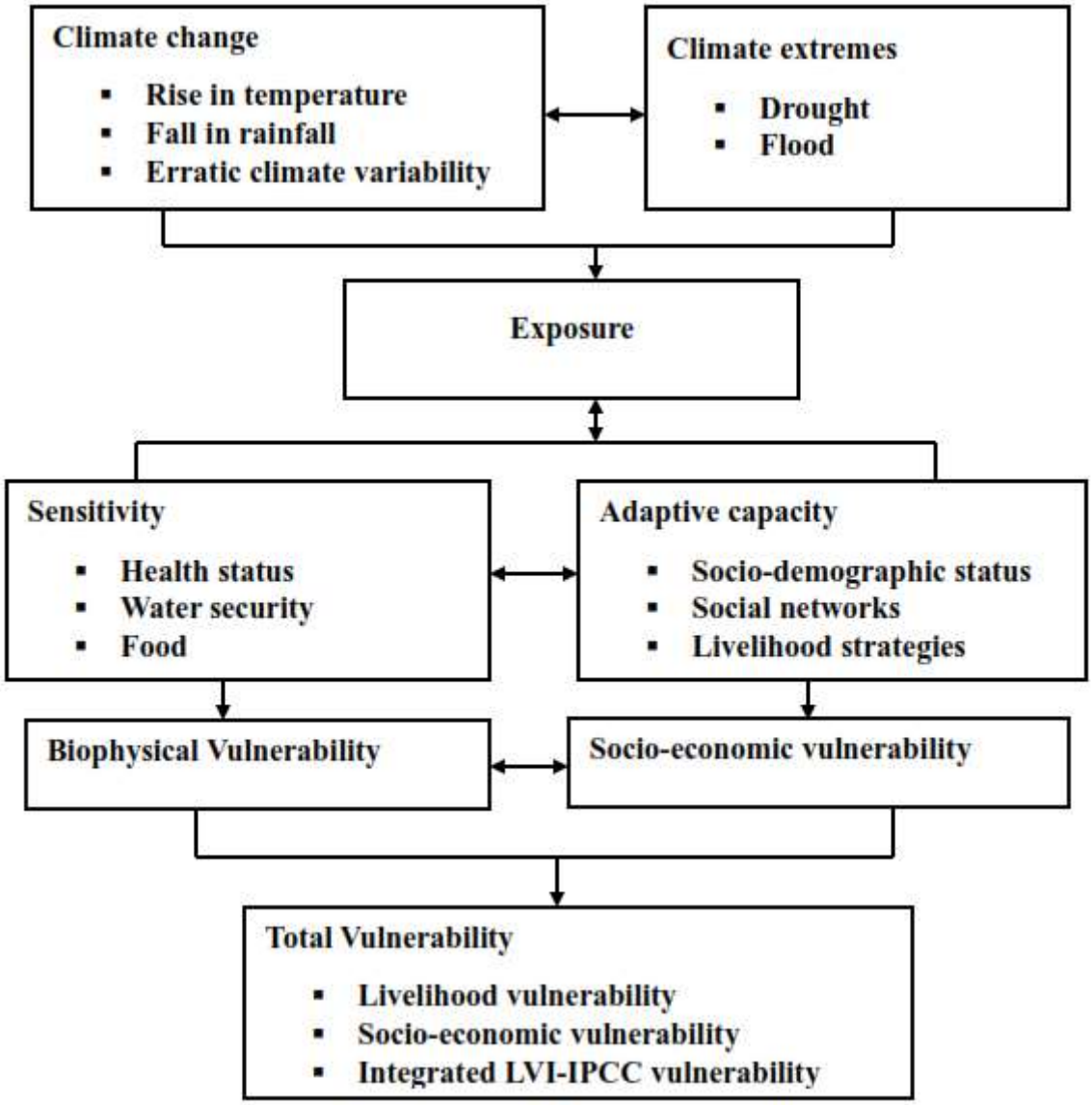

Figure 1. 3. Conceptual framework of the study.

8. Organization of the dissertation

The dissertation consists of a total of six chapters, each possessing its unique focus and purpose. The introductory chapter provides background information and outlines the research questions while presenting the vulnerability assessment framework. Additionally, it sets out the research methodology and design. Chapter two investigates into local-scale climate variability and trends, providing in-depth analysis on the subject. The third chapter examines extreme precipitation indices and provides valuable insights into the observed trends. Chapter four provides a comprehensive investigation of the susceptibility of farmers to climate variability. The focus of chapter five is directed towards the perceptions held by farmers and their strategies for adapting in the face of risks posed by climate change. Finally, chapter six, provides a summary of the main results from the preceding chapters. This chapter also presents scientific

understandings and suggestions for climate risk management, ideas for further research, and policy implications of the study.

References

Abdallah, A. H., Ayamga, M., & Awuni, J. A. (2019). Impact of agricultural credit on farm income under the Savanna and Transitional zones of Ghana. *Agricultural Finance Review*, 79(1), 60-84.

Abdela, U. (2022). Climate change adaptation and mitigation strategies in madda walabu district, bale zone, southeast Ethiopia. *International Journal of Ecology*, 2022, 1-12.

Abdella, K., & Mekuanent, F. (2021). Application of hydrodynamic models for designing structural measures for river flood mitigation: the case of Kulfo River in southern Ethiopia. *Modeling Earth Systems and Environment*, 7, 2779-2791.

Abebe, G. (2017). Long-term climate data description in Ethiopia. *Data in brief*, 14, 371-392.

Abeje, M. T., Tsunekawa, A., Haregeweyn, N., Nigussie, Z., Adgo, E., Ayalew, Z., ... & Masunaga, T. (2019). Communities' livelihood vulnerability to climate variability in Ethiopia. *Sustainability*, 11(22), 6302.

Adego, T., & Woldie, G. A. (2022). The complementarity and determinants of adoption of climate change adaptation strategies: evidence from smallholder farmers in Northwest Ethiopia. *Climate and Development*, 14(5), 487-498.

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.

Ado, A. M., Leshan, J., Savadogo, P., Bo, L., & Shah, A. A. (2019). Farmers' awareness and perception of climate change impacts: Case study of Aguie district in Niger. *Environment, Development and Sustainability*, 21, 2963-2977.

Adu, D. T., Kuwornu, J. K., Anim-Somuah, H., & Sasaki, N. (2018). Application of livelihood vulnerability index in assessing smallholder maize farming households' vulnerability to climate change in Brong-Ahafo region of Ghana. *Kasetsart Journal of Social Sciences*, 39(1), 22-32.

Amare, A., & Simane, B. (2017). Climate change induced vulnerability of smallholder farmers: agroecology-based analysis in the Muger sub-basin of the upper Blue-Nile basin of Ethiopia. *American Journal of Climate Change*, 6(4), 668-693.

Antwi-Agyei, P., & Stringer, L. C. (2021). Improving the effectiveness of agricultural extension services in supporting farmers to adapt to climate change: Insights from northeastern Ghana. *Climate Risk Management*, 32, 100304.

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), 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.

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.

Atinkut, B., & Mebrat, A. (2016). Determinants of farmers choice of adaptation to climate variability in Dera woreda, south Gondar zone, Ethiopia. *Environmental Systems Research*, 5, 1-8.

Austin, K. G., Beach, R. H., Lapidus, D., Salem, M. E., Taylor, N. J., Knudsen, M., & Ujeneza, N. (2020). Impacts of climate change on the potential productivity of eleven staple crops in Rwanda. *Sustainability,* 12(10), 4116.

Baarsch, F., Granadillos, J. R., Hare, W., Knaus, M., Krapp, M., Schaeffer, M., & Lotze-Campen, H. (2020). The impact of climate change on incomes and convergence in Africa. *World Development*, 126, 104699.

Barnes, M. L., Wang, P., Cinner, J. E., Graham, N. A., Guerrero, A. M., Jasny, L., ... & Zamborain-Mason, J. (2020). Social determinants of adaptive and transformative responses to climate change. *Nature Climate Change*, 10(9), 823-828.

Bazezew, A., Bewket, W., & Nicolau, M. (2013). Rural households' livelihood assets, strategies and outcomes in drought-prone areas of the Amhara Region, Ethiopia: Case Study in Lay Gaint District. African Journal of Agricultural Research, 8, 5716–5727.

Bedeke, S. B., Vanhove, W., Wordofa, M. G., Natarajan, K., & Van Damme, P. (2020). Vulnerability to climate change among maize-dependent smallholders in three districts of Ethiopia. *Environment, Development and Sustainability*, 22, 693-718.

Behailu, G., Ayal, D. Y., Zeleke, T. T., Ture, K., & Bantider, A. (2021). Comparative analysis of meteorological records of climate variability and farmers' perceptions in Sekota woreda, Ethiopia. *Climate Services*, 23, 100239.

Belay, A., Oludhe, C., Mirzabaev, A., Recha, J. W., Berhane, Z., Osano, P. M., ... & Solomon, D. (2022). Knowledge of climate change and adaptation by smallholder farmers: evidence from southern Ethiopia. *Heliyon,* 8(12), 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.

Bewket, W., Radeny, M. A., & Mungai, C. (2015). Agricultural adaptation and institutional responses to climate change vulnerability in Ethiopia. CCAFS Working Paper.

Bisrat, E., & Berhanu, B. (2019). Drought in Ethiopia: temporal and spatial characteristics. In *Extreme Hydrology and Climate Variability* (pp. 263-274).

Bogale, G. A., & Erena, Z. B. (2022). Drought vulnerability and impacts of climate change on livestock production and productivity in different agro-Ecological zones of Ethiopia. *Journal of Applied Animal Research*, 50(1), 471-489.

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.

Central Statistics Authority (CSA). (2007). Summary and statistical report of 2007 population and housing censuses. Federal Democratic Republic of Ethiopia Census Commission, Addis Ababa.

Connolly & Smit, B. (2016). Climate change, food security, and livelihoods in sub-Saharan Africa. *Regional Environmental Change*, 16, 385-399.

Conway, D., & Schipper, E. L. F. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global Environmental Change*, 21(1), 227-237.

Crozier, L. G., McClure, M. M., Beechie, T., Bograd, S. J., Boughton, D. A., Carr, M., ... & Willis-Norton, E. (2019). Climate vulnerability assessment for Pacific salmon and steelhead in the California Current Large Marine Ecosystem. *PloS One*, 14(7), e0217711.

Dapilah, F., Nielsen, J. Ø., & Friis, C. (2020). The role of social networks in building adaptive capacity and resilience to climate change: A case study from northern Ghana. *Climate and Development*, 12(1), 42-56.

Das, M., Das, A., Momin, S., & Pandey, R. (2020). Mapping the effect of climate change on community livelihood vulnerability in the riparian region of Gangatic Plain, India. *Ecological Indicators*, 119, 106815.

Demissie, B., Teklemariam, D., Haile, M., Meaza, H., Nyssen, J., Billi, P., ... & Van Eetvelde, V. (2021). Flood hazard in a semi-closed basin in northern Ethiopia: Impact and resilience. *Geo: Geography and Environment*, 8(2), e00100.

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.

Dumenu, W. K., & Takam Tiamgne, X. (2020). Social vulnerability of smallholder farmers to climate change in Zambia: the applicability of social vulnerability index. *SN Applied Sciences*, 2, 1-16.

Ebrahim, A. A., Miheretu, B. A., & Alemayehu, A. (2022). Vulnerability of smallholder farmers to climate variability and change across different agro-ecological Zones in Oromo Nationality Administration (ONA), North east Ethiopia. *Plos one*, 17(6), e0268094.

Endalew, H. A., & Sen, S. (2020). Effects of climate shocks on Ethiopian rural households: An integrated livelihood vulnerability approach. *Journal of Environmental Planning and Management*, 64(3), 399-431.

Eshetu, G., Johansson, T. P., Garedew, W., & Yisahak, T. (2018). Climate variability and small-scale farmer adaptation strategy in setema-Gatira area of Jimmaa, southwestern Ethiopia. *American Journal of Biological and Environmental Statistics*.

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.

Ethiopian Panel on Climate Change (EPCC). (2015), First Assessment Report. An Assessment of Ethiopia's Policy and Institutional Frameworks for Addressing Climate Change, Published by the Ethiopian Academy of Sciences, Addis Ababa, Ethiopia.

Ethiopian Panel on Climate Change (EPCC). (2015). First assessment report working group II. Climate change impact, vulnerability, adaptation and mitigation. Published by the Ethiopian Academy of Sciences, Addis Ababa, Ethiopia.

Eze, E., Girma, A., Zenebe, A., Okolo, C. C., Kourouma, J. M., & Negash, E. (2022). Predictors of drought-induced crop yield/losses in two agroecologies of southern Tigray, Northern Ethiopia. *Scientific Reports*, 12(1), 1-14.

Federal Democratic Republic of Ethiopia (FDRE). (2007). Climate change national adaptation programme of action (Napa) of Ethiopia. National Meteorological Services Agency, Ministry of Water Resources, Addis Ababa, Ethiopia.

Federal Democratic Republic of Ethiopia (FDRE). (2011). Green economy strategy of Ethiopia; Ethiopia's Climate-Resilient Green Economy (CRGE). Addis Ababa, Ethiopia.

Federal Democratic Republic of Ethiopia (FDRE). (2015). Ethiopia's Second National Communication to the United Nations Framework Convention on Climate Change (UNFCCC). Ministry of Environment and Forest (MEF), Addis Ababa, Ethiopia.

Federal Democratic Republic of Ethiopia (FDRE). (2016). Growth and Transformation Plan II (GTP II) (2015/16-2019/20), volume I: Main text. National Planning Commission (NPC), Addis Ababa, Ethiopia.

Federal Democratic Republic of Ethiopia (FDRE). (2020). Ethiopia's climate-resilient green economy: National adaptation plan (NAP). Addis Ababa, Ethiopia.

Fierros-González, I., & López-Feldman, A. (2022). Farmers' perception of climate change: A review of the literature for Latin America. *Frontiers in Climate Change and Society*, 9, 672399.

Foguesatto, C. R., Artuzo, F. D., Talamini, E., & Machado, J. A. D. (2020). Understanding the divergences between farmer's perception and meteorological records regarding climate change: a review. *Environment, Development and Sustainability*, 22, 1-16.

Gebrechorkos, S. H., Hülsmann, S., & Bernhofer, C. (2019). Long-term trends in rainfall and temperature using high-resolution climate datasets in East Africa. *Scientific Reports*, 9(1), 11376.

Gebrehiwot, T., & van der Veen, A. (2013). Climate change vulnerability in Ethiopia: disaggregation of Tigray Region. *Journal of Eastern African Studies*, 7(4), 607-629.

Gebrehiwot, T., Van der Veen, A., & Maathuis, B. (2011). Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, 13(3), 309-321.

Gemeda, D. O., Feyssa, D. H., & Garedew, W. (2021). Meteorological data trend analysis and local community perception towards climate change: a case study of Jimma City, Southwestern Ethiopia. *Environment, Development and Sustainability*, 23, 5885-5903.

Getachew, B. (2017). Impacts of climate change on crop yields in South Gonder Zone, Ethiopia. *World Journal of Agricultural Research*, 5(2), 102-110.

Hein, W., Wilson, C., Lee, B., Rajapaksa, D., de Moel, H., Athukorala, W., & Managi, S. (2019). Climate change and natural disasters: Government mitigation activities and public property demand response. *Land Use Policy*, 82, 436-443.

Hilemelekot, F., Ayal, D. Y., Ture, K., & Zeleke, T. T. (2021). Climate change and variability adaptation strategies and their implications for household food Security: the case of Basona Worena District, North Shewa zone, Ethiopia. *Climate Services*, 24, 100269.

Hundera, H., Mpandeli, S., & Bantider, A. (2019). Smallholder farmers' awareness and perceptions of climate change in Adama district, central rift valley of Ethiopia. *Weather and Climate Extremes*, 26, 100230.

Hurni, H., Berhe, W. A., Chadhokar, P., Daniel, D., Gete, Z., & Grunder, M. K. G. (2016). Soil and Water Conservation in Ethiopia: Guidelines for Development Agents. Volume 1. Centre for Development and Environment (CDE), University of Bern: Bern, Switzerland.

IPCC, (2001). Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change (Vol. 2). Cambridge University Press, Cambridge, United Kingdom.

IPCC, (2014). Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC, (2022). Africa. In: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 1285–1455.

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, 1-13.

Kogo, B. K., Kumar, L., & Koech, R. (2021). Climate change and variability in Kenya: a review of impacts on agriculture and food security. Environment, Development and *Sustainability*, 23, 23-43.

Kothari, C. R. (2004). Sample size determination. Research Methodology. New Age International Publications, 1, 74-1.

Li, S., Juhász-Horváth, L., Harrison, P. A., Pintér, L., & Rounsevell, M. D. (2017). Relating farmer's perceptions of climate change risk to adaptation behavior in Hungary. *Journal of Environmental Management*, 185, 21-30.

Likinaw, A., Alemayehu, A., Bewket, W. (2022). Smallholder farmers' perceptions and adaptation strategies to climate change risks in northwest Ethiopia. *International Journal of Climate Change Strategies and Management*.

Makate, C. (2019). Effective scaling of climate smart agriculture innovations in African smallholder agriculture: A review of approaches, policy and institutional strategy needs. *Environmental Science & Policy*, 96, 37-51.

Mamo, S., Berhanu, B., & Melesse, A. M. (2019). Historical flood events and hydrological extremes in Ethiopia. In *Extreme hydrology and climate variability* (pp. 379-384).

Masih, I., Maskey, S., Mussá, F. E. F., & Trambauer, P. (2014). A review of droughts on the African continent: a geospatial and long-term perspective. *Hydrology and Earth System Sciences*, 18(9), 3635-3649.

Matewos, T. (2020). The state of local adaptive capacity to climate change in drought-prone districts of rural Sidama, southern Ethiopia. *Climate Risk Management*, 27, 100209.

Mekonen, A. A., & Berlie, A. B. (2021). Rural households' livelihood vulnerability to climate variability and extremes: a livelihood zone-based approach in the Northeastern Highlands of Ethiopia. *Ecological Processes*, 10, 1-23.

Mekonnen, T. M., Mitiku, A. B., & Woldemichael, A. T. (2023). Flood Hazard Zoning of Upper Awash River Basin, Ethiopia, Using the Analytical Hierarchy Process (AHP) as Compared to Sensitivity Analysis. *The Scientific World Journal*, 2023.

Moussa Kourouma, J., Eze, E., Negash, E., Phiri, D., Vinya, R., Girma, A., & Zenebe, A. (2021). Assessing the spatio-temporal variability of NDVI and VCI as indices of crops productivity in Ethiopia: a remote sensing approach. *Geomatics, Natural Hazards and Risk*, 12(1), 2880-2903.

Negash, E., Gebresamuel, G., Embaye, T. A., Nguvulu, A., Meaza, H., Gebrehiwot, M., ... & Zenebe, A. (2020). Impact of headwater hydrological deficit on the downstream flood-based farming system in northern Ethiopia. *Irrigation and Drainage*, 69(3), 342-351.

Nematchoua, M. K., Orosa, J. A., & Reiter, S. (2019). Climate change: Variabilities, vulnerabilities and adaptation analysis-A case of seven cities located in seven countries of Central Africa. *Urban climate*, 29, 100486.

Ojara, M. A., Yunsheng, L., Babaousmail, H., & Wasswa, P. (2021). Trends and zonal variability of extreme rainfall events over East Africa during 1960–2017. *Natural Hazards*, 109(1), 33-61.

Onyutha, C. (2019). African food insecurity in a changing climate: The roles of science and policy. *Food and Energy Security*, 8(1), e00160.

Pedersen, J. S. T., Santos, F. D., van Vuuren, D., Gupta, J., Coelho, R. E., Aparício, B. A., & Swart, R. (2021). An assessment of the performance of scenarios against historical global emissions for IPCC reports. *Global Environmental Change*, 66, 102199.

Ramli, M. F., Aris, A. Z., Jamil, N. R., & Aderemi, A. A. (2019). Evidence of climate variability from rainfall and temperature fluctuations in the semi-arid region of the tropics. *Atmospheric research*, 224, 52-64.

Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., ... & Wijermans, N. (2017). A framework for mapping and comparing behavioral theories in models of social-ecological systems. *Ecological economics*, 131, 21-35.

Seife, T. K. (2021). The impact of climate change on agriculture and food security in the greater horn of Africa. *Politikon*, 48(1), 98-114.

Singh, R. K., Zander, K. K., Kumar, S., Singh, A., Sheoran, P., Kumar, A., ... & Garnett, S. T. (2017). Perceptions of climate variability and livelihood adaptations relating to gender and wealth among the Adi community of the Eastern Indian Himalayas. *Applied Geography*, 86, 41-52.

Solomon, N., Birhane, E., Gordon, C., Haile, M., Taheri, F., Azadi, H., & Scheffran, J. (2018). Environmental impacts and causes of conflict in the Horn of Africa: *A review. Earth-science reviews*, 177, 284-290.

Tan, G., Ayugi, B., Ngoma, H., & Ongoma, V. (2020). Projections of future meteorological drought events under representative concentration pathways (RCPs) of CMIP5 over Kenya, East Africa. *Atmospheric Research*, 246, 105112.

Tessema, K. B., Haile, A. T., & Nakawuka, P. (2021). Vulnerability of the community to climate stress: An indicator-based investigation of the Upper Gana watershed in the Omo Gibe basin in Ethiopia. *International Journal of Disaster Risk Reduction*, 63, 102426.

Thomas, K., Hardy, R. D., Lazrus, H., Mendez, M., Orlove, B., Rivera-Collazo, I., ... & Winthrop, R. (2019). Explaining differential vulnerability to climate change: A social science review. *Wiley Interdisciplinary Reviews: Climate Change*, 10(2), e565.

UNDP, (2020). Sustainable Development Goals. United Nations Development Programme, New York, NY, USA.

USAID, (2016). Ethiopia Country Development Cooperation Strategy 2016-2021. United States Agency for International Development, Washington, DC, USA.

Van Weezel, S. (2019). On climate and conflict: Precipitation decline and communal conflict in Ethiopia and Kenya. *Journal of Peace Research*, 56(4), 514-528.

Weldegebriel, Z.B., & Amphune, B.E. (2017). Livelihood resilience in the face of recurring floods: empirical evidence from Northwest Ethiopia. *Geoenvironmental Disasters*,4, 1-19.

WMO, (2020). State of the Climate in Africa, 2020. World Meteorological Organization, Geneva, Switzerland.

World Bank, (2016). World Bank Annual Report 2016. World Bank, Washington, DC, USA.

Zandalinas, S. I., Fritschi, F. B., & Mittler, R. (2021). Global warming, climate change, and environmental pollution: recipe for a multifactorial stress combination disaster. *Trends in Plant Science*, 26(6), 588-599.

Zeleke, G., Teshome, M., & Ayele, L. (2023). Farmers' livelihood vulnerability to climate-related risks in the North Wello Zone, northern Ethiopia. *Environmental and Sustainability Indicators*, 17, 100220.

Zeleke, T., Beyene, F., Deressa, T., Yousuf, J., & Kebede, T. (2022). Smallholder farmers' perception of climate change and choice of adaptation strategies in East Hararghe Zone, Eastern Ethiopia. *International Journal of Climate Change Strategies and Management*.

Chapter Two

Local scale climate variability and trends in a vulnerable rural landscape, northwest Ethiopia[1]

Abstract

This study analyses local-scale climate variability and trends in northwest Ethiopia, covering three food-insecure and vulnerable districts: Lay Gaynt, Tach Gaynt, and Simada. We examined temperature and rainfall data on 4 × 4 km grids. The coefficient of variation and standardized anomaly index were used to assess rainfall and temperature variability. As a result, annual and seasonal rainfall show high inter-annual variability, except for *Kiremt*, which shows a moderate coefficient of variation. The proportion of negative anomalies ranges from 39% (Lay Gayint) to 65% (Simada) over the observation period. Moreover, trend analysis was conducted using the Mann-Kendall (MK) and Innovative Trend Analysis (ITA) tests. The MK test for annual rainfall exhibited a significant rising trend for the Lay Gayint and Tach Gayint districts. The ITA for annual and seasonal rainfall indicated positive trends for Lay Gayint and Tach Gayint, while negative trends were observed in Simada. The ITA and MK tests showed similar increasing tendencies in seasonal and annual temperatures. The MK technique revealed positive patterns in the 28-time series and negative patterns in the 20-time series for monthly, seasonal, and annual rainfall data, whereas the ITA method revealed positive trends in the 23-time series and negative trends in the 25-time series. The results of this study are helpful for local development planning that should consider current and possible future climate patterns.

Keywords: MK, ITA, Trend, Rainfall, and Temperature, Ethiopia.

[1] Likinaw, A., Alemayehu, A., & Bewket, W. (2023). (2022). Local-scale climate variability and trends in a vulnerable rural landscape, northwest Ethiopia. *Malaysian Journal of Tropical Geography* (MJTG), 48(1), 19-44.

1. Introduction

Climate change is one of the most pressing global concerns of the twenty-first century (Abidoye and Odusola, 2015). Developing countries are particularly susceptible as their principal economic activities rely on climate-sensitive products with limited adaptability (Mesfin et al., 2020). Weather and climate extremes affect most Sub-Saharan African countries, including Ethiopia, causing low agricultural production (Amare and Simane, 2017). Ethiopia's climate has evolved in recent decades, with temperatures rising by 0.4℃ in the last four decades (Gebrechorkos et al., 2019). Since the 1990s, Ethiopia has experienced a decrease in rainfall (Abebe, 2017), significantly influencing the country's agricultural production and water availability.

The El Niño Southern Oscillation (ENSO) and an increase in anthropogenic activities significantly contributed to the reported variations in climate across the country (Diro et al., 2012; Rowell et al., 2015). According to recent literature (Dubache et al., 2019; Minda et al., 2018), the rainfall patterns over East Africa are primarily determined by inter-oceanic processes and large-scale atmospheric phenomena. High-pressure systems in the Indian and Atlantic oceans are primarily responsible for the variability in rainfall over East Africa. Due to the variations in altitude and terrain, determining historical climatic patterns and future estimates for Ethiopia can be challenging (Philip et al., 2018). The country's rainfall patterns are quite diverse, with some places seeing only one rainy season while others have two or more (Ayalew et al., 2012). Recent studies on multidecadal climate variability in East Africa, particularly Ethiopia, have yielded contradictory results. Various studies have found decreasing annual rainfall in various sections of Ethiopia, whereas others have found rising rainfall patterns. For instance, Alemayehu and Bewket (2017) found rising trends in annual and *Kiremt* rainfall but a significantly declining trend in *Belg* rainfall. *Kiremt* is the primary rainy season for most parts of Ethiopia, covering the period from June to September, while *Belg* is the short rainy period for most parts of Ethiopia from March to May. Asfaw et al. (2018) reported significant declining trends in *Kiremt* and annual rainfall but a slight decline in *Belg* rainfall. In the northern highlands of Ethiopia, Miheretu (2020) observed an increasing trend in *Kiremt* rainfall, but *Belg* rainfall exhibited a declining trend. Moreover, Gebrehiwot et al. (2019) suggested decreasing Kiremt and Belg season rainfall trends. Therefore, it is critical to conduct trend and variability analyses of rainfall and temperature patterns to accurately predict climate extremes and take appropriate adaptation and mitigation actions.

Methodologically, previous studies used parametric techniques such as the t-test and linear regression in trend identification studies (Benti and Abara, 2019; Hundera et al., 2019). These techniques, however, have limitations because they usually require distributed data. Other researchers applied non-parametric techniques like the Mann-Kendall (MK) test without considering serial association in the data set (Ayalew et al., 2012; Chala et al., 2020; Miheretu, 2020). For these reasons, several studies have suggested applying a Modified Mann-Kendall (MMK) test, which is efficient in checking auto-correlation (Hamed and Rao 1998). Moreover, Sen (2012) suggested the Innovative Trend Analysis (ITA) test, which does not necessitate assumptions like non-normality, collinearity, or length of time series data. Therefore, the present study applies the ITA technique to local climate data analysis, which has not been conducted before in the study districts, and compares the results of the ITA with those of the MMK test.

By combining the strengths of both ITA and MK trend tests, researchers can compensate for the limitations of each method. ITA excels at capturing non-linear trends and providing trend magnitude estimates, while MK trend test accommodates non-linearity, considers autocorrelation, and provides formal statistical significance assessments. This combined approach enhances the reliability and robustness of trend analysis in climate research, improving our understanding of long-term climate patterns and changes. This study is helpful for context-specific planning of climate risk management and local development in the study area, where agriculture depends on rainwater and constitutes almost the sole means of subsistence for the population.

2. Materials and methods

2.1. The study sites

The study site includes three districts (*woredas* in *Amharic*): Lay Gayint, Tach Gayint, and Simada in the South Gondar Zone Administration (Figure 2.1). Lay Gayint is in the *High Dega* (3200–3700 m a.s.l) agro-ecological zone, and Tach Gayint and Simada are in the *Dega* (2300–3200 m a.s.l) and *Woyna Dega* (1500–2300 m a.s.l) agro-ecological zones, respectively (Hurni et al., 2016). The area is a heavily degraded part of the country because of a long history of settlement and cultivation, overgrazing, and other socioeconomic and policy-related factors (Getachew, 2017). Extensive farming and shrubland dominate the current land cover.

The main rainy season (*Kiremt*) occurs from June to mid-September, and the short rainy season (*Belg*) occurs from March to May (Rosell, 2011). The short rainy season is inconsistent with crop failures, making *Belg* harvesting difficult (Rosell, 2011). The study area lacks food due to

late onset, early termination, and poor *Belg* performance. Furthermore, steep topography and barren mountains accelerate runoff, resulting in land degradation and, as a result, low production. Hence, the area is part of the country's drought-stricken and food-insecure areas. The farming system is a mixed crop-livestock characterized by intensive and continuous cropping. Barley (*Hordium vulgare*), wheat (*Triticum aestivum*), maize (*Zea mays*), and tef (*Eragrostis tef*) are the main cereals grown in the area. Cattle, sheep, goats, and equines are the dominant livestock raised. The benefit of livestock to people's livelihoods is limited due to the frequency of livestock diseases (Getachew, 2017). Crop production is affected by erratic rainfall, poor soil fertility, small per capita landholding, poor per acre land, and limited use of improved agricultural technologies (Ayalew et al., 2012). Low agricultural productivity is further affected by its dependence on unreliable rainfall. Overall, most households do not harvest sufficient food and depend largely on food assistance or are supported by the PSNP. According to information from the South Gondar Zone Administration office, five districts benefited from the PSNP, including the study area (Libokemkem, Ebnat, Simada, Lay Gayint, and Tach Gayint). Non-farm livelihood activities are not well established due to inadequate access to infrastructure, ineffective and inefficient agricultural marketing systems, and limited access to institutional support services, to name a few.

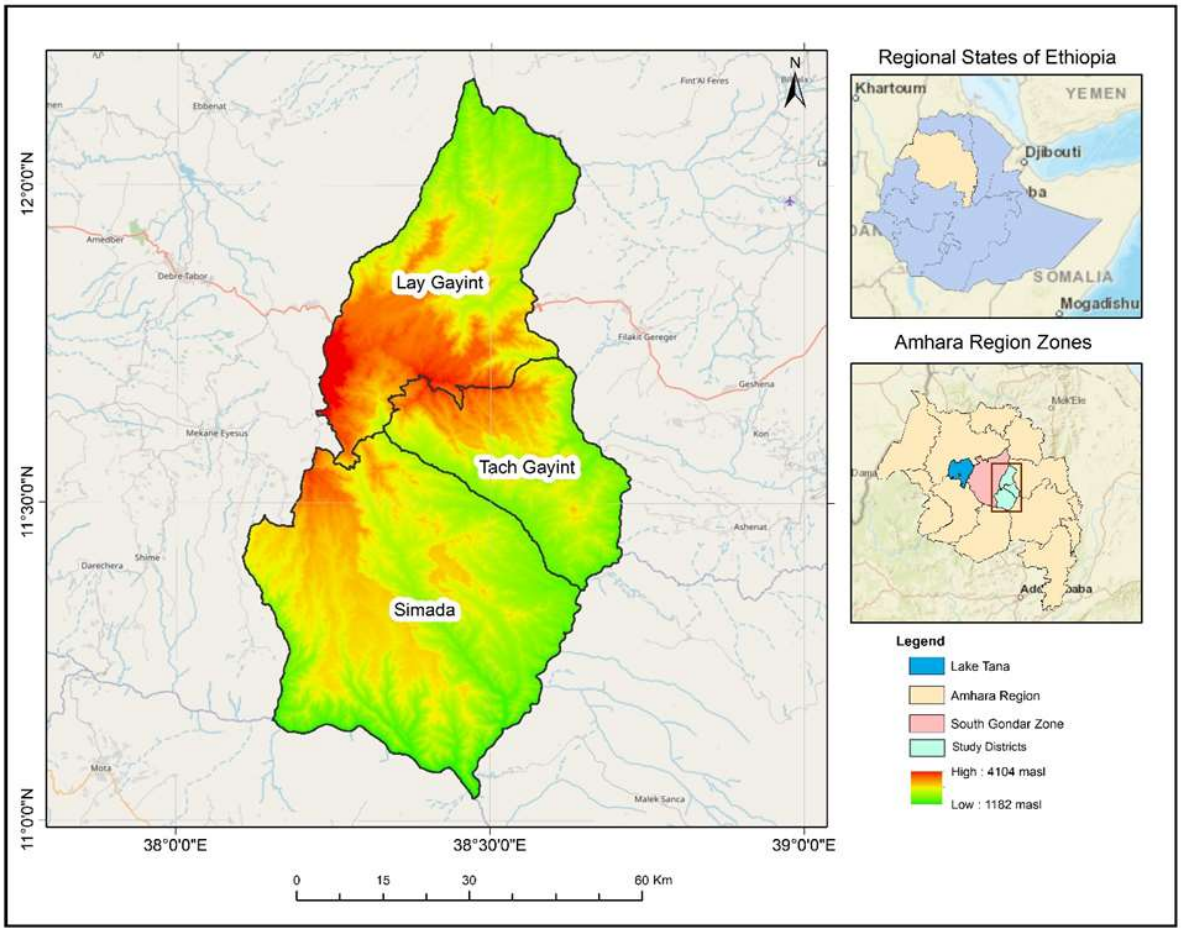

Figure 2. 1. Location map of the study area

2.2. Data type and source

The study used temperature and rainfall data extracted from the Enhancing National Climate Services (ENACTS) dataset obtained from Ethiopia's National Meteorological Agency (NMA). ENACTS is a 4 × 4 km gridded dataset reconstructed from meteorological satellites and weather stations from 1981 to 2018. ENACTS has been calibrated and validated, revealing robust performance when weighed at station sites in Ethiopia (Dinku et al., 2018). Because ENACTS data were chosen for analysis, (1) there are many missing values in station datasets (Asfaw et al., 2018), and (2) most stations are new and do not have enough data records to perform trend analysis (Alemayehu and Bewket, 2017; Asfaw et al., 2018), and (3) stations across the study area are scarce (Alemayehu and Bewket 2017) and do not cover all of the study sites.

2.3. Data preparation and quality control

Daily data were averaged monthly, seasonally, and annually as needed for each analysis. RHtestsV3 and RHtests dlyPrcp software tools were used to detect and account for erroneous shifts in climatic data series. Since these tests indicated no major change points or

homogeneities requiring mean adjustments, the original data set was used for further analysis. Serial autocorrelation was estimated using the autocorrelation function (acf package) in R statistical software (Kafadar et al., 2006).

2.4. Methods of data analysis

Rainfall and temperature variability was assessed by calculating coefficients of variation (CVs) at various time scales and mapping the CVs to examine their spatial patterns. Annual and seasonal rainfall and temperature variations were assessed using the standardized anomaly. The one-way ANOVA was applied to check whether the mean rainfall and temperature differences across the study districts were significantly different. Trend analyses were performed using the MK and ITA trend test techniques.

2.4.1. Innovative Trend Analysis (ITA)

The ITA technique was first suggested by Sen (2012) for the detection of time series trends. Unlike the MK trend test, the ITA technique is not affected by serial correlation or data length. It is simple to grasp and compute, and the results can be visually represented. In this method, the first step involves dividing the data into two halves and arranging them in increasing order. For example, in the present study, there were 38 rainfall and temperature observations (1981–2018); hence, the first 19 observations were placed in the first half, and the following 19 observations were placed in the second half of the data. In the second procedure, the first half of the sub-series is placed on the X-axis of a Cartesian coordinate system, while the second half is placed on the Y-axis, as indicated in (Figure 2.2). If the data points in a scatter plot fall above or below the bisector line at 1:1 (45^0), the time series has an upward or downward trend (Sen, 2012). There would be no sign of a pattern if the data points were collected on the 1:1 line. This paper applied a 10% confidence band to visualize the distance of points from the no-trend line. The purpose of this band is to enable the user to identify the distance between the points and the line of no-trend with no statistical interpretation (Caloiero, 2018; Nisansala, 2020).

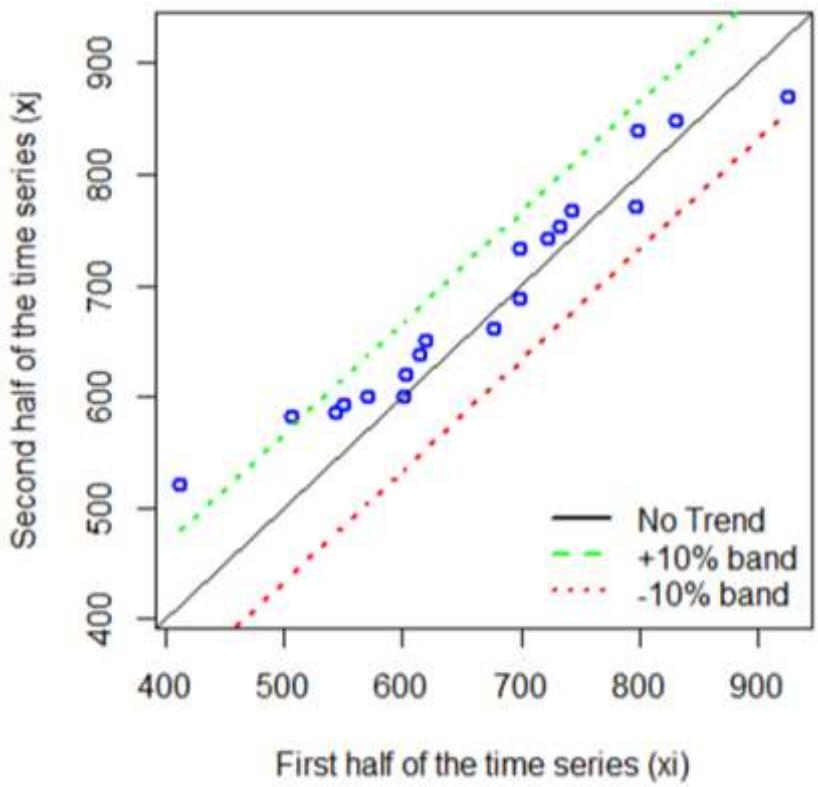

Figure 2. 2. Illustration of the ITA technique (Sen, 2012).

The 1:1 line is represented by the central black solid line (trendless). Broken green and red lines indicate confidence bands at +10% and -10%, respectively. A significant decreasing trend is shown by points below -10%, whereas points above +10% show a significant increasing trend.

The actual value of the inconsistency between the y and x values is the distance from the 1:1 line (Nisansala, 2020; Wu and Qian, 2017), and the ITA trend pointer is derived by:

$$D = \frac{1}{n}\sum_{i=1}^{n} 10\frac{(y_i - x_i)}{\bar{x}} \quad (1)$$

Where *D* is the trend, a positive *D* number represents an increasing trend, a negative *D* number represents a decreasing trend, and *n* denotes the number of subseries and the first subseries' average. For comparison with the MK test, Equation (1) uses a multiplication factor of ten (Sen, 2012).

2.4.2. Mann-Kendall (MK) test

The MK (Kendall, 1975; Mann, 1945) is a non-parametric test that can be used with data that is not normally distributed. Because the statistic is based on the sign of differences rather than the actual values of the random variable, it is less affected by outliers. The trend statistic (S) of MK is obtained as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=k+1}^{n} \text{sgn}(X_j - X_k) \quad (2)$$

Where X_k and X_j are time-series data values k and j ($j > k$), n is the value of data points, and $(X_j - X_k)$ is given as:

$$\text{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if} \quad (x_j - x_i) > 0 \\ 0 & \text{if} \quad (x_j - x_i) = 0 \\ -1 & \text{if} \quad (x_j - x_i) < 0 \end{cases} \quad (3)$$

The variance of Mann-Kendal's test is computed as:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)}{18} \quad (4)$$

Where $q\ is$ the number of tied groups and t_p is the number of data points in the p^{th}group. the summary of Equation (4) can be omitted if there are no ties.

The values of S and (S) are used to calculate the Z statistic:

$$Z = \begin{cases} \frac{S-1}{V_S} & \text{for} \quad S > 0 \\ 0 & \text{for} \quad S = 0 \\ \frac{S+1}{V_S} & \text{for} \quad S < 0 \end{cases} \quad (5)$$

The MK test, in contrast, ignores this sequential correlation (Hamed and Rao, 1998). Since sequential association increases the possibility of identifying a notable trend when there is no significant trend, it might lead to a misunderstanding of the results. Therefore, this study uses the modified MK test, which considers all sequential correlations as implemented in the R-software version 3.6.1 (command *modifiedmk*). When sequential autocorrelation was insignificant, a conventional set of tests (command *mkktest*) was employed. However, when it was significant, the test was done using a technique described by Hamed (2009). This technique applies a bias correction when utilizing the same R package's pre-whitening (*bcpw*) tool.

2.4.3. Sen's Slope Estimator (SSE)

Sen's estimator frequently estimates the extent of the trend because the MK test only detects trends (increasing or decreasing) (Sen, 1968). The extent of the trend is computed as follows:

$$Q_i = \frac{X_j - X_k}{j - k}, \quad \text{for} \quad i = 1, 2, \ldots, N, \tag{6}$$

Where $X_j \ and \ X_k$ are data at time $j \ and \ k \ (j > k)$, respectively. The median of N values of Q_i is shown as Sen's slope, which is computed as:

$$Q_i = \begin{cases} T_{\frac{N+1}{2}}, & \text{if } N \text{ is odd,} \\ \frac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right), & \text{if } N \text{ is even.} \end{cases} \tag{7}$$

When the number of N slope observations is odd, the Sen's estimator is obtained as "Qmed" = (N+1)/2, and for even times of observations, the slope is computed as "Qmed" = [(N/2) + ((N+1)/2)]. A positive slope indicates an upward trend, whereas a negative slope indicates a downward trend. There is no trend if the slope is 0.

3. Results and discussion

3.1. Rainfall

3.1.1. Temporal rainfall variability

The average annual rainfall was 971.3 mm, with a spatial variability of 788.8 mm in Simada and 1096.2 mm in Lay Gayint. *Kiremt* rainfall accounts for the largest portion of the study area (> 75%), followed by *Belg* rainfall, which contributes about 13% of the annual rainfall (Table 2.1). The coefficient of variability (CV) for annual rainfall ranged from 20.6% in Tach Gayint to 25.2% in Simada. *Belg* rainfall showed a high CV compared to *Kiremt* rainfall. Variability in seasonal rainfall has implications for farming practices since rainfall's onset, duration, and offset determines the amount and quality of agricultural produce. The result agrees with Alemayehu and Bewket's (2017; Asfaw et al., 2018) findings, who reported more variability in *Belg* rainfall than Kiremt rainfall in their respective study areas.

Table 2. 1. Patterns of seasonal and annual rainfall

District	Parameter	Rainfall (mm)	Contribution to annual (%)	Coefficient of variation (CV, %)
Lay Gayint	Annual	1096.0	-	22.2
	Kiremt	746.4	76.1	15.4
	Belg	143.1	13.1	51.2
Tach Gayint	Annual	820.2	-	20.6
	Kiremt	622.7	78.2	14.9
	Belg	128.5	12.2	49.3
Simada	Annual	788.8	-	25.2
	Kiremt	596.8	73.2	17.5
	Belg	123.1	13.2	44.2

Note: CV< 20% = low variability; 20 %< CV<30% = medium variability; and CV>30% = high variability (Alemu and Bawoke, 2020).

Figure 2.3 illustrates normalized seasonal and annual rainfall anomalies from long-term averages from 1981 to 2018. The percentage of negative deviations varies from 39% (Lay Gayint) to 65% (Simada) throughout the observation. Anomalies in seasonal rainfall exhibit similar distributions. Annual rainfall shows negative anomalies between 1981 and 1992 throughout the study area. Positive anomalies for *Kiremt* rainfall are observed in Simada from 1986 to 1996, except for 1987 and 1995. However, for 2003, 2005, 2006, and 2007, *Kiremt* rainfall showed negative anomalies from 1997 to 2013. *Kiremt* rainfall showed positive deviations for 1988-1995, except for 1987 in Tach Gayint. Likewise, positive anomalies in *Kiremt* rainfall were observed in Lay Gayint from 1988 to 1996 and 2007 to 2015, except for 2013. *Belg* rainfall showed high inter-annual variation throughout the observation. Negative and positive deviations for *Belg* rainfall accounted for 42% and 58% of the total in Lay Gayint and Tach Gayint, respectively. On the other hand, in Simada, positive and negative anomalies for *Belg* rainfall accounted for 34% and 66%, respectively, throughout the observation. Most of the historical drought occurrences in the study area correlate to the country's documented historical droughts.

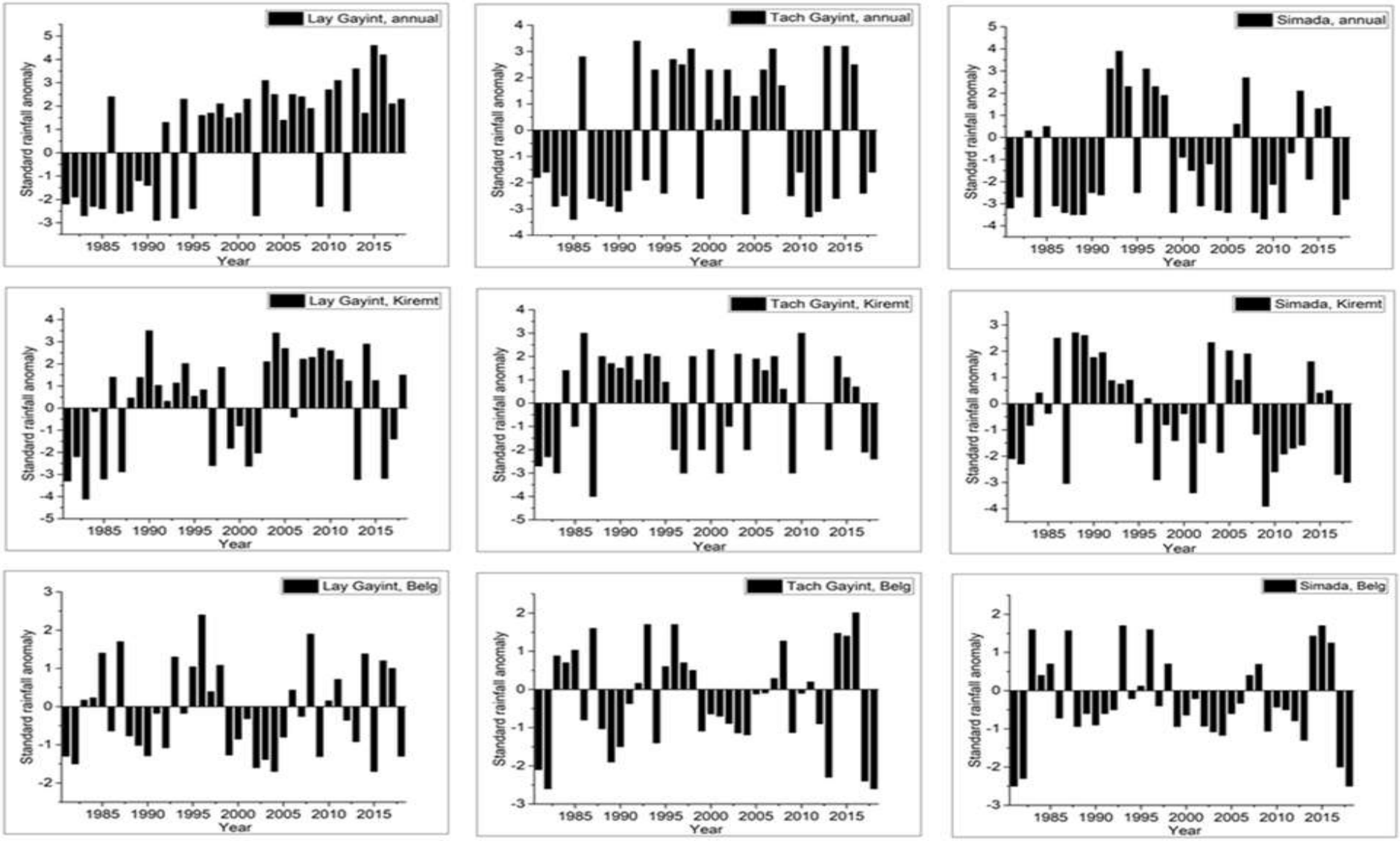

Figure 2. 3. Annual and seasonal rainfall anomalies.

3.1.2. Rainfall trends

The MK and ITA techniques examine seasonal, annual, and rainfall trends (Table 2.2). Based on the MK test, annual rainfall exhibited a significant increasing trend (7.9 mm/year) in Lay Gayint at $p < 0.01$ level and an increasing trend (7.0 mm/year) in Tach Gayint at $p < 0.1$ level but a non-significant decreasing trend in annual rainfall was observed in Simada. *Kiremt* and *Belg* rainfall at the seasonal level presented a non-significant upward trend in Lay Gayint and Tach Gayint. However, *Kiremt* and *Belg* rainfall revealed a non-significant downward trend in Simada. Similarly, a downward trend in *Kiremt* and *Belg* rainfall was informed by Alemayehu and Bewket (2017). Coupled with the long dry period from October to February (*Bega* season), the declining trend of *Belg* rainfall affects water and fodder availability for livestock in the study area.

MK and SSE indicated that July (3.4 mm/year) and August (2.9mm/year) rainfall exhibited a statistically significant increasing trend in Lay Gayint at $p < 0.01$ level. At $p < 0.01$ level, rainfall in Tach Gayint significantly increased in August (1.9 mm/year) and November (0.4 mm/year). September rainfall in Simada (-0.9 mm/year) showed a significantly decreasing trend at $p < 0.01$ level over the study period.

Table 2. 2. The MK and ITA trend test values of rainfall

	Lay Gayint			Tach Gayint			Simada		
Month	Z_{MK}	β	*D*	Z_{MK}	β	*D*	Z_{MK}	β	*D*
January	-0.46	0.00	-1.29	-0.63	-0.00**	-1.04	-0.83	-0.00	-2.72
February	-1.20	-0.10	-2.66	-1.77	-0.16	-4.45	-1.64	-0.03	-3.01
March	0.05	0.03	-0.32	-0.57	-0.16	-0.67	-0.42	-0.11	-0.65
April	0.54	0.25	0.16	0.50	0.18	-1.06	-1.10	-0.34	-2.32
May	0.88	0.53	0.02	0.70	0.46	0.02	0.21	0.16	-1.10
June	1.08	0.75	0.77	1.26	0.60	-0.75	0.20	0.11	-1.42
July	2.13	3.40**	1.66	1.45	1.82	1.15	-0.21	-0.37	-1.01
August	2.43	2.98**	2.74	1.96	1.90**	1.70	0.95	1.15	0.12
September	1.30	0.62	1.56	-0.15	-0.04	0.04	-2.23	-0.90**	-1.73
October	-0.01	0.00	-3.09	0.26	0.05	-1.63	0.06	0.03	-2.30
November	1.78	3.44	3.05	2.21	0.36**	3.77	1.76	0.30	2.67
December	-0.60	-0.01	-0.81	-0.19	-0.00	-0.33	-0.24	-0.00	-3.11
Belg	1.43	1.56	1.90	0.12	0.21	0.77	-0.31	-0.37	-1.48
Kiremt	1.88	7.45	1.72	0.77	1.95	0.57	-1.33	-3.08	-1.22
Annual	2.73	7.89***	1.02	2.47	7.00**	1.13	-0.47	-0.78	-0.52

, and * are significant at alpha values of 0.05 and 0.01, respectively.
Z_{MK}, standardized MK; β, Sen's slope; *D*, trend indicator of ITA.

Table 2.2 presents a trend analysis using the ITA technique. It is shown that mean seasonal and annual rainfall mostly exhibited positive *D* values. The majority of annual rainfall data at Lay Gayint and Tach Gayint fell beyond the 1:1 line, as shown in Figure 2.4, indicating an increasing trend within the +10% confidence band, but most of the data points in Simada fell below the 1:1 line, showing a downward trend in annual rainfall within the -10% confidence band throughout the observation. For the *Kiremt* rainfall, most of the data points were above the +10% confidence band parallel to the 1:1 line in Lay Gayint and Tach Gayint, indicating a significant increasing trend, whereas most of the data points were within the +10% confidence band parallel to the 1:1 line, showing an increasing tendency for *Kiremt* rainfall for Simada. *Belg* rainfall indicated a downward trend in Tach Gayint and Simada but an unclear trend in Lay Gayint.

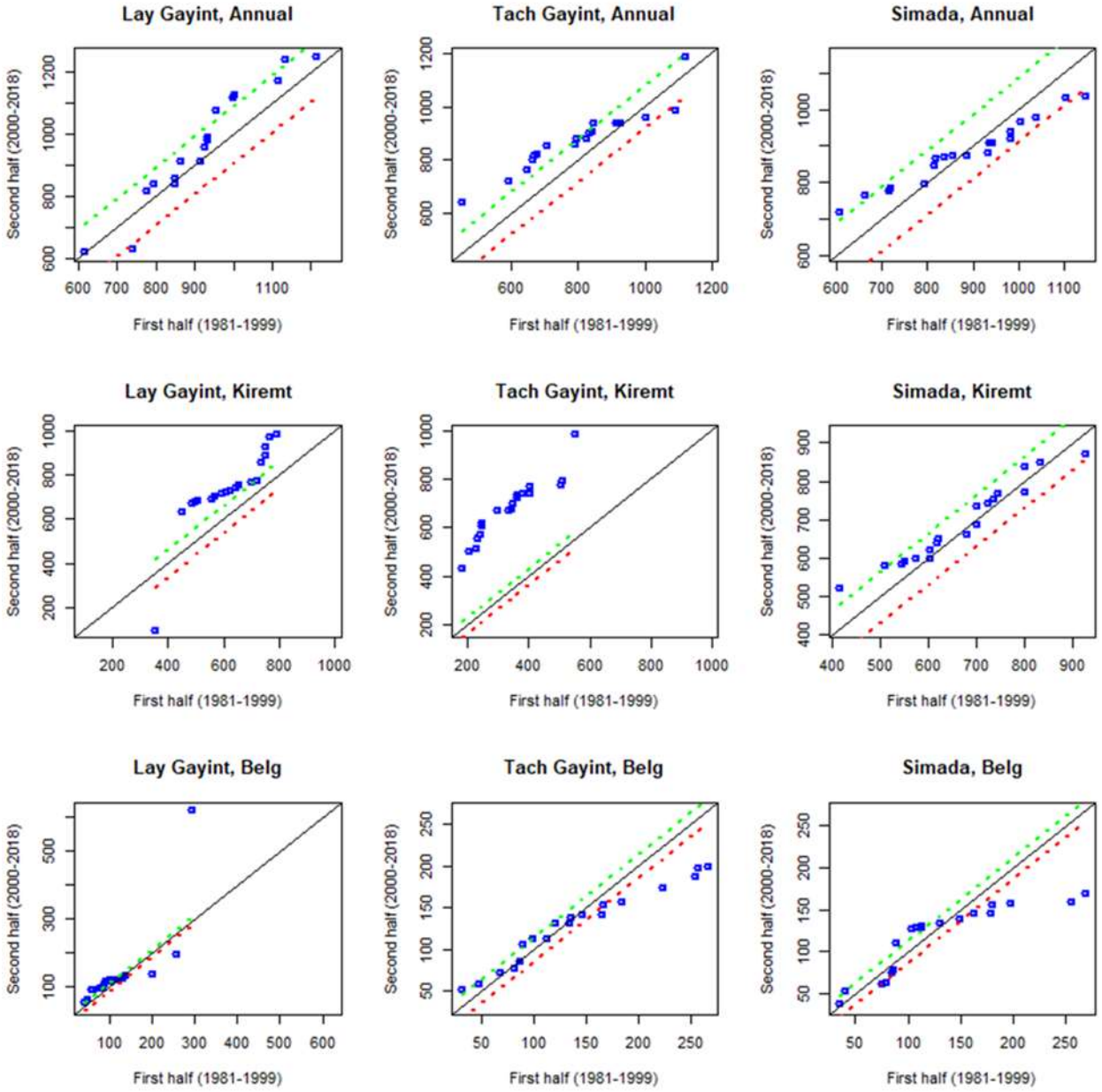

Figure 2. 4. Annual and seasonal rainfall trends using the ITA technique

The results of ITA for mean monthly rainfall are shown in (Figures 2.5–2.7). A significant increasing trend was found in Lay Gayint in June, July, August, and September (*Kiremt* season) and November, but March, April, and May (*Belg* season) showed mixed increasing and decreasing trends (Figure 2.5). In Tach Gayint, a negative trend was found for all months except June, July, August, and November (Figure 2.6). In Simada, all months showed decreasing trends except June, August, and November (Figure 2.7).

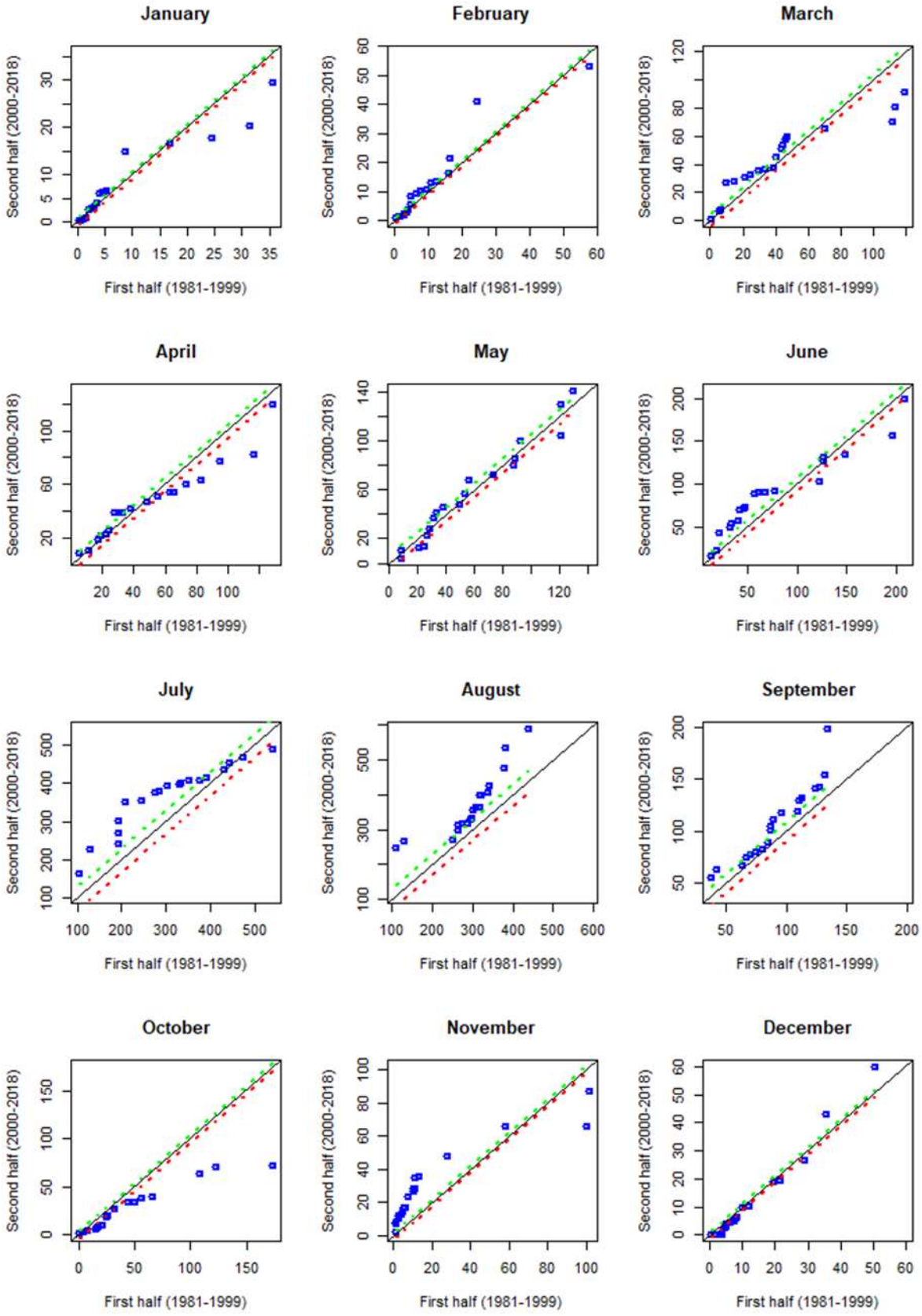

Figure 2. 5. Mean monthly rainfall trends in Lay Gayint using the ITA method.

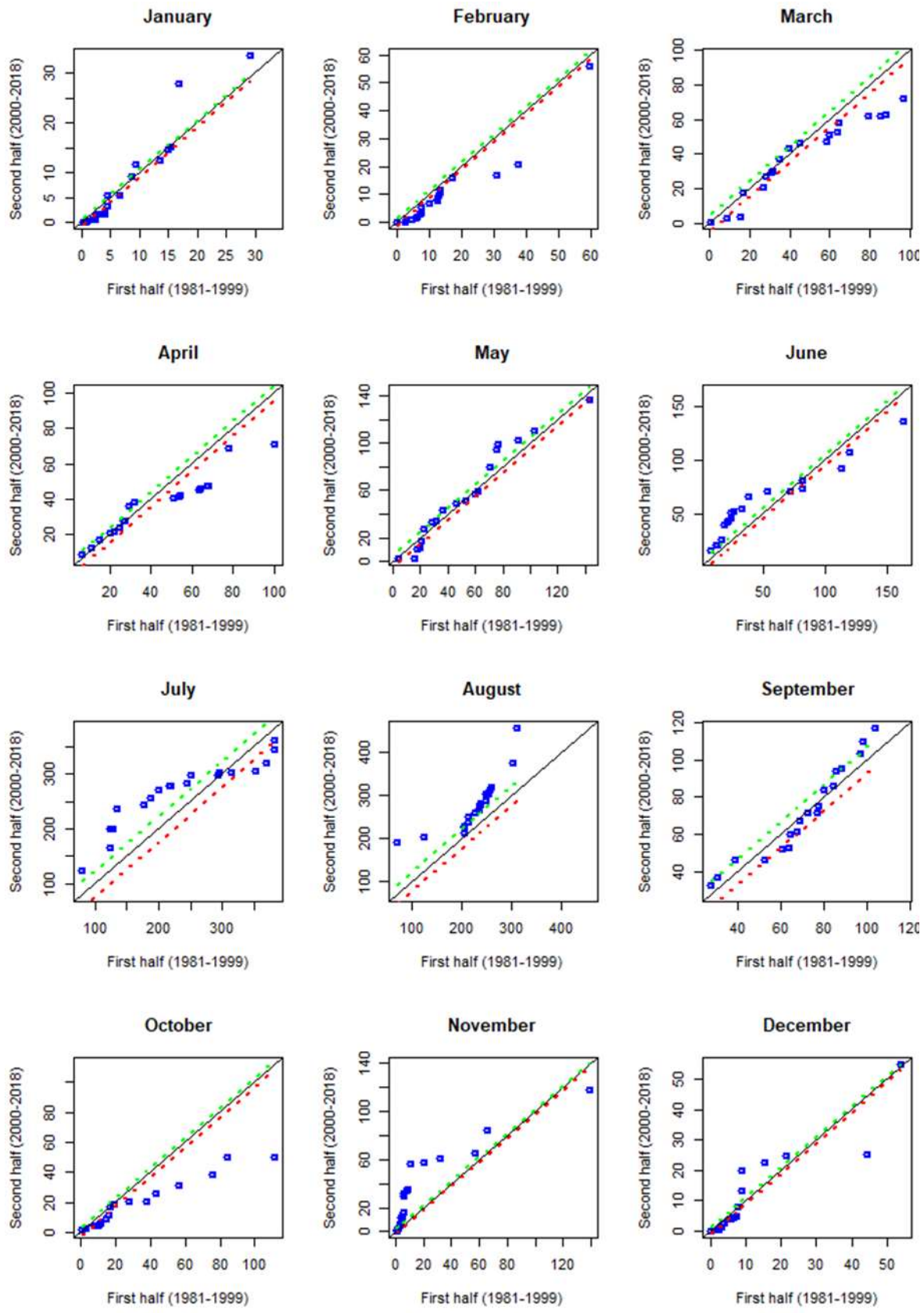

Figure 2. 6. Mean monthly rainfall trends in Tach Gayint using the ITA method.

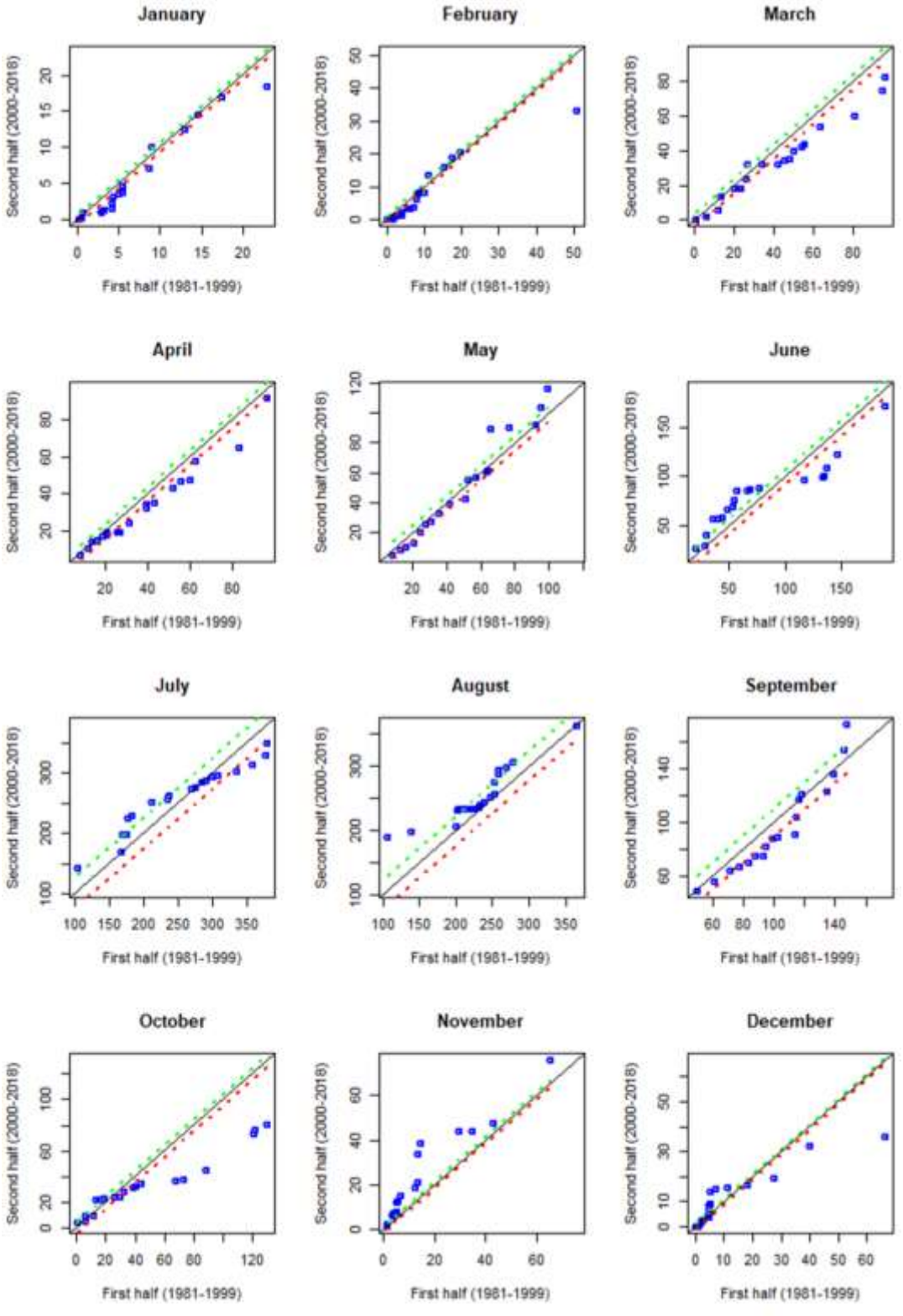

Figure 2. 7. Mean monthly rainfall trends in Simada using the ITA method

3.1.3. Spatial variability of rainfall

Seasonal and annual rainfall showed considerable spatial variation. The western part receives more rainfall than the eastern part (Figure 2.8). Lay Gayint gets 760 to 860mm of yearly rainfall

in 46% of the area. Annual rainfall ranges from 861 to 961mm in 30% of the area and 962-1200mm in the remaining 24%, respectively. Tach Gayint receives annual rainfall from 760 to 860mm in about 78% of the area, while the remaining 22% receives annual rainfall from 861 to 961mm. Simada receives annual rainfall ranging from 760 to 860mm in approximately 82% of the area. Over 48% of Lay Gayint receives *Kiremt* rainfall between 550 and 750mm. *A Kiremt* rainfall ranging from 550 to 750mm falls on a large portion of Tach Gayint (85%). More than 89% of Simada receives *kiremt* rainfall between 550 and 750mm. In Tach Gayint, nearly 57% of the area receives *Belg* rain between 40 and 100mm. A large part of Simada (68%) receives *Belg* rainfall between 40 and 100mm. One-way ANOVA showed that annual and *kiremt* rainfall significantly varied at a $p < 0.001$ level among the three districts. Tukey's post-hoc mean evaluation indicated that mean annual rainfall in Lay Gayint was higher by 243 mm than in Tach Gayint and by 204mm in Simada at a $p < 0.01$ level. As shown in Table 2.3, the amount of *Kiremt* rainfall in Lay Gayint is 220mm higher than in Tach Gayint and 172mm in Simada, at $p < 0.01$ and $p < 0.01$ levels, as shown in (Table 2.3), whereas the mean annual and *Kiremt* rainfall did not show significant variation between Tach Gayint and Simada.

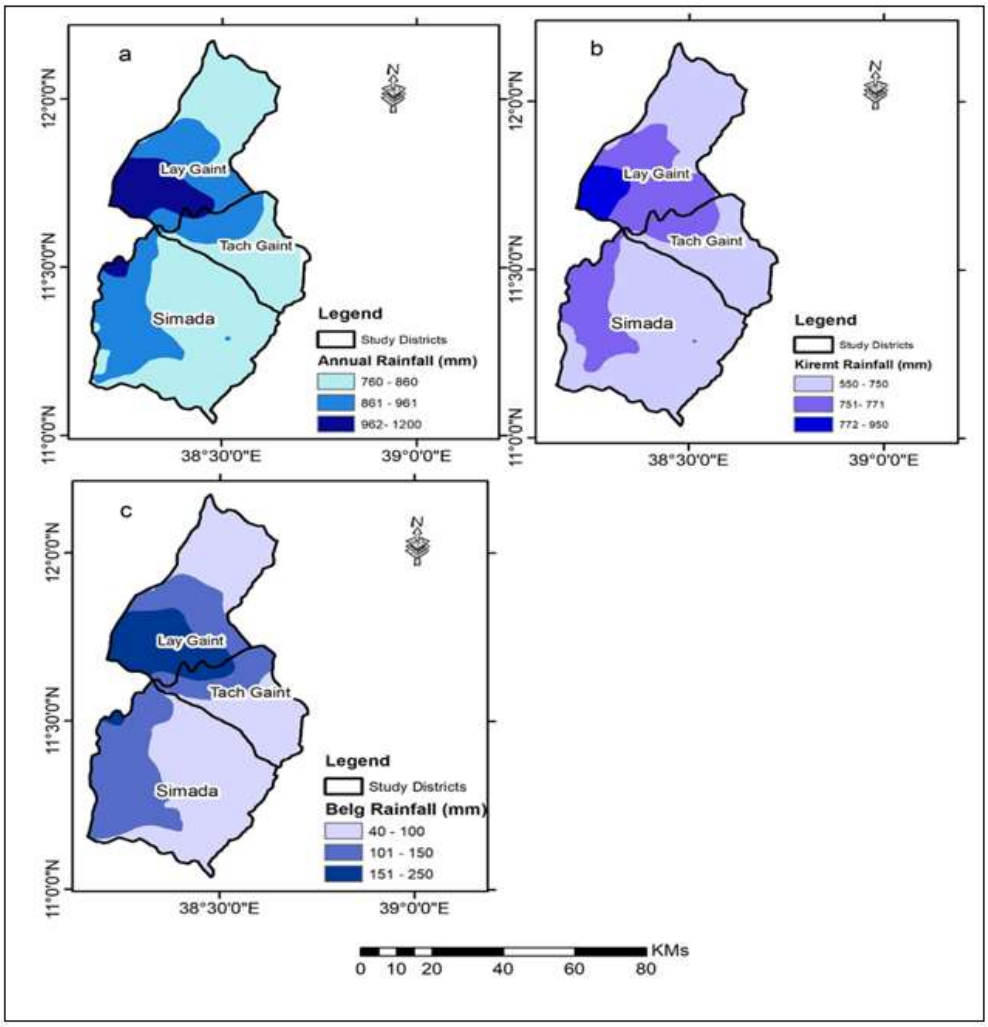

Figure 2. 8. Spatial distribution of rainfall.

Table 2. 3. ANOVA and Tukey's post hoc comparison test. (I) and (J) refer to the two districts being compared in each case.

		Mean difference (I-J)	
(I) District	(J) District	Annual rainfall	Kiremt rainfall
Lay Gayint	Tach Gayint	243.66***	220.83***
	Simada	204.23***	172.21**
Tach Gayint	Simada	-39.42	-48.62
ANOVA F-ratio		22.91***	20.35***

** and *** are significant at alpha values of 0.05 and 0.01, respectively.

The spatial distribution of coefficient variation (CV) of rainfall is shown in (Figure 2.9). Annual and *Kiremt* rainfall exhibited relatively similar coefficients of variation (CV) across the study area. The CV is generally low across the area as rainfall is relatively abundant in the Kiremt season. The CV is the smallest in the high-elevation district (Lay Gayint).

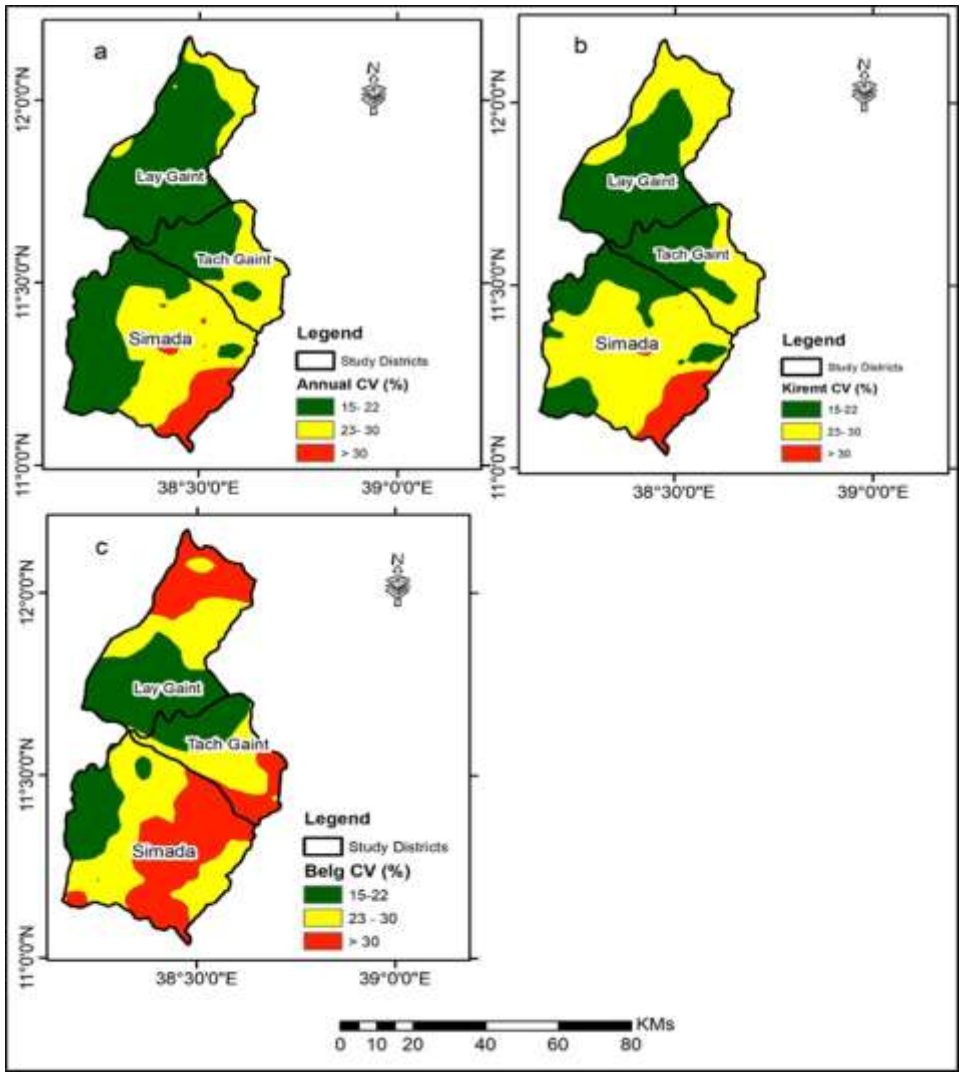

Figure 2. 9. Spatial distribution of the coefficient of variation for rainfall.

3.2. Temperature

3.2.1. Temporal variability of temperature

The mean annual temperature ranges from 14℃ in Lay Gayint to 18℃ in Simada (Figure 2.10). The highest monthly temperature for Lay Gayint is 22℃ (March), and its lowest is 6℃ (December). The highest and lowest values for Simada are 25℃ (March) and 8℃ (December), respectively. The highest temperature recorded for Tach Gayint is 22℃ (March), and the lowest is 6℃ (December).

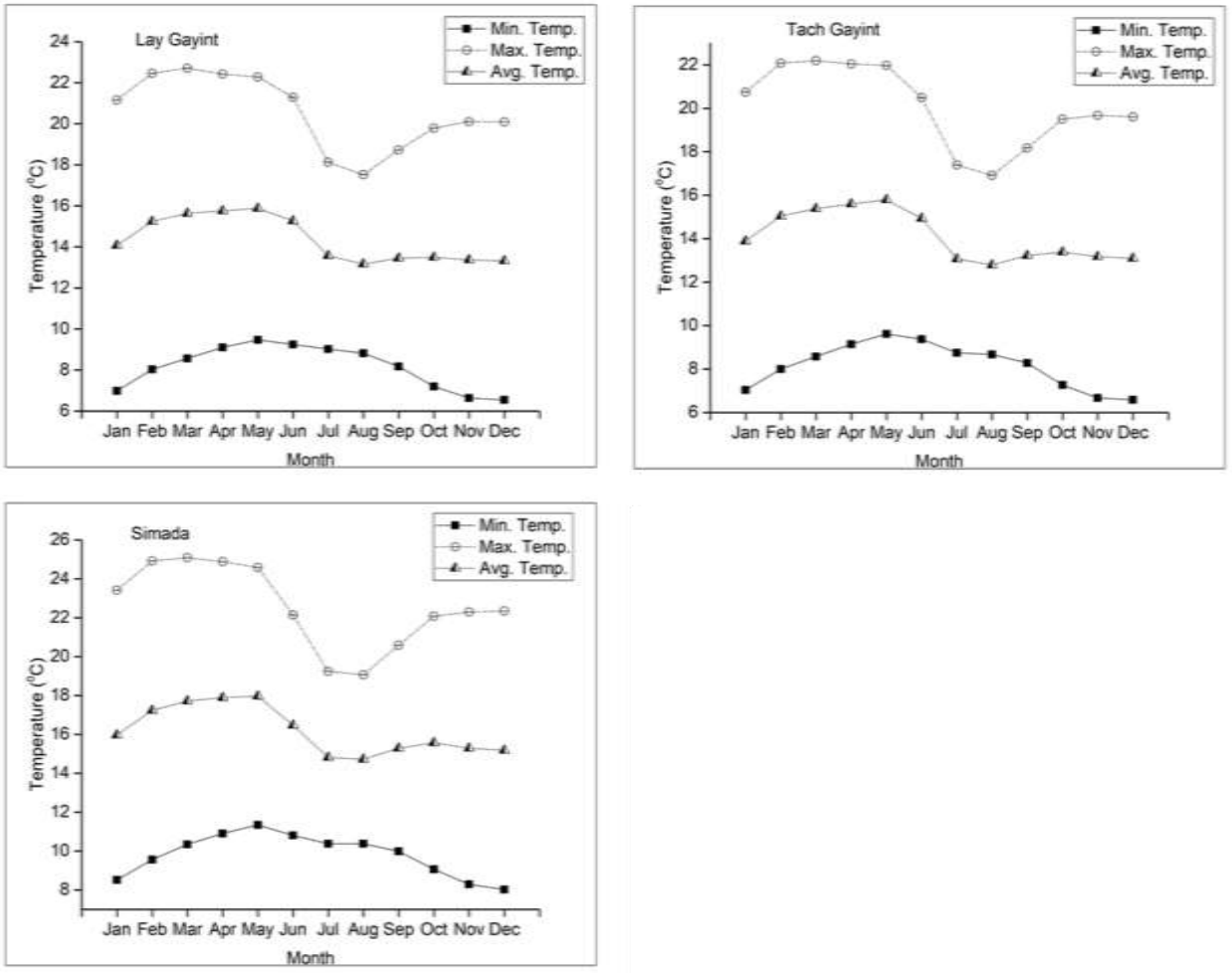

Figure 2. 10. Mean monthly temperature distribution.

Figures 2.11 and 2.12 show the variation in mean annual maximum and minimum temperatures yearly. The decade of the 2000s was found to be warmer than the 1980s and 1990s. The seasonal anomalies in maximum and minimum temperatures follow the same trends as the mean annual maximum and minimum temperatures. The 2000s were warmer than the preceding decades in all seasons.

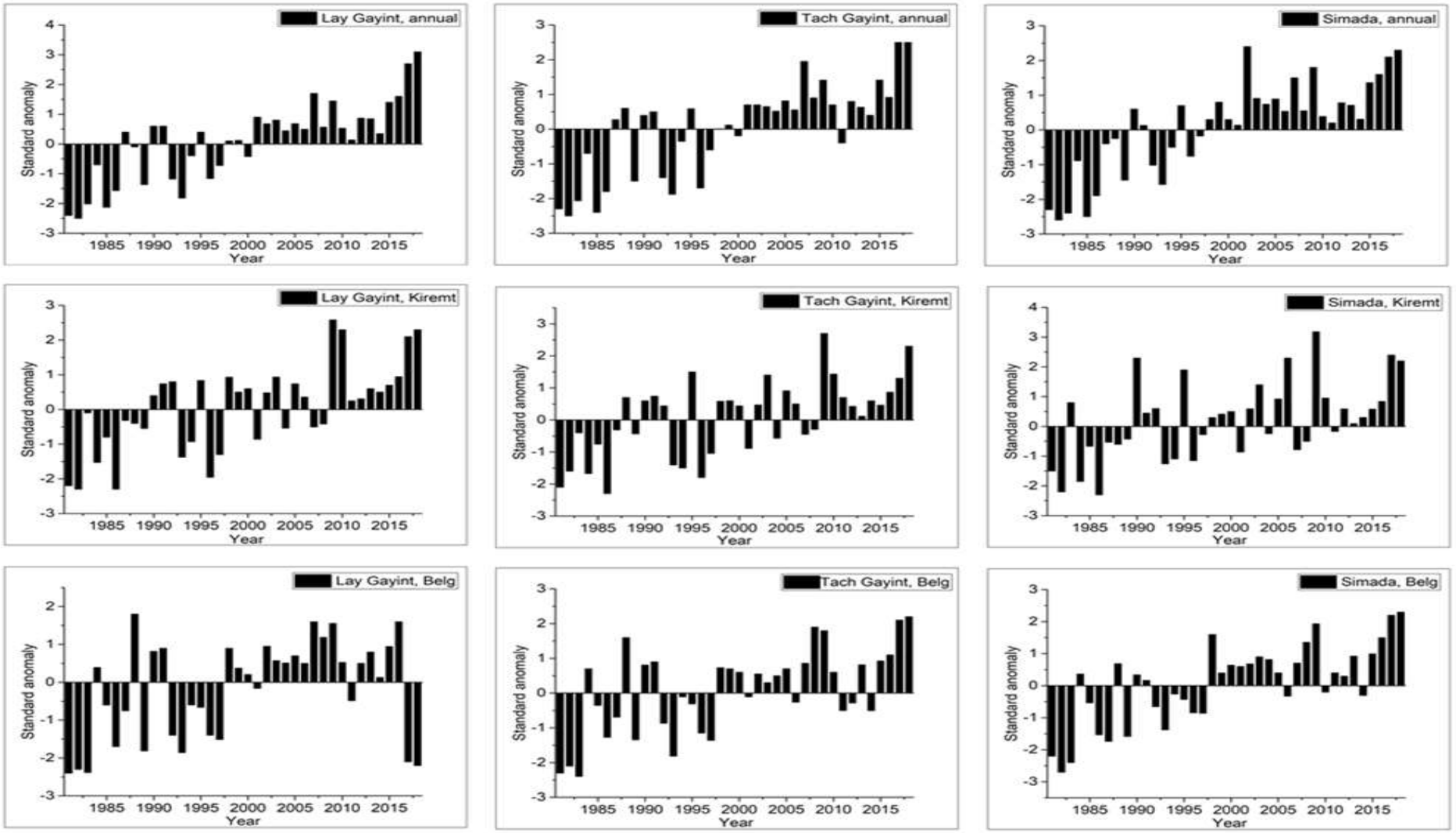

Figure 2. 11. Anomaly in temporal and spatial variation in the mean maximum temperature

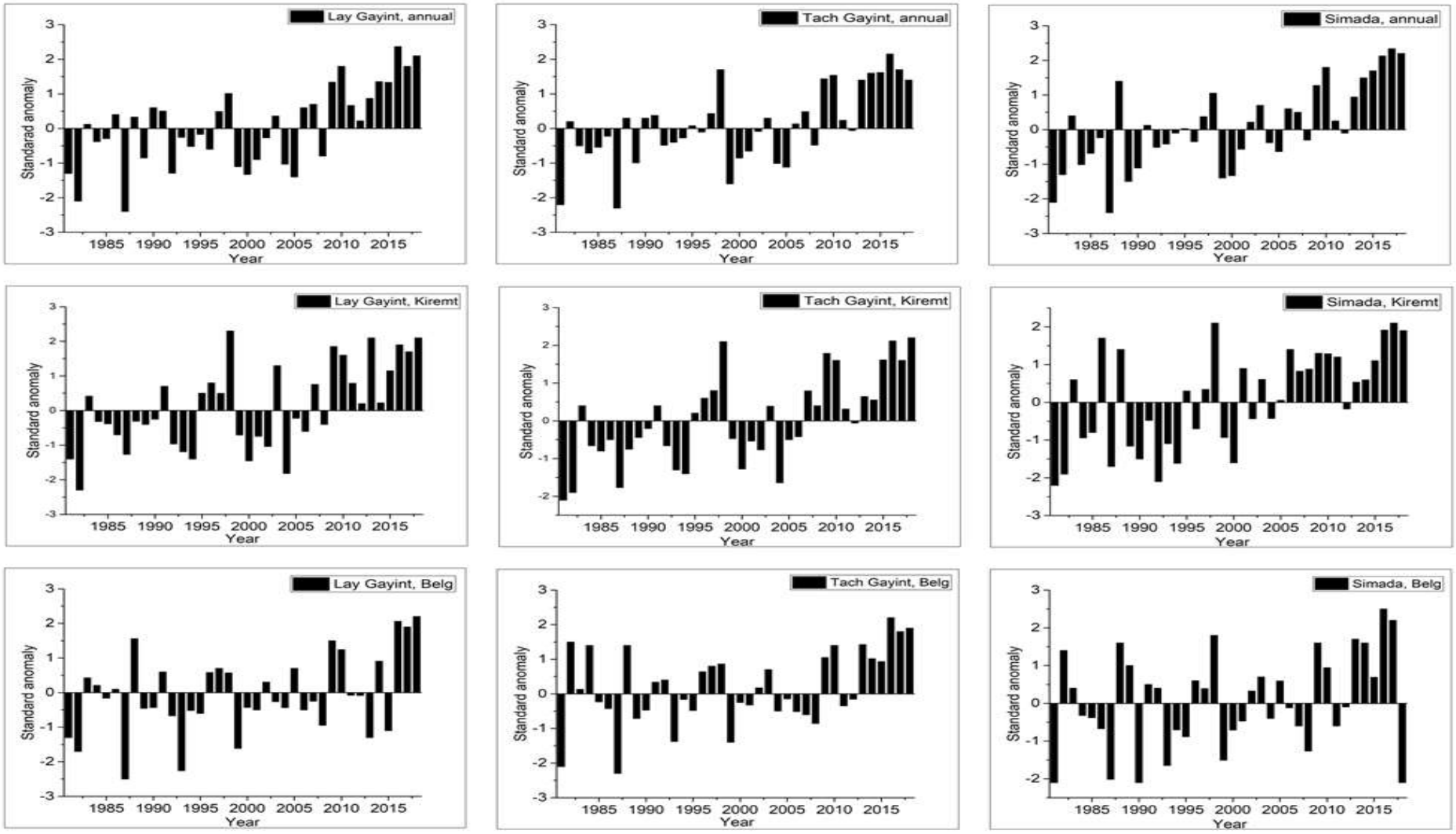

Figure 2. 12. Anomaly in temporal and spatial variation in the mean minimum temperature.

3.2.2. Temperature trends

Like rainfall trend analysis, ITA and MK techniques assessed annual and seasonal temperature trends. The MK's trend test showed annual, *Kiremt* and *Belg* minimum temperatures to have experienced significant warming trends in Simada and Lay Gayint at a $p < 0.1$ level (Table 2.4). Our findings coincide with the results reported by Ademe et al. (2020), Alemayehu and Bewket (2017), Asfaw et al. (2018), Belihu et al. (2018), and Gebrehiwot et al. (2019), where significant warming trends in mean annual minimum temperatures were described for different parts of Ethiopia. Our findings differ from those of Alemayehu and Bewket (2017) and Asfaw et al. (2018), who reported that the minimum temperature had increased substantially more in recent years than the maximum. However, other studies, for instance, Ademe et al. (2020), Berhane et al. (2020), and Kahsay et al. (2019) agree with the findings of the present study, which found an increase in the maximum temperature has increased substantially more in recent years than the minimum. The ITA technique showed an overall warming trend of mean annual and seasonal minimum temperatures (Table 2.4; Figure 2.13). The ITA's results for seasonal minimum temperatures (not shown here) were similar to the mean annual minimum temperature.

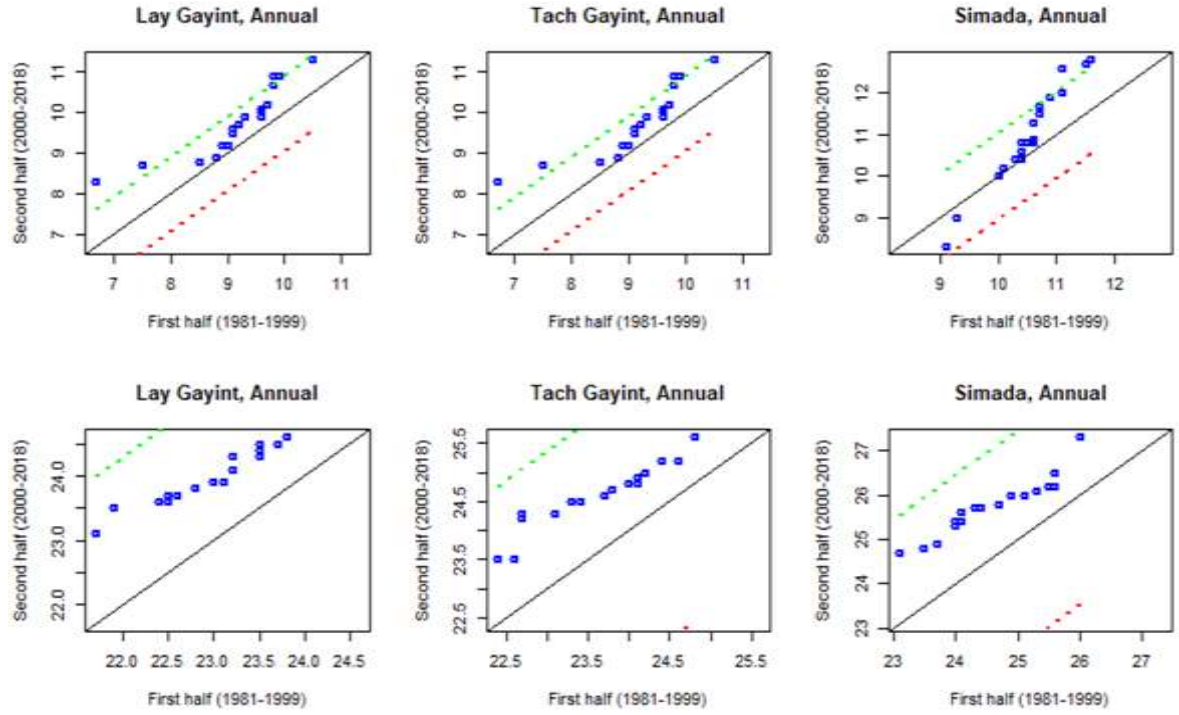

Figure 2. 13. ITA technique for annual mean minimum (above) and maximum (below) temperatures.

Table 2. 4. MK and ITA trend test values of mean minimum temperature at seasonal and annual timescales

	Lay Gayint			Tach Gayint			Simada		
Month	Z_{MK}	β	*D*	Z_{MK}	β	*D*	Z_{MK}	β	*D*
January	0.54	0.01	0.37	0.34	0.00	0.85	0.87	0.01	0.60
February	1.05	0.02	1.12	1.84	0.02	0.93	2.45	0.04**	0.89
March	0.88	0.01	1.09	0.31	0.00***	0.76	2.10	0.04**	0.79
April	2.57	0.03**	0.95	0.87	0.01	0.64	2.72	0.04***	0.62
May	3.13	0.05***	0.98	1.92	0.02**	0.74	1.83	0.03**	0.47
June	3.40	0.05***	1.02	3.12	0.03***	0.59	1.28	0.01**	0.25
July	3.23	0.04***	0.74	2.09	0.02**	0.23	1.66	0.02	0.24
August	2.65	0.04***	0.66	1.88	0.02	0.20	0.56	0.01**	0.12
September	1.90	0.02**	0.42	1.97	0.03**	0.21	1.78	0.02	0.14
October	1.82	0.03	0.09	1.58	0.03	0.06	1.35	0.03	0.33
November	2.03	0.04**	0.37	1.90	0.04**	0.50	0.67	0.01	0.36
December	0.52	0.01	-0.05	1.68	0.03	0.58	0.94	0.02	0.46
Belg	2.02	0.02**	1.01	1.29	0.01	0.73	2.79	0.04**	0.62
Kiremt	2.26	0.02**	0.73	1.50	0.01	0.30	1.44	0.02**	0.17
Annual	1.56	0.01**	0.67	1.19	0.01	0.55	2.01	0.02**	0.44

, and * are significant at alpha values of 0.05, and 0.01, respectively

Z_{MK}, standardized MK; β, Sen's slope; *D*, trend indicator of ITA.

Based on the Mk test, seasonal and annual maximum temperature trends exhibited considerable warming tendencies at a $p < 0.01$ level. Moreover, the mean monthly maximum temperature shows a statistically significant warming trend at the $p < 0.01$ level across the study area, except for June, July, and November (Table 2.5). Our findings coincide with those of Ademe et al. (2020), Alemayehu and Bewket (2017), Gebrehiwot et al. (2019), and Kahsay et al. (2019), where a significant warming trend in the mean annual maximum temperature was exhibited in their study areas. The result of the ITA technique revealed an overall warming trend in the mean maximum temperature in the area, as shown in (Table 2.5). The graphical results of the ITA technique revealed that most of the temperature data points fell above the 1:1 line, implying a warming trend of the mean annual maximum temperature concerning a +10%

confidence band parallel to the 1:1 line in the study area (Figure 2.13). The ITA results (not presented here) for seasonal and monthly maximum temperatures are similar to the mean annual maximum temperature.

Table 2 5. MK and ITA trend test values of mean maximum temperature at seasonal and annual timescales.

	Lay Gayint			Tach Gayint			Simada		
Month	Z_{MK}	β	*D*	Z_{MK}	β	*D*	Z_{MK}	β	*D*
January	2.09	0.02**	0.31	0.51	0.00	0.37	2.95	0.03***	0.47
February	3.20	0.05***	0.53	1.05	0.02	1.12	2.91	0.04***	0.63
March	3.19	0.05***	0.45	2.99	0.05***	1.09	3.54	0.06***	0.55
April	2.70	0.05***	0.51	3.80	0.05***	0.95	3.76	0.09***	0.70
May	2.21	0.05**	0.61	3.13	0.05**	0.98	2.21	0.04**	0.59
June	1.22	0.03	0.37	3.40	0.05***	1.02	1.72	0.04	0.24
July	1.87	0.02	0.20	3.23	0.04***	0.74	2.17	0.03**	0.25
August	3.22	0.03***	0.32	2.65	0.04***	0.66	2.17	0.03**	0.22
September	2.85	0.03***	0.22	1.90	0.05**	0.42	2.93	0.04***	0.30
October	3.76	0.06***	0.61	1.13	1.72***	0.09	2.49	0.04**	0.55
November	3.51	0.04***	0.56	1.64	0.03**	0.37	1.79	0.03	0.51
December	3.62	0.04***	0.50	0.11	0.03**	-0.05	2.78	0.04**	0.52
Belg	3.26	0.05***	0.51	3.61	0.05***	1.01	3.80	0.07***	0.62
Kiremt	3.20	0.03***	0.28	3.00	0.03***	0.73	2.53	0.03**	0.25
Annual	4.09	0.03***	0.44	1.56	0.01	0.67	2.31	0.02**	0.47

, and * are significant at alpha values of 0.05, and 0.01, respectively

Z_{MK}, standardized MK test; β, Sen's slope; *D,* trend pointer of ITA.

3.2.3. Spatial variability of temperature

The north-eastern portions experience relatively lower temperatures than the south-western portions (Figure 2.14) due to the influence of climatic controls such as elevation. The one-way ANOVA showed that mean annual minimum and maximum temperatures significantly varied among the three districts at a $p < 0.01$ level. The mean minimum temperature in Simada was 1.3℃ and 0.2℃ higher than in Lay Gayint and Tach Gayint, respectively (significant at $p < 0.01$), and the mean minimum temperature in Tach Gayint was higher by 1.0℃ than in Lay Gayint (significant at $p < 0.01$). At $p < 0.01$, Simada had a 1.0℃ higher mean maximum

temperature than Tach Gayint, and Tach Gayint had a 0.7℃ higher mean maximum temperature than Lay Gayint (both significant at $p < 0.01$) (Table 2.6).

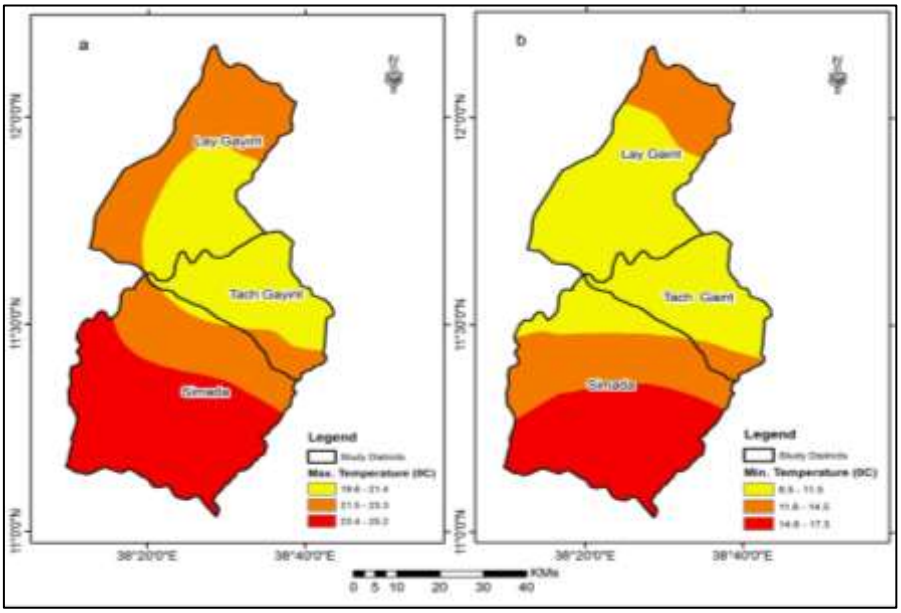

Figure 2. 14. Spatial distribution of mean maximum (left) and mean minimum (right) temperature.

Table 2. 6. ANOVA and Tukey's post hoc comparison for temperatures.

		Mean difference (I-J)	
(I) District	(J) District	Minimum Temp.	Maximum Temp.
Lay Gayint	Tach Gayint	-1.02***	-0.71***
	Simada	-1.26***	-1.73
Tach Gayint	Simada	-0.24***	-1.02***
ANOVA F-ratio		19.27***	43.62***

*** is significant at alpha values of 0. 01.

3.3. Comparison of ITA and MK techniques

The reliability of the ITA technique was assessed by comparing its results with those of the MK trend test. Table 2.7 presents a summary and comparison of the MK test's Z values and the ITA technique's *D* statistic for monthly, seasonal, and annual rainfall and minimum and maximum temperatures. It is shown that most of the trends sensed by the MK test (in the 28-time series, the result was positive, while in the 20-time series, the result was negative) were also identified by the ITA (in the 23-time series, the result was positive, whereas, in 25-time series, the result was negative) (Table 2.7). However, the ITA and MK tests detected positive trends for monthly, annual, and seasonal temperatures. But the ITA method was found to have some advantages as it identified some hidden trends that the MK test might not have identified.

Also, it overcomes assumptions about, for instance, the length of records, the normality of the distribution, and the independent structure of the time series (Wu and Qian, 2017). But the ITA technique does not allow the determination of whether the variations between each point and the 1:1 line are significant. Therefore, we used a +10% confidence band to detect trends.

Table 2.7. Comparison of values of Z of MK test and statistics D of ITA method for rainfall and temperature.

	Rainfall			Minimum temperature			Maximum temperature		
	Lay Gayint	Tach Gayint	Simada	Lay Gayint	Tach Gayint	Simada	Lay Gayint	Tach Gayint	Simada
Month	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D	Z_{MK}/D
January	-0.46/-1.29	-0.63/-1.04	-0.83/-2.72	0.54/0.37	0.34/0.85	0.87/0.60	2.09/0.31	0.51/0.37	2.95/0.47
February	-1.20/-2.66	-1.77/-4.45	-1.64/-3.01	1.05/1.12	1.84/0.93	2.45/0.89	3.20/0.53	1.05/1.12	2.91/0.63
March	0.05/-0.32	-0.57/-0.67	-0.42/-0.65	0.88/1.09	0.31/0.76	2.10/0.79	3.19/0.45	2.99/1.09	3.54/0.55
April	0.54/0.16	0.50/-1.06	-1.10/-2.32	2.57/0.95	0.87/0.64	2.72/0.62	2.70/0.51	3.80/0.95	3.76/0.70
May	0.88/0.02	0.70/0.02	0.21/-1.10	3.13/0.98	1.92/0.74	1.83/0.47	2.21/0.61	3.13/0.98	2.21/0.59
June	1.08/0.77	1.26/-0.75	0.20/-1.42	3.40/1.02	3.12/0.59	1.28/0.25	1.22/0.37	3.40/1.02	1.72/0.24
July	2.13/1.66	1.45/1.15	-0.21/-1.01	3.23/0.74	2.09/0.23	1.66/0.24	1.87/0.20	3.23/0.74	2.17/0.25
August	2.43/2.74	1.96/1.70	0.95/0.12	2.65/0.66	1.88/0.20	0.56/0.12	3.22/0.32	2.65/0.66	2.17/0.22
September	1.30/1.56	-0.15/0.04	-2.23/-1.73	1.90/0.42	1.97/0.21	1.78/0.14	2.85/0.22	1.90/0.42	2.93/0.30
October	-0.01/-3.09	0.26/-1.63	0.06/-2.30	1.82/0.09	1.58/0.06	1.35/0.33	3.76/0.61	1.13/0.09	2.49/0.55
November	1.78/3.05	2.21/3.77	1.76/2.67	2.03/0.37	1.90/0.50	0.67/0.36	3.51/0.56	1.64/0.37	1.79/0.51
December	-0.60/-0.81	-0.19/-0.33	-0.24/-3.11	0.52/-0.05	1.68/0.58	0.94/0.46	3.62/0.50	0.11/-0.05	2.78/0.52
Bega	-0.86/1.50	0.07/9.19	0.17/0.70	0.82/0.36	1.32/0.60	1.24/0.55	3.91/0.51	0.82/0.36	1.88/0.54
Belg	1.43/1.90	0.12/0.77	-0.31/-1.48	2.02/1.01	1.29/0.73	2.79/0.62	3.26/0.51	3.61/1.01	3.80/0.62
Kiremt	1.88/1.72	0.77/0.57	-1.33/-1.22	2.26/0.73	1.50/0.30	1.44/0.17	3.20/0.28	3.00/0.73	2.53/0.25

3.4. The potential implication of temperature and rainfall variability

Changes in rainfall and temperature can have significant implications for crop production and agricultural practices. Adequate and timely rainfall is necessary for successful farming during the *Belg* and *Kiremt* seasons, while irregular and variable rainfall can hinder farming activities and reduce production in the study area. In the northeastern highlands of Ethiopia, Mekonnen and Berlie (2020) found that the variability of rainfall during the *Kiremt* and *Belg* seasons discourages farming practices and reduces production. Delayed onset of rainfall in February and the cessation of rainfall in September have also impacted farmers' enthusiasm for early and timely planting, active growing, and maturation of various crops. Alemayehu and Bewket (2016) and Bewket (2009) also noted that climate variability and changes significantly influence food security and crop production in the north-central highlands and Amhara region, respectively. An increase in temperature could have a distinct impact on crop production (Pachauri et al., 2014), leading to invasive plants and crop pests that appear at different times during the agricultural calendar (EPCC 2015; Mekonnen and Berlie, 2020). Temperature fluctuations have also impacted pasture and forage production and caused animal diseases (Gebreegziabher et al., 2020). When climate variability peaks, it can result in total crop failure, leading to starvation and the death of people and animals, which is unfortunately commonplace in different parts of Ethiopia.

4. Conclusions

Temperature and rainfall data from 1981 to 2018 were analysed using various meteorological indices to highlight spatiotemporal fluctuations and their potential consequences. Temperature and rainfall fluctuate in space and time, according to the findings. In recent times, there has been more unpredictability in temperature and rainfall. In all three districts, *Kiremt* rainfall provides the highest annual rainfall. Except for *Kiremt*, which has a moderate coefficient of variation, annual and seasonal rainfall show substantial inter-annual variability. The percentage of negative deviations varies from 39% (Lay Gayint) to 65% (Simada) over the observation period. The MK test and ITA techniques were applied to the rainfall and temperature data for annual and seasonal time scales. On an annual scale, the results of the MK test showed a significant increasing trend in Lay Gayint and Tach Gayint but a non-significant decreasing trend in Simada. On a seasonal scale, in Simada, *Kiremt* rainfall showed a non-significant decreasing trend, whereas Lay Gayint and Tach Gayint showed non-significant increasing trends. *Belg* rainfall exhibited a non-significant increasing trend in Lay Gayint and Tach Gayint but a non-significant decreasing trend in Simada. The mean seasonal and annual minimum and

maximum temperatures increased considerably in the study area. The ITA technique results for annual and seasonal rainfall showed positive trends in Lay Gayint and Tach Gayint, while negative trends were detected in Simada. The ITA results for mean annual and seasonal minimum and maximum temperatures showed that the area was warming overall. Climate-sensitive activities, including agriculture and water resource development, are already susceptible to contemporary climate-related threats, as evidenced by annual and seasonal rainfall variability and average annual minimum and maximum temperatures. This suggests the need for climate risk management to be part of local economic development planning in the study area.

Acknowledgments

We would like to express our gratitude to Addis Ababa University and Dilla University for their financial assistance to the first author. Additionally, we are thankful to the Ethiopian National Meteorological Agency for providing climate data free of charge.

References

Abebe, G. (2017). Long-term climate data description in Ethiopia. *Data Brief*, 14, 371–392.

Abidoye, B. O., & Odusola, A. F. (2015). Climate change and economic growth in Africa: an econometric analysis. *Journal of African Economics*, 24(2), 277–301.

Ademe, D., Ziatchik, 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.

Alemayehu, A., & Bewket, W. (2016). Local climate variability and crop production in the central highlands of Ethiopia. *Environmental & Development Economics*, 19, 36-48.

Alemayehu, A., & Bewket, W. (2017). 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.

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.

Amare, A., & Simane, B. (2017). Assessment of Household Food Security in the Face of Climate Change and Variability in the Upper Blue-Nile of Ethiopia. *Journal of Agricultural Science*, 7, pp.285–300.

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.

Ayalew, D., Tesfaye, K., Mamo, G., Yitaferu, B., & Bayu, W. (2012). Variability of rainfall and its current trend in Amhara region, Ethiopia. *African Journal of Agricultural Research*, 7(10), 1475–1486.

Belihu, M., Abate, B., Tekleab, S., & Bewket, W. (2018). Hydro-meteorological trends in the Gidabo catchment of the Rift Valley Lakes Basin of Ethiopia. *Phys Chem Earth*, 104, 84–101.

Benti, F., & Abara, M. (2019). Trend analyses of temperature and rainfall and their response to global CO2 emission in Masha, Southern Ethiopia. Caraka Tani: Journal of Sustainable. Agriculture, 34(1), 67–75.

Berhane, A., Hadgu, G., Worku, W., & Abrha, B. (2020). Trends in extreme temperature and rainfall indices in the semi-arid areas of Western Tigray, Ethiopia. *Environmental Systems Research*, 9(3), 1–20.

Bewket, W. (2009). Rainfall variability and crop production in Ethiopia: case study in the Amhara region. In: Proceedings of the 16th International Conference of Ethiopian Studies. Trondheim: Norwegian University of Science and Technology, Vol. 3, pp. 823–836.

Caloiero, T. (2018). Application of the innovative trend analysis method for the trend analysis of rainfall anomalies in Southern Italy. *Water Management*, 32(15), 4971–4983.

Chala, D., Belay, S., & Bamlaku, A. (2020). Analysis of farmers perceived and observed climate variability and change in Didessa sub-basin, Blue Nile River, Ethiopia. *African Journal of Agricultural Resource*, 15(2), 149–164.

Dinku, T., Thomson, M. C., Cousin, R., del Corral, J., Ceccato, P., Hansen, J., & Connor, S. J. (2018). Enhancing National Climate Services (ENACTS) for development in Africa. *Environment and Development Economics*, 10(7), 664–672.

Diro, G. T., Tompkins, A. M., & Bi, X. (2012). Dynamical downscaling of ECMWF Ensemble seasonal forecasts over East Africa with RegCM3. *Journal of Geophys Research*, 117, D16103.

Dubache, G., Ogwang, B. A., Ongoma, V., Islam, T., & Md AR (2019). The effect of Indian Ocean on Ethiopian seasonal rainfall. *Meteorology and Atmospheric Physics*, 131(6), 1753-1761.

Ethiopian Panel on Climate Change (EPCC). (2015). First assessment report working group II. Climate change impact, vulnerability, adaptation and mitigation. Published by the Ethiopian Academy of Sciences, Addis Ababa, Ethiopia.

Funk, C., Nicholson, S. E., Landsfeld, M., Klotter, D., Peterson, P., & Harrison, L. (2015). The centennial trends greater horn of Africa precipitation dataset. *Scientific Data*, 2(1), 1-17.

Gebrechorkos, S. H., Hülsmann, S., & Bernhofer, C. (2019). Changes in temperature and precipitation extremes in Ethiopia, Kenya, and Tanzania. *International Journal of Climatology*, 39(1), 18-30.

Gebreegziabher, Z., Mekonnen, A., Bekele, R. D., Zewdie, S. A., & Kassahun, M. M. (2020). Crop-Livestock inter-linkages and climate change implications for Ethiopia's agriculture: a Ricardian approach. In *Climate Change, Hazards and Adaptation Options* (pp. 615-640). Springer, Cham.

Gebrehiwot, B., 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.

Getachew, B. (2017). Impacts of Climate Change on Crop Yields in South Gonder Zone, Ethiopia. *World Journal of Agricultural Research*, 5(2), 102-110.

Hamed, K. H. (2009). Enhancing the effectiveness of prewhitening in trend analysis of hydrologic data. *Journal of Hydrology*, 368(1-4), 143-155.

Hamed, K. H., & Ramachandra Rao, A. (1998). A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, 204(1-4), 182-196.

Hundera, H., Mpandeli, S., & Bantider, A. (2019). Smallholder farmers' awareness and perceptions of climate change in Adama district, central rift valley of Ethiopia. *Weather and Climate Extremes*, 26, 100230.

Hurni, H., Berhe, W. A., Chadhokar, P., Daniel, D., Gete, Z., & Grunder, M. K. G. (2016). Soil and Water Conservation in Ethiopia: Guidelines for Development Agents. Volume 1. Centre for Development and Environment (CDE), University of Bern: Bern, Switzerland.

Kafadar, K., Koehler, J. R., Venables, W. N., & Ripley, B. D. (1999). Modern Applied Statistics with S-Plus. *The American Statistician*, 53(1), 86.

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, 1–13.

Kendall, M. G. (1975). Rank correlation methods (4th ed.). Griffin, London.

Mann, H. B. (1945). Nonparametric tests against trend. Econometrica, 13, 245–259.

Mekonen, A. A., & Berlie, A. B. (2020). Spatiotemporal variability and trends of rainfall and temperature in the North-eastern Highlands of Ethiopia. *Modeling Earth Systems and Environment*, 6, 285–300.

Mesfin, D., Simane, B., Belay, A., Recha, J. W., & Schmiedel, U. (2020). Assessing the adaptive capacity of households to climate change in the Central Rift Valley of Ethiopia. Climate, 8(10), p.106.

Miheretu, B. A. (2020). Temporal variability and trend analysis of temperature and rainfall in the Northern highlands of Ethiopia. *Physical Geography*, 42(5), 434–451.

Minda, T. T., van der Molen, M. K., Struik, P. C., Combe, M., Jiménez, P. A., Khan, M. S., & de Arellano, J. V. G. (2018). The combined effect of elevation and meteorology on potato crop dynamics: a 10-year study in the Gamo Highlands, Ethiopia. *Agricultural and Forest Meteorology*, 262, 166–177.

Nisansala, W. D. S., Abeysingha, N. S., Islam, A., & Bandara, A. M. K. R. (2020). Recent rainfall trend over Sri Lanka. *International Journal of Climatology*, 40(7), 3417–3435.

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., & van Ypserle, J. P. (2014). 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 (p. 151). Ipcc.

Philip, S., Kew, S. F., Jan van Oldenborgh, G., Otto, F., O'Keefe, S., Haustein, K., ... Singh, R. (2018). Attribution analysis of the Ethiopian drought of 2015. *Climate Research*, 31(6), 2465–2486.

Rosell, S. (2011). Regional perspective on rainfall change and variability in the central highlands of Ethiopia. *Applied Geography*, 31(1), 329–338.

Rowell, D. P., Booth, B. B., Nicholson, S. E., & Good, P. (2015). Reconciling past and future rainfall trends over East Africa. *Climate Research*, 28(24), 9768–9788.

Sen, P. K. (1968). Estimates of the Regression Coefficient Based on Kendall's Tau. *Journal of the American Statistical Association*, 63(324), 1379–1389.

Şen, Z. (2012). Innovative Trend Analysis Methodology. *Journal of Hydrologic Engineering*, 17(9), 1042–1046.

Wu, H., & Qian, H. (2017). Innovative trend analysis of annual and seasonal rainfall and extreme values in Shaanxi, China. *International Journal of Climatology*, 37(5), 2582–2592.

Chapter Three

Trends in extreme precipitation indices in northwest Ethiopia: comparative analysis using the Mann Kendall and Innovative trend analysis methods[2]

Abstract

This study analyzed long-term extreme precipitation indices using 4 × 4 km gridded data obtained from the National Meteorological Agency of Ethiopia between 1981 and 2018. The study examined trends in extreme precipitation over three districts (Lay Gayint, Tach Gayint, and Simada) in the northwestern highlands of Ethiopia. Innovative Trend Analysis (ITA) and Mann–Kendall (MK) trend tests were used to study extreme precipitation trends. Based on the ITA result, the calculated values of nine indices (90% of the analyzed indices) showed significant increasing trends ($p < 0.01$) in Lay Gayint. In Tach Gayint, 70% (seven indices) showed significantly increasing trends at $p < 0.01$. On the other hand, 60% of the extreme indices showed significant downward trends ($p < 0.01$) in Simada. The MK test revealed that 30% of the extreme indices had significantly increasing trends ($p < 0.01$) in Lay Gayint. In Tach Gayint, 30% of the extreme indices showed significant increasing trends at $p < 0.05$, while 10% of the extreme indices exhibited significant increasing trends at $p < 0.01$. In Simada, 20% of the extreme indices showed significant increasing trends at $p < 0.05$. Overall, the results showed that the ITA method can identify a variety of significant trends that the MK test misses.

Keywords: precipitation extremes; trends; climate change; Northwest Ethiopia.

[2] Likinaw, A., Alemayehu, A., & Bewket, W. (2023). Trends in extreme precipitation indices in northwest Ethiopia: comparative analysis using the Mann–Kendall and Innovative trend analysis methods. *Climate*, 11(8), 164. https://doi.org/10.3390/cli11080164

1. Introduction

Climate change has altered the circulation and distribution of water resources while increasing the likelihood of extreme disasters (Marie et al., 2020; Mukherjee and Mishra, 2021; Wang et al, 2019; Yang et al., 2020). Precipitation is an important variable in local climate characteristics and a critical element of the global water cycle (Jin et al., 2021). The recurrence of extreme precipitation events, such as droughts and floods, has a significant impact on human livelihoods and socioeconomic development (Ferijal et al., 2021; Gebrechorkos et al., 2019; Janizadeh et al., 2021). Average global mean temperature has been rising since the pre-industrial period, with 2015–2019 being the warmest period since records began in 1850 (WMO, 2020). Every 1 °C temperature rise increases the moisture holding capacity of the air by 7% (Marak et al., 2020). An increase in humidity leads to heavier precipitation and increases the risk of flooding. Recent studies on global precipitation trends show an increase in the frequency of extreme events (Myhre et al., 2019; Papalexiou and Montanari, 2019). Climate-related events cause more than 70% of reported natural disasters worldwide, with most of these disasters being caused by extreme precipitation events of floods and droughts (Wang et al., 2019). According to the World Meteorological Organization (WMO, 2020), the weather in Africa in 2019 was characterized by steadily rising temperatures, and the negative effects of weather and climate extreme events were large. East Africa in particular is prone to severe climate extremes such as droughts and floods (Gebrechorkos et al., 2019). The climate of the Horn of Africa had changed abruptly from drought conditions in 2018 to floods and landslides in late 2019 (WMO, 2020).

Ethiopia is one of the East African countries facing climate-related risks, such as floods and droughts, caused by climate change and variability (Gezie, 2019). Several studies con-firmed that Ethiopia's economy and food security, which are largely based on rain-fed agriculture, are very sensitive to fluctuations in rainfall and extreme events (Gebrechorkos et al., 2019; Geremew et al., 2020). According to Bezu (2020), Ethiopia has experienced at least two catastrophic droughts per decade. This has had an impact on the country's environment and natural resources. The tropical cur-rents of the Pacific Ocean are the primary global climatic drivers for such severe events (i.e., floods and droughts) in Ethiopia (Nicholson, 2017). In addition, changes in precipitation extremes in the country are influenced by local-scale climate controls (Gebrehiwot et al., 2019; Terefe et al., 2022).

The current study districts (Lay Gayint, Tach Gayint, and Simada) in the northwest-ern part of the country are among the drought-prone and food-insecure districts of the Amhara Region (Endalew and Sen, 2020; Likinaw et al., 2022). These districts are classified as chronically food insecure because of their reliance on regularly receiving food aid (Bazezew et al., 2013; Tizazu, 2019). The food insecurity of the area is mainly caused by rainfall variability and associated drought episodes.

Investigating daily precipitation extreme indices within the context of climate change and variability holds significant importance for multiple reasons. The knowledge gained from this study can prove valuable for policymakers in their efforts to manage floods, control runoff, and understand hydrological processes. This understanding can also help assess the risk of altered rainfall patterns, particularly those that arise from extreme rainfall events resulting from climate change (Salameh et al., 2022; Srivastava et al., 2021; Vondou et al., 2021) highlight the need for a more comprehensive comprehension of extreme rainfall variability to aid in water resource management, drought monitoring, and flood control. Additionally, Obada et al. (2021) emphasize the critical role that scientific analysis of extreme rainfall and its evolution plays in implementing effective operational management and mitigating flood risks. Overall, studying daily precipitation extreme indices is a substantial contribution to our understanding of climate change and its environmental impacts.

There are many studies on rainfall patterns and trends in Ethiopia. For instance, Berhan et al. (2022) performed a trend analysis for observed trends in climatic extremes at Choke Mountain and reported a significant decrease in total precipitation along with a decrease in wet extremes. A significant decrease in extreme climate indices was found in the semi-arid areas of western Tigray (Berhane et al., 2020). Most precipitation extreme indices considered in their study in the southern and southwestern parts of Ethiopia showed increasing trends (Beyene et al., 2022). According to Damtew et al. (2022), most extreme climate indices decreased in the Awash River basin. The disparity in the findings of extreme precipitation trends in Ethio-pia might be attributed to extremely variable topography features, data analysis method-ologies utilized, time series data length, number of meteorological stations, data quality, and spatial coverage of the studied area.

In southeastern Ethiopia, Degefu et al. (2021) observed the emergence of different trend signals across seasons and spatial locations in the study area. The results of trend tests for total rainfall amount and extreme indices indicated a significant global downward tendency for both the annual

and March-May seasons. However, when considering the annual timescale, the number of wet and dry days, maximum consecutive wet and dry spells, and wet day rainfall intensity exhibited mixed significant upward and downward tendencies. Conversely, the number of dry days and maximum consecutive dry spells displayed a globally significant increasing trend for the March-May season across the study area. In the June-September season, over the northern part of the study area, all rainfall indices demonstrated mixed significant upward and downward tendencies. Nonetheless, only a few of the upward trends were statistically significant compared to the two wet seasons. In contrast, most of the stations indicated decreasing trends in the number of dry days and maximum dry spell length for this season. Dendir and Birhanu (2022) identified inconsistencies in the trend of extreme climate events in the Gurage Zone in Central Ethiopia. Esayas et al. (2018) reported that very wet days showed a positive trend in the midlands and highlands of Southern Ethiopia. Gedefaw et al. (2018) found significantly increasing trends in seasonal and annual precipitation in the Amhara Region. Geremew et al. (2020) discovered that extreme rainfall trends in Enebsie Sar Midir district, central Ethio-pian highlands, did not show a systematic pattern. Worku et al. (2019) found decreasing trends in annual precipitation extremes in the southern parts of the Blue Nile basin. Terefe et al. (2022) found clearly decreasing trends for most extreme precipitation indices in the Meki watershed of the central rift valley basin. In addition, Terefe et al. (2022) found significant decreasing trends for most extreme precipitation indices in the same watershed (the Meki watershed of the central Rift Valley basin).

The Mann–Kendall (MK) test (Kendall, 1975; Mann, 1945) is widely used to detect monotonic trends. It is well-known that the MK and MMK methods rely on several assumptions. Therefore, the validity of utilizing these methods and the results they generate is contingent upon adhering to these assumptions (Birpınar et al., 2023).

The MK trend test offers several advantages over parametric tests (Salameh et al., 2022; Srivastava et al., 2021; Vondou et al., 2021). Firstly, it is a non-parametric test and does not make any assumptions about the distribution of the data, making it useful for analyzing data that may not follow a normal distribution. Secondly, the MK trend test is a robust test and is less sensitive to outliers and missing values than other trend tests, making it more reliable when analyzing data that may contain extreme values or noise. Lastly, the MK trend test can handle ties in the data, which are multiple data points having the same value, making it useful for analyzing data with repeated values. Although the MK test is widely used in hydrological trend analysis, studies have shown

that the presence of autocorrelation could affect trend identification using the MK and Sen's slope methods (Hamed and Rao, 1998; Yue et al., 2002). Some studies have used pre-whitening technique to re-move autocorrelation from datasets (Hamed and Rao, 1998; Yue et al., 2002). However, several studies have shown that pre-whitening can remove some of the true trends and may be ineffective when serial correlation persists beyond the first-order autoregressive process and the sample size is large (Kumar et al., 2009; Yue and Wang, 2004). To address this problem, Sen (Şen, 2012) proposed the Innovative Trend Analysis (ITA) approach, which can solve the challenge of trend detection in autocorrelated time series data. Studies around the world have confirmed the reliability of the ITA method (Caloiero, 2020; Serencam, 2019; Şişman et al., 2022; Wang et al., 2020; Wu and Qian, 2017).

This paper is novel in its application and comparison of Sen's innovative trend test with the Mann–Kendall test, despite the widespread use of ITA trend analysis in various regions worldwide. However, to our knowledge, only a few studies in Ethiopia have utilized ITA trend analysis, including one in the Amhara regional state (Gedefaw et al., 2018), another in the Meki watershed of the central rift valley basin of Ethiopia (Terefe et al., 2022), and a third in Addis Ababa (Alemu and Dioha, 2020). In contrast, most studies that analyze hydro-climatological data for trend analysis in Ethiopia have used the MK test, t-test, and linear regression test. The paper highlights the potential benefits of using Sen's innovative trend test, particularly in countries like Ethio-pia where there may be limited research on the use of ITA trend analysis. Overall, comparing these trend analysis methods can provide valuable insights into the strengths and limitations of each approach, helping researchers choose the most appropriate method for their specific research context.

The aim of this study is to analyze trends of extreme precipitation events in North-western Ethiopia and covering the three food-insecure districts of Lay Gayint, Tach Gayint, and Simada. The specific objectives are: (i) to examine trends in extreme precipitation using the ITA and MK methods; and (2) to compare the results of the ITA method with the MK test.

2. Materials and methods

2.1. Study area description

The study area covers Tach Gayint, Lay Gayint, and Simada districts in the South Gondar Administrative Zone of the Amhara National Regional State of Ethiopia (Figure 3.1). Lay Gayint

is located in the *High Dega* agroecological zone (3200–3700 m a.s.l.), while Tach Gayint and Simada are located in *Dega* (2300–3200 m a.s.l.) and *Woyna Dega* (1500–2300 m a.s.l.), respectively (Hurni et al., 2016). Average annual rainfall ranges from 788mm in Simada to 1096 mm in Lay Gayint, while the average annual temperature ranges from 14°C in Lay Gayint to 18 °C in Simada. The main rainy season (*Kiremt*) lasts from June to mid-September, and the small rainy season (*Belg*) lasts from March to May (Endalew and Sen, 2020). The bimodal precipitation system allows for two harvest seasons (peak and off-season, known locally as *Meher* and *Belg*, respectively). However, the *Belg* harvest is hampered by the short, highly variable, and often insufficient rainy season (Endalew and Sen, 2020). The study area is generally food insecure due to a delayed start, early finish, and low *Belg* outputs. Most households struggle to produce enough food and rely heavily on the Productive Safety Nets Program (PSNP). The PSNP is a national program implemented in al-most all areas that are vulnerable to persistent food insecurity, with support from development partners, to help the poor build assets, improve their living standards, and eventually become self-sufficient in terms of nutrition and resilience to shocks and stresses. According to information from the South Gondar Zone Administration Office, five districts, including the study area, benefit from the PSNP (Simada, Libokemkem, Lay Gayint, Ebnat, and Tach Gayint). Due to limited access to infrastructure, inadequate and inefficient agricultural marketing system, and limited access to institutional support services, non-agricultural livelihood activities are not well established in the study area.

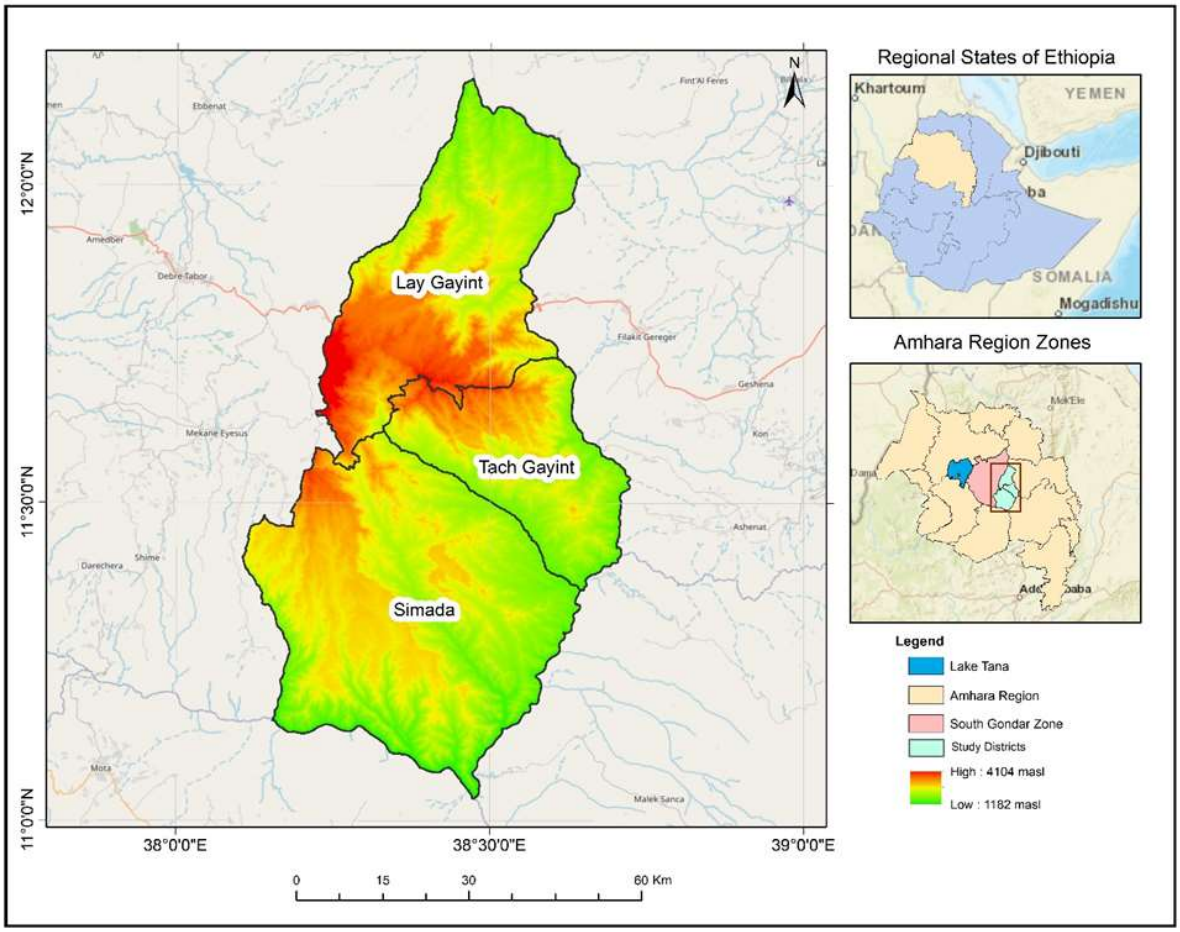

Figure 3. 1. Location map of the study area

2.2. Data sources and quality control

The National Meteorological Agency (NMA) of Ethiopia provided the precipitation data used for the study, which covered the period from 1981 to 2018. It is a gridded dataset (4×4 km grid) obtained by merging station records with remote sensing-based estimates (Dinku et al., 2018). The satellite-based estimates are used to bridge temporal and spatial gaps in station records. The gridded dataset is particularly useful in data-sparse regions (Alemayehu and Bewket, 2017). The dataset has been evaluated extensively and has demonstrated strong performance when evaluated at station locations across Ethiopia (Alemayehu and Bewket, 2017; Dinku et al., 2016). It also provides a homogeneous dataset (Dinku, 2019) and is therefore recommended for climate analysis. The gridded dataset with a 4 × 4 km grid was chosen for analysis due to three reasons: (1) weather stations over the study area are scarce and do not cover all the study sites (Alemayehu and Bewket,

2017), (2) station datasets have many missing values (Asfaw et al., 2018), and (3) most stations are recently established and lack sufficient data records to support trend analysis (Alemayehu and Bewket, 2017; Asfaw et al., 2018; Dinku, 2016).

Homogeneity testing of climate data is crucial in climatological research, particularly when evaluating climate change (Wu et al., 2013). When weather stations record long-term series cli-mate data, non-climatic factors of the data are inevitably influenced due to changes in instruments, observers, site locations, or surrounding environments (Wang et al., 2007). In this study, the homogeneity of precipitation data was examined using the RHtests_dlyPrcp software, a tool developed in the R programming language for testing the homogeneity of daily precipitation data. The software is designed to identify and adjust for artificial shifts in cli-mate data series caused by various factors unrelated to climate change. The tool utilizes statistical tests to detect the presence of inhomogeneities in the data. If significant inhomogeneities are detected, the tool can then adjust the data by eliminating the effects of non-climatic factors, allowing for a more precise analysis of climate trends. The RHtests_dlyPrcp package is commonly used in climatological research and has been documented in the literature (Wang and Feng, 2010). In this study, the RHtests_dlyPrcp software indicated no significant inhomogeneities that necessitated mean adjustments. Hence, the original data series was used for further analysis.

2.3. Data analysis

Extreme precipitation indices were calculated with the specially developed software RClimDex (version 1.0) (Zhang and Yang, 2004) running under the programming environment R (http://www.rproject.org/ (accessed on 23 February 2023)). There are many extreme precipitation indices compiled by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Tank et al., 2009). Climate indices are easy to understand and are also statistically reliable quantitative indicators for climate extremes (Gebremichael et al., 2022). Based on the ETCCDI, 10 precipitation extreme indices were selected for the present study. Table 3.1 presents the selected indices with their descriptions and units. The Mann–Kendall (MK), Modified Mann–Kendall (MMK), Sen's slope (SS), and ITA (both the statistical and graphical techniques) were used to detect trends and magnitudes in precipitation extreme indices. The "trend change" package in RStudio version 4.2.1 was applied for the test statistics.

Table 3. 1. Definition of the extreme precipitation indices used in the study.

Index	Indicator Name	Definition of the Index	Units
SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days	mm/day
Rx1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
Rx5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
R10mm	Number of heavy precipitation days	Annual count of days when PRCP ≥ 10 mm	Days
R20mm	Number of very heavy precipitation days	Annual count of days when PRCP ≥ 20 mm	Days
CDD	Consecutive dry days	Maximum number of consecutive days with RR < 1 mm	Days
CWD	Consecutive wet days	Maximum number of consecutive days with RR ≥ 1 mm	Days
R95p	Very wet days	Annual total PRCP when RR > 95th percentile	mm
R99p	Extremely wet days	Annual total PRCP when RR > 99th percentile	mm
PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR ≥ 1 mm)	mm

2.3.1. The Mann–Kendall (MK) Test

The Mann–Kendall (MK) test (Kendall, 1975; Mann, 1945) was used to detect significant trends in time-series data (Gajbhiye et al., 2016; Kumar et al., 2017). The presence of serial autocorrelation often affects the detection of trends in time series data (Novotny and Stefan, 2007). Hence, the lag-1 autocorrelation coefficient in the data series was| calculated and assessed at a 5% confidence level.

Equation (1) is used to compare the ordered x_i and x_j datasets in this test. The test involves sorting a x_i dataset up to $i = 1\ldots, n-1$ and a xj dataset up to $j = i+1\ldots, n$ before conducting the comparison.

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if} \quad (x_j - x_i) > 0 \\ 0 & \text{if} \quad (x_j - x_i) = 0 \\ -1 & \text{if} \quad (x_j - x_i) < 0 \end{cases} \tag{1}$$

Secondly, the MK test statistic S is calculated through Equation (2) below.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \tag{2}$$

Equation (2) represents the assumed value of *n*, which corresponds to the total data for the basic period being analyzed (e.g., a month or a year). Moving on to Equation (3), it provides the vs. variance value for the *S* test statistic, considering a normal probability distribution with a mean of zero. Lastly, Equation (4) outlines the calculation process for the *Z* statistic.

$$V_S = \frac{n(n-1)(2n+5)}{18} \tag{3}$$

$$Z = \begin{cases} \dfrac{S-1}{V_S} & \text{for} \quad S > 0 \\ 0 & \text{for} \quad S = 0 \\ \dfrac{S+1}{V_S} & \text{for} \quad S < 0 \end{cases} \tag{4}$$

When comparing the calculated *Z* value to the normal distribution value corresponding to the selected significance level, two possible outcomes emerge. Firstly, if the calculated *Z* value is below this normal distribution value, the null hypothesis holds true, indicating no trend in the analyzed time series. Conversely, if the calculated value exceeds this absolute value, a trend is present, and the direction of the trend can be determined. Specifically, a negative *Z* value indicates a decreasing trend, while a positive *Z* value indicates an increasing trend.

2.3.2. The Modified Mann–Kendall (MMK) Test

The modified Mann–Kendall (MMK) test was used for serially correlated data with a significant lag-1 autocorrelation coefficient using the variance correction method of (Yue et al., 2002). The negative and positive values of the MK and MMK test statistics show decreasing and increasing trends, respectively (Likinaw et al., 2022). This test calculates the corrected z value and adjusts the variance of the original MK test. In this method, the variance value in Equation (4) for the MK test should be calculated according to Equations (5) and (6) below.

$$V_S^* = V_S \frac{n}{n^*} \tag{5}$$

$$\frac{n}{n^*} = 1 + \frac{2}{n(n-1)(n-2)} \sum_{x=1}^{n-1} (n-x)(n-x-1)(n-x-n)\theta_x \quad (6)$$

In the context of the MMK test, the autocorrelation function between sequence numbers of data, denoted as θ_x, plays a crucial role as it influences the effective data number, n^*, causing autocorrelation within the time series. Meanwhile, n represents the overall data number in the series. To determine the *Z* value of the MMK test, the variance value in Equation (4) is replaced with Vs^*. Subsequently, trends are identified by comparing this newly calculated *Z* value with the standard *Z* value, following a similar approach to the MK method. The comparison is based on α significance levels.

The Sen's slope (*SS*) estimator is used to estimate the magnitude of the trend (Sen, 1968; Theil, 1950). Negative and positive values of *SS* indicate decreasing and increasing trends, respectively. The test statistic is determined using Equations (5) and (6):

$$SS = \text{median}\left(\frac{Q_j - Q_i}{j - i}\right) i < j \quad (7)$$

$$SS_{\text{medium}} = \begin{cases} SS_{\left(\frac{N+1}{2}\right)}; \text{ if } N \text{ is odd} \\ \frac{1}{2}\left[SS_{\left(\frac{N}{2}\right)} + SS_{\left(\frac{N+2}{2}\right)}\right]; \text{ if } N \text{ is even} \end{cases} \quad (8)$$

where Q_j and Q_i are consecutive data series, and *SS* is the magnitude of the trend. When *SS* has a positive or negative value, it shows that the trend's magnitude is increasing or decreasing.

2.3.3. Innovative Trend Analysis (ITA)

The ITA technique proposed by Sen (2012) was also applied to detect trends in the precipitation time series. The ITA method is free from the assumptions of serial autocorrelation, normality, and record length.

2.3.3.1. Graphical Innovative Trend Assessment (G-ITA)

The G-ITA method is essential for identifying (1) non-monotonic trends, (2) monotonic trends, and (3) distributional changes in climate parameter values between the first and second halves of a time series (Datta and Behera, 2022).

In this method, the initial phase involves dividing time-series data into two equal parts and arranging each sub-series independently in ascending order. For instance, in the present study,

there were 38 precipitation observations (1981–2018) in the time series. In the subsequent phase, the first half of the sub-series is placed on the X axis, and the second half is placed on the Y axis, as shown in Figure 3.2. If the data points are 1:1 above or below the bisecting line, there is an upward or downward trend in the time series Sen (2012). The presence of no trend is indicated when the data under study is collected on the 1:1 line. If the data points scatter on both sides of the 1:1 line, this indicates a non-monotonic trend (Datta and Behera, 2022; Sen, 2012).

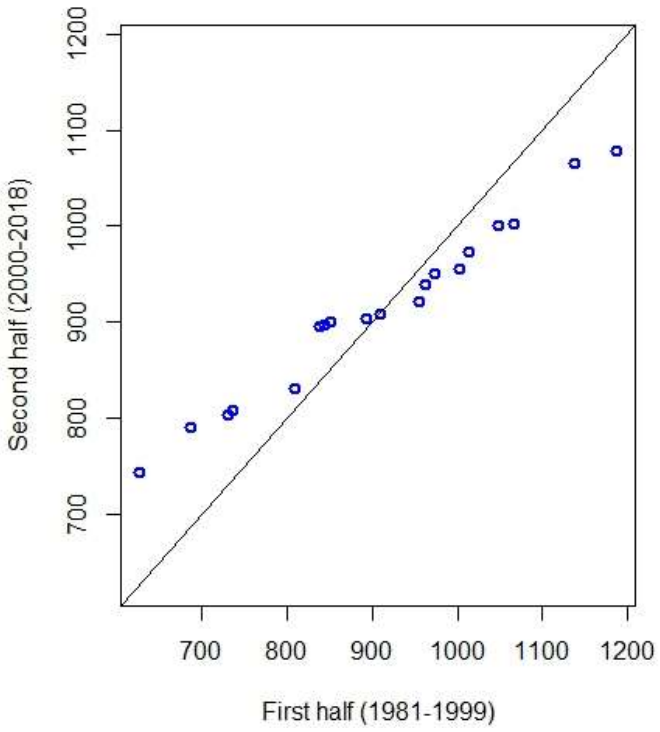

Figure 3. 2. Illustration of the G-ITA method (Sen, 2012).

The central black solid line shows the 1:1 line (untrended). Points below the 1:1 line indicate a downward, while points above the 1:1 line indicate an upward. The presence of no trend is indicated when the data points fall on the 1:1 line.

2.3.3.2. Statistical Innovative Trend Assessment (S-ITA)

In the S-ITA method, the time series is divided into two equal halves and ordered in ascending order. According to Sen (2017), the slope, S_m, can be determined using the arithmetic mean of the ordered two-parts as follows:

$$S_m = \frac{x_2 - x_1}{(n/2)} \tag{9}$$

In this Equation, n stands for the number of observations, x_2 and x_1, respectively, represent the mean values of the second and first half. Here, $(n/2)$ is the time difference between the two halves.

The trend direction, i.e., positive or negative, is derived based on the slope sign (+ or −). The probability density function (PDF) of the slope fits the normal distribution and the standard deviation of the slope can be represented as:

$$\sigma_s = \frac{\sqrt[2]{2}}{\sqrt[n]{n}}\sigma\sqrt{1-}\,\rho\bar{x}_1\bar{x}_2 \tag{10}$$

where $(\rho\bar{x}_1\bar{x}_2)$ is the cross-correlation between the arithmetic means of the two halves in ascending order. S_{cri} is the confidence limit of a standard normal PDF at α percent significance level, and Şen (2017), suggested finding the (1 − α) percent confidence limits for the trend slope as follows:

$$\mathrm{CL}_{1-\alpha} = 0 \pm S_{cri} \times \sigma_S \tag{11}$$

where σ_S is the calculated standard deviation of the slope, S_m, from Equation (1). The null hypothesis, H_0 (there is no significant trend), is accepted if the calculated slope is within the upper and lower CL limits (Equation (11)), or an alternative hypothesis, H_a (there is a significant trend) is concluded. Moreover, this study includes a flow chart outlining the methodologies employed (Figure 3.3).

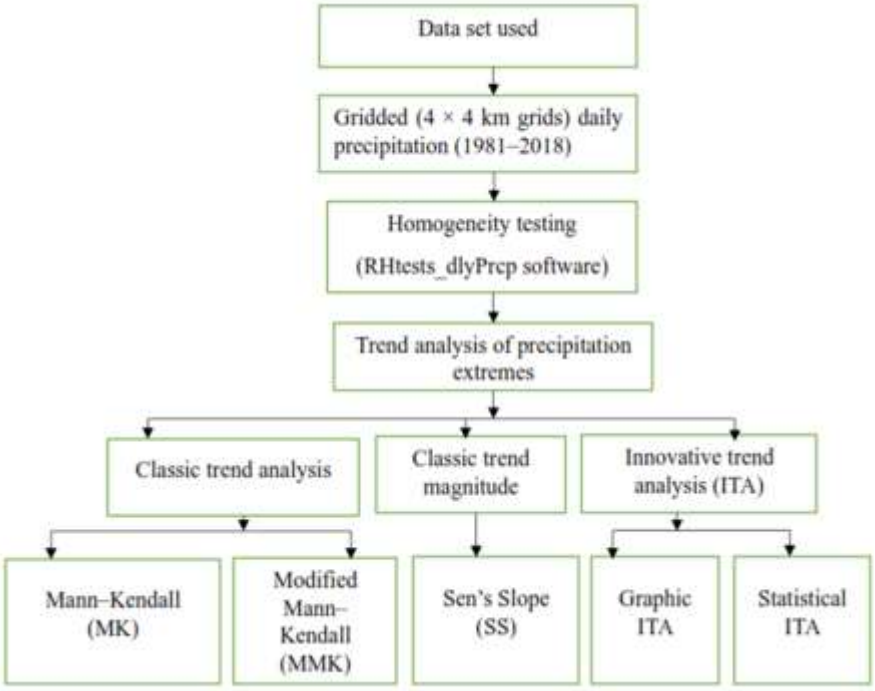

Figure 3. 3. Methodological flowchart of the study.

3. Results

3.1. Trends in Precipitation Extremes

3.1.1. Simple Daily Intensity Index (SDII), Consecutive Dry Days (CDD), Consecutive Wet Days (CWD), and Annual Total Wet-Day Precipitation (PRCPTOT)

The trend in precipitation extremes from 1981 to 2018 as recorded by the MK/MMK test is summarized in Table 3.2. The trend of the SDII showed a significantly increasing trend at a rate of 0.04 mm/day for Lay Gayint ($p < 0.05$). The rate of change in Tach Gayint was 0.03 mm/day ($p < 0.05$). CDD showed a significantly increasing trend ($p < 0.05$) at a rate of 0.26 days/year in Simada. The result suggests that a drier condition was observed in both Simada and Tach Gayint compared to Lay Gayint. In all districts, CWD showed a statistically significant increasing trend ($p < 0.01$). The rate of change was 0.86 mm/day for Lay Gayint, 0.85 mm/day for Tach Gayint, and 0.79 mm/day for Simada. In Lay Gayint, PRCPTOT showed a statistically significant upward trend ($p < 0.01$) at a rate of 9.16 mm/year. The rate of change in Tach Gayint was 5.42 mm/year at $p < 0.05$.

Table 3. 2. The Mann-Kendall/Modified-Mann-Kendall trend test and Sen Slope values of the extreme indices (1981–2018).

Indices	Lay Gayint		Tach Gayint		Simada	
	MK/MMK	SS	MK/MMK	SS	MK/MMK	SS
Rx1day	1.10	0.12	-0.55	-0.05	-1.53	-0.15
Rx5day	1.70	0.45	-0.12	**-0.03**	-1.25	**-0.22**
R10mm	2.96	**0.46****	2.33	0.31*	1.10	0.12
R20mm	1.98	0.14*	0.49	**0.02**	-0.75	-0.01
CDD	-0.74	-0.13	1.70	0.26	1.88	0.26*
CWD	3.57	0.86**	2.86	**0.85****	3.34	**0.79****
R95p	1.50	2.06	0.27	0.53	-1.00	-1.08
R99p	1.50	0.72	-0.59	-0.29	-1.23	**-0.58**
PRCPTOT	2.91	9.16**	2.46	5.42*	0.65	**1.70**
SDII	2.47	**0.04***	2.35	0.03*	1.32	0.01

* and ** significant at α 0.05 and 0.01 level, respectively. Bold values indicate MMK test values (series with significant autocorrelation)

The trend of precipitation extremes using the ITA method is given in Tables 3.3–3.5. Results showed a statistically significant increasing SDII trend in Lay Gayint (0.05 mm/day) and Tach Gayint (0.04 mm/day) at $p < 0.01$. In Tach Gayint, CDD increased at a statistically significant rate of 0.33 days/year ($p < 0.01$). The corresponding value for Simada was 0.18 days/year ($p < 0.01$).

On the other hand, CDD showed a statistically significant decreasing trend ($p < 0.01$) in Lay Gayint at a rate of 0.21 days/year. CWD showed a statistically significant increasing trend at a rate of 0.72 days/year in Lay Gayint ($p < 0.01$).

Table 3. 3. The innovative trend analysis results in precipitation extreme indices in Lay Gayint (1981–2018).

Indices	SITA	SSD	Correlation $(\boldsymbol{\rho\bar{x}_1\bar{x}_2})$	UCL/LCL Sig. (p < 0.05)	UCL/LCL Sig. (p < 0.01)
Rx1day	0.10**	0.01	0.97	±0.03	±0.03
Rx5day	0.38**	0.04	0.97	±0.07	±0.09
R10mm	0.44**	0.04	0.92	±0.07	±0.09
R20mm	0.15**	0.01	0.98	±0.02	±0.02
CDD	-0.21**	0.03	0.98	±0.05	±0.07
CWD	0.72**	0.04	0.97	±0.07	±0.09
R95p	2.21**	0.15	0.99	±0.28	±0.37
R99p	0.78**	0.08	0.97	±0.15	±0.20
PRCPTOT	7.70**	0.72	0.92	±1.41	±1.85
SDII	0.05**	0.00	0.95	±0.01	±0.01

** significant at α 0.01 level. UCL/LCL represent upper and lower confidence limits.

Table 3. 4. The innovative trend analysis results in precipitation extreme indices in Tach Gayint (1981–2018).

Indices	SITA	SSD	Correlation $(\boldsymbol{\rho\bar{x}_1\bar{x}_2})$	UCL/LCL Sig. (p < 0.05)	UCL/LCL Sig. (p < 0.01)
Rx1day	-0.11**	0.02	0.94	±0.04	±0.05
Rx5day	-0.01	0.05	0.92	±0.09	±0.12
R10mm	0.29**	0.03	0.93	±0.05	±0.07
R20mm	0.04**	0.01	0.97	±0.01	±0.01
CDD	0.33**	0.02	0.98	±0.04	±0.05
CWD	0.59**	0.06	0.94	±0.11	±0.15
R95p	0.97**	0.17	0.96	±0.33	±0.44
R99p	-0.44**	0.05	0.98	±0.11	±0.14
PRCPTOT	3.93**	0.40	0.95	±0.79	±1.04
SDII	0.04**	0.00	0.96	±0.00	±0.01

** significant at α 0.01 level. UCL/LCL represent upper and lower confidence limits.

Table 3. 5. The innovative trend analysis results in precipitation extreme indices in Simada (1981–2018).

Indices	SITA	SSD	Correlation $(\rho\bar{x}_1\bar{x}_2)$	UCL/LCL Sig. (p < 0.05)	UCL/LCL Sig. (p < 0.01)
Rx1day	-0.17**	0.01	0.98	±0.01	±0.02
Rx5day	-0.29**	0.02	0.97	±0.04	±0.06
R10mm	-0.08**	0.01	0.97	±0.02	±0.03
R20mm	-0.03**	0.00	0.98	±0.01	±0.01
CDD	0.18**	0.02	0.97	±0.05	±0.06
CWD	0.42**	0.04	0.94	±0.09	±0.12
R95p	-1.29**	0.13	0.97	±0.26	±0.34
R99p	-0.79**	0.05	0.98	±0.09	±0.12
PRCPTOT	0.27	0.16	0.99	±0.31	±0.41
SDII	0.01	0.00	0.96	±0.01	±0.02

** significant at α 0.01 level. UCL/LCL represent upper and lower confidence limits.

The corresponding values for Tach Gayint and Simada were 0.59 days/year and 0.42 days/year, respectively ($p < 0.01$). A statistically significant increasing PRCPTOT trend was observed in Lay Gayint (7.70 mm/year) and Tach Gayint (3.93 mm/year) at $p < 0.01$. The result showed that some significant increasing trends masked by the MK/MMK test are detected with the ITA method; indicating the ITA's ability to identify trends in time series. The increasing trend towards the

extremes mentioned above can also be clearly seen from the scattered points that lie above the 1:1 line in the cartesian coordinate system (Figures 3.4–3.6).

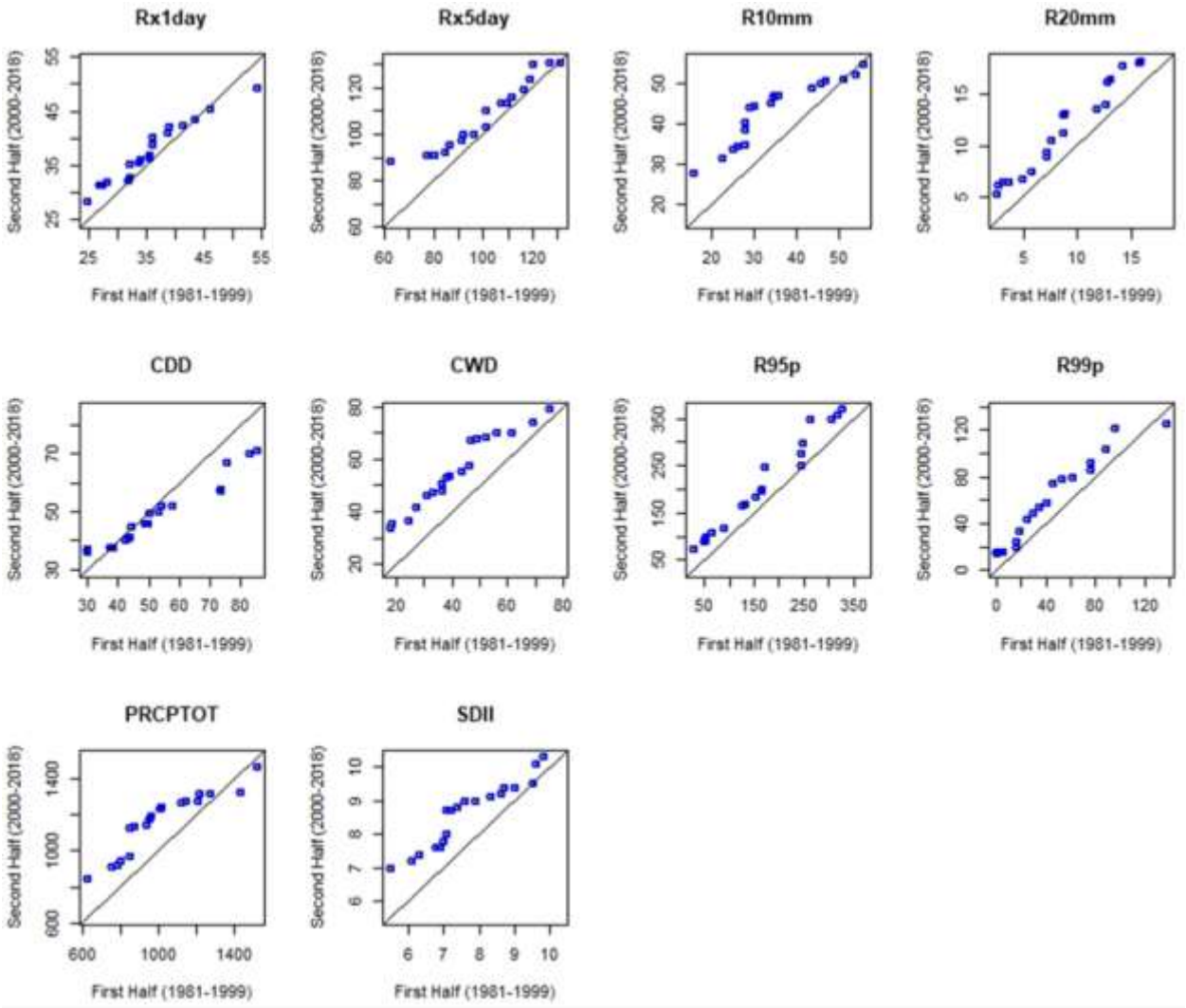

Figure 3. 4. Trend of precipitation extremes in Lay Gayint using G-ITA method from 1981–2018.

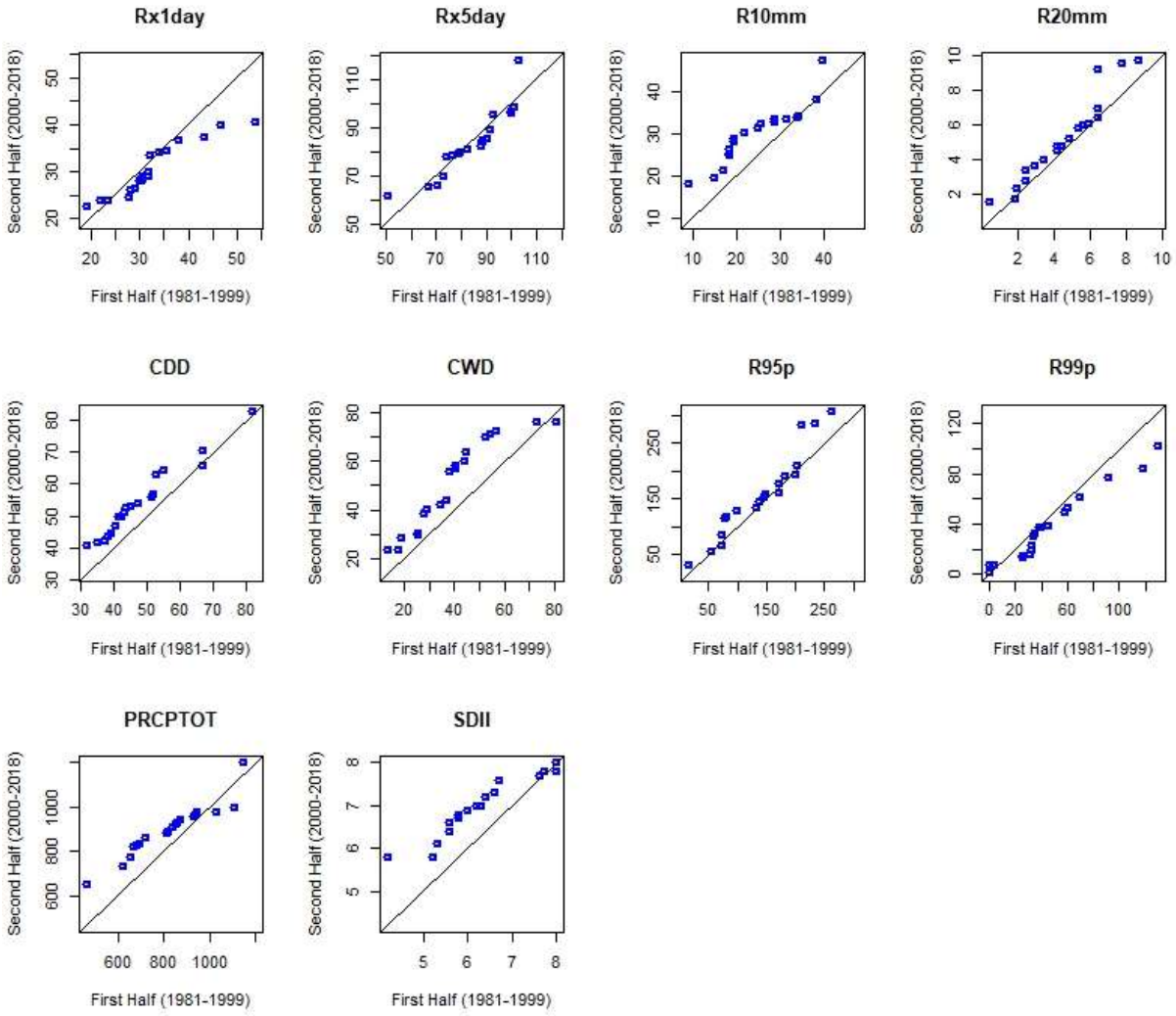

Figure 3. 5. Trend of precipitation extremes in Tach Gayint using G-ITA method from 1981–2018.

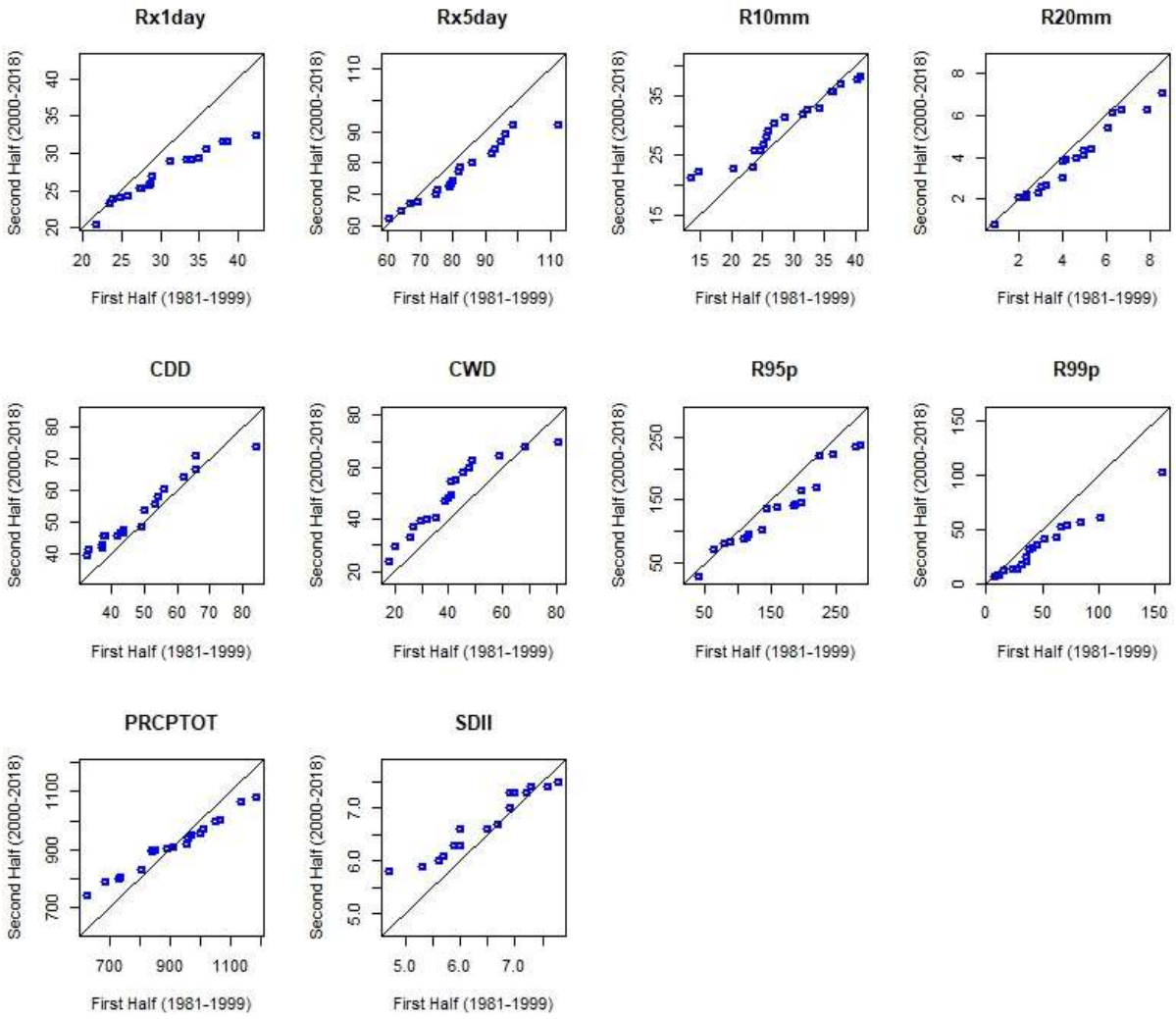

Figure 3. 6. Trend of precipitation extremes in Simada using G-ITA method from 1981–2018.

3.1.2. Number of Heavy (R10mm) and Very Heavy (R20mm) Precipitation Days

Based on analysis of the MK/MMK test, R10mm showed a statistically significant increasing trend in Lay Gayint (0.46 days/year) at $p < 0.01$ and Tach Gayint (0.31 days/year) at $p < 0.05$. Regarding the trend of R20mm, Lay Gayint showed a statistically significant increasing trend ($p < 0.01$) at a rate of 0.14 days/year (Table 3.2). According to ITA analysis, the trends of R10mm and R20mm showed statistically significant decreasing trends in Simada at a rate of 0.08 days/year and 0.03 days/year, respectively, at $p < 0.01$. On the other hand, the trend of R10mm showed a significantly increasing trend ($p < 0.01$) with rates of 0.44 days/year and 0.29 days/year in Lay Gayint and Tach Gayint, respectively. R20mm showed a significantly increasing trend ($p < 0.01$) at rates of 0.15 days/year in Lay Gayint and 0.04 days/year in Tach Gayint. The increase in R10mm and R20mm

indicates potential risks related to soil erosion and flooding (Tables 3.3–3.5). As shown in Figures 3.4–3.6, the scatter points for R10mm and R20mm values in Tach Gayint and Lay Gayint districts are above the 1:1 line. The trends in Simada are unclear.

3.1.3. Maximum 1-Day (Rx1day) and 5-Day (Rx5day) Precipitation

As indicated in Table 3.2, the results of the MK/MMK test analysis showed that the trends of Rx1day and Rx5day in Lay Gayint increased at rates of 0.12 mm/year and 0.45 mm/year, respectively, but the trends were not statistically significant. On the other hand, the values in Tach Gayint decreased by 0.05 mm/year (Rx1day) and 0.03 mm/year (Rx5days), while in Simada they decreased by 0.15 mm/year (Rx1day) and 0.22 mm/year (Rx5days). ITA analysis showed that a statistically significant increasing trend of Rx5day was recorded in Lay Gayint (0.38 mm/year) at $p < 0.01$. Tach Gayint, on the other hand, showed a statistically significant decreasing trend in Rx1day at $p < 0.01$. In addition, the Rx1day and Rx5day values in Simada showed statistically significant decreasing trends at rates of 0.17 mm/year and 0.29 mm/year, respectively, at $p < 0.01$ (Tables 3.3 –3.5). Further examination of the ITA graph showed inconsistent trends for Rx1day and Rx5day values. As a result, the scatter points lying above and below the 1:1 line in Lay Gayint and Simada indicate rising and falling trends, respectively. For Tach Gayint, the scatter points showed unclear trends (Figures 3.4–3.6).

3.1.4. Very Wet Days (R95p) and Extremely Wet Days (R99p)

The trend of R95p using the MK/MMK test showed a tendency to increase at both Lay Gayint and Tach Gayint. The trend of R99p showed an increasing trend in Lay Gayint but a decreasing trend in both Tach Gayint and Simada over the study period. However, the observed trends were not statistically significant in either case (Table 3.2). In contrast, the ITA test showed that the trends of R95p (2.21 mm/year) and R99p (0.78 mm/year) had statistically significant increasing trends in Lay Gayint at $p < 0.01$. Statistically significant decreasing trends of R95p (1.29 mm/year) and R99p (0.79 mm/year) were observed in Simada at $p < 0.01$. In Tach Gayint, R95p and R99p showed statistically significant increasing and decreasing trends, respectively, at $p < 0.01$ (Tables 3.3–3.5). The finding supports the ability of the ITA method to identify masked trends in time-series data; several significant increasing trends that the MK/MMK test missed were detected using the ITA. As shown in Figures 3.4–3.6, the scatter points in Lay Gayint and Simada fall above and below the 1:1 line, representing rising and falling trends, respectively. The scatter points in Tach Gayint district showed unclear trends.

3.2. Comparison of Trend Analysis Methods

The comparison between the trend detection results by the two methods, i.e., the MK and ITA tests, is shown in Table 3.6. It is shown that statistically significant increasing or decreasing trends are observed in 11 (37%) of the precipitation time series with the MK test. The ITA found a significantly increasing or decreasing trend in 27(90%) of the precipitation time series, indicating that a large number of significant trends are detected by the ITA method. Likewise, any statistically significant trend detected by the MK test is identified by the ITA. The ITA detects trends in 16 (53%) of the extreme rainfall index time series that the MK tests failed to do.

Table 3. 6. Comparisons of results of trend analysis of precipitation extremes by the MK and ITA methods (1981–2018).

Indices	Lay Gayint		Tach Gayint		Simada	
	MK	ITA	MK	ITA	MK	ITA
Rx1day	No	Yes (++)	No	Yes (− −)	No	Yes (- -)
Rx5day	No	Yes (++)	No	No	No	Yes (- -)
R10mm	Yes (++)	Yes (++)	Yes (+)	Yes (++)	No	Yes (++)
R20mm	Yes (+)	Yes (++)	No	Yes (++)	No	Yes (- -)
CDD	No	Yes (- -)	No	Yes (++)	Yes (+)	Yes (++)
CWD	Yes (++)	Yes (++)	Yes (++)	Yes (++)	Yes (- -)	Yes (++)
R95p	No	Yes (++)	No	Yes (++)	No	Yes (- -)
R99p	No	Yes (++)	No	Yes (- -)	No	Yes (- -)
PRCPTOT	Yes (++)	Yes (++)	Yes (+)	Yes (++)	No	No
SDII	Yes (+)	Yes (++)	Yes (+)	Yes (++)	No	No

Yes (+) and Yes (−) indicate significant increasing and decreasing trends at 5% significance level ($p < 0.05$); Yes (++) and Yes (− −) indicate significant increasing and decreasing trends at 1% significance level ($p < 0.01$). No indicates non-significant result.

4. Discussions

The study investigated variations and trends in precipitation extremes. According to the ITA results, the CDD, CWD, PRCPTOT, SDII, R95p, R10mm, and R20mm exhibited statistically significant increasing trends in Tach Gayint, while the Rx1day and R99p showed statistically significant decreasing trends at $p < 0.01$. With the exception of CDD, all extreme precipitation indices in Lay Gayint exhibited statistically significant increasing trends at $p < 0.01$. In Simada, CDD, and CWD exhibited statistically significant increasing trends, while R95p, R99p, R10mm, R20mm, Rx1day, and Rx5day showed statistically significant decreasing trends. The MK test findings in Lay Gayint showed statistically significant increasing trends for R10mm, CWD,

PRCPTOT, R20mm, and SDII at $p < 0.05$. The CWD, R10mm, PRCPTOT, and SDII in Tach Gayint showed statistically significant increasing trends at $p < 0.01$. On the other hand, only CDD and CWD showed statistically significant increasing trends in Simada at $p < 0.05$ and $p < 0.01$, respectively.

The significance of extreme precipitation indices in the study area can be attributed to differences in elevation. Specifically, the Lay Gayint district is situated in the *High Dega* agroecological zone, with an elevation ranging from 3200 to 3700 m.a.s.l. In contrast, the Tach Gayint and Simada districts are located in the *Dega* zone (2300–3200 m.a.s.l) and the *Woyna Dega* zone (1500–2300 m.a.s.l), respectively (Hurni et al., 2016), as it is explained in the methodology section of this study. Agroecological zones are defined based on the interactions between climate, topography, and soil characteristics, and can provide a useful framework for understanding the spatial distribution of extreme precipitation events. Different agroecological zones can have different temperature and moisture regimes, which can affect the timing, intensity, and type of extreme precipitation events that occur. This indicates that variations in elevation play a significant role in the spatial distribution of precipitation extremes. Previous research studies consistently demonstrate a strong correlation between elevation in Ethiopia and the spatial variability of precipitation extremes (Berhane et al., 2020; Gebrechorkos et al., 2019; Gummadi et al., 2018; Shawul and Chakma, 2020; Terefe et al., 2022). Overall, the study highlights the importance of considering elevation and agroecological zones when studying extreme precipitation events in the study area. The differences in elevation between the districts can lead to variations in the spatial distribution of extreme precipitation indices, which can have important implications for water resource management and disaster risk reduction.

The trend results we found for some extreme precipitation indices are similar to findings reported in previous studies (Esayas et al., 2018; Shawul and Chakma, 2020; Terefe et al., 2022; Worku et al., 2019) reported the existence of statistically significant increasing trends for R10 mm and R20 mm in the Ejersalele and Tora stations in the Meki watershed, central Ethiopia. Similarly, increasing trends of R10 mm and R20 mm were reported by Esayas et al. (2018), Shawul and Chakma (2020), and Worku et al. (2019) in the majority of weather stations in Southern Ethiopia, in the Upper Awash ba-sin and Jemma Sub-basin of Ethiopia, respectively. Furthermore, studies by Damtew et al. (2022), Degefu et al. (2021), and Geremew et al. (2020) found increasing trends of CWD and CDD in the Awash River basin and Southeastern and Northwestern Ethiopia,

respectively. On the other hand, our results did not agree with the findings of some other studies. For ex-ample, a study by Esayas et al. (2018) found statistically significant decreasing trend in CWD in Southern Ethiopia. The trend in PRCPTOT showed a statistically non-significant decreasing trend in the Jemma Sub-Basin of the Upper Blue Nile Basin (Worku et al., 2019). Statistically non-significant decreasing trends in the Rx1day and Rx5day precipitation were observed in most of the studied agroecologies in the Gurage Zone, Southern Ethiopia (Dendir and Birhanu, 2022). Esayas et al. (2018) reported that lowland and midland agroecologies in the Wolaita Zone of Southern Ethiopia exhibited statistically non-significant increasing trends for Rx1-day and Rx5-day. In general, topography, variations in record lengths, number of stations, and method of data analysis used account for the majority of observed discrepancies (Dawit et al., 2019; Gebrechorkos et al., 2019; Gummadi et al., 2018).

Comparison of the ITA and MK trend detection methods indicates that the ITA method is superior to the MK test. The ITA method detected statistically significant increasing and decreasing trends in 27 (90%) of the precipitation time series, which indicated that a large number of significant trends that were missed by the MK test were detected using the ITA method. The ITA method detected trends in 16 (53%) of the precipitation extreme time series that the MK tests did not detect. Singh et al. (2021) compared the ITA with the MK test for assessing spatiotemporal variations of precipitation extremes in India and recommended the ITA as the better option. Harka et al. (2021) found the ITA approach to be more reliable than the MK test in their study on the Wabe Shebelle River Basin of Ethiopia. Similarly, in their investigation of seasonal and annual rainfall variability in the Amhara Regional State, Gedefaw et al. (2018) reported that the ITA was preferable to the MK test.

Several studies also noted the ITA method and its capacity to detect trends more effectively than the MK test in different parts of the world (Caloiero et al., 2018; Kişi et al., 2018; Marak et al., 2020; Wang et al., 2020). The ITA approach enables more in-depth interpretations of trend identification, which is advantageous for detecting trends that are hidden from view as well as for illustrating the trend variability of extreme events in a graphical form (Alifujiang et al., 2020; Caloiero, 2020; Wu and Qian, 2017). It illustrates monotonic and non-monotonic trends (Sen, 2012; Wang et al., 2020).

In general, the results provided useful information for policy makers and water re-source managers, given that extreme precipitation events can result in natural disasters such as flooding and landslides. These events can cause significant damage to infrastructure and pose a threat to communities, thereby warranting careful and strategic management of water resources. There are several ways in which policy makers and water re-source managers can prepare for extreme precipitation events, including developing early warning systems, building and maintaining infrastructure, implementing land-use planning and zoning, promoting sustainable agriculture, educating and training communities, and investing in research. By implementing these strategies, policy makers and water re-source managers can help reduce the risk and impact of extreme precipitation events and promote the safety and well-being of communities.

Although the study may have identified long-term trends in extreme precipitation in-dices in the study area, it may not have explored the underlying causes of these trends. Therefore, future investigations could focus on examining the meteorological, climatological, and environmental factors that contribute to changes in extreme precipitation. Additionally, while the study may have focused on three districts of Northwest Ethiopia (Lay Gayint, Tach Gayint, and Simada), expanding the analysis to other districts could help identify spatial patterns in extreme precipitation indices and vulnerable regions. Further-more, while the study may have focused on the trends in extreme precipitation indices themselves, future investigations could examine the impacts of these events on the environment, agriculture, infrastructure, and communities in the area. Such research could help inform adaptation and mitigation strategies to reduce the negative impacts of extreme precipitation events. Finally, investigating the potential for future changes in extreme precipitation could be valuable. Although the study may have analyzed trends in extreme precipitation indices over a historical period, using climate models to project how these trends may change in the future under different scenarios of greenhouse gas emissions and climate change could help inform planning and decision-making for future climate risks and impacts in the study area.

5. Conclusions

The study conducted an analysis of the frequency and intensity of extreme precipitation events in Northwest Ethiopia using both the MK/MMK methods. The findings revealed significant changes in the patterns of extreme precipitation events in the area over the past few decades, with an increase in both frequency and intensity. It is noteworthy that trend detection studies in the

literature typically rely on both the MK/MMK test and the SS investigation. While the MK/MMK test determines the existence of a trend and its direction, the trend magnitude is calculated using the SS method only if a significant trend is found according to these methodologies. Otherwise, the SS method is generally not employed. It is worth noting that the validity of the results obtained from the MK/MMK methods is subject to several assumptions. The study also compared the MK/MMK and SS methodologies with the ITA method, another popular trend detection tool. Although the different methodologies resulted in some variations in trend magnitudes, the ITA and SS methods' trend direction results matched up in some extreme precipitation indices. The ITA method provides graphical and statistical trend analysis that objectively interprets the trends. Another significant finding of the study is that neither the SS nor the ITA methods rely on assumptions or statistical significance levels. Therefore, employing and comparing different methods such as MK/MMK, SS, and ITA for trend analysis can provide more de-tailed information on trend identification in the studied data. This can ultimately lead to more accurate climate analysis and better-informed decision-making. By using multiple methodologies, researchers can gain a comprehensive understanding of trends and minimize the impact of potential bias resulting from a single method.

Acknowledgments

We would like to express our gratitude to Addis Ababa University and Dilla University for their financial assistance to the first author. Additionally, we are thankful to the Ethiopian National Meteorological Agency for providing climate data free of charge.

References

Alemayehu, A., & Bewket, W. (2017). Local spatiotemporal variability and trends in rainfall and temperature in the central highlands of Ethiopia. *Geografiska Annaler: Series A, Physical Geography*, 99, 85–101.

Alemu, Z. A., & Dioha, M. O. (2020). Climate change and trend analysis of temperature: The case of Addis Ababa, Ethiopia. *Environmental Systems Research*, 9, 1–5.

Alifujiang, Y., Abuduwaili, J., Maihemuti, B., Emin, B., & Groll, M. (2020). Innovative trend analysis of precipitation in the Lake Issyk-Kul Basin, Kyrgyzstan. *Atmosphere*, 11, 332.

Asfaw, A., Simane, B., Hassen, A., & Bantider, A. (2018). Variability and time series trend analysis of rainfall and temperature in north-central Ethiopia: A case study in Woleka sub-basin. *Weather and Climate Extremes*, 19, 29–41.

Bazezew, A., Bewket, W., & Nicolau, M. (2013). Rural households' livelihood assets, strategies and outcomes in drought-prone areas of the Amhara Region, Ethiopia: Case Study in Lay Gaint District. *African Journal of Agricultural Research*, 8, 5716–5727.

Berhane, A., Hadgu, G., Worku, W., & Abrha, B. (2020). Trends in extreme temperature and rainfall indices in the semi-arid areas of Western Tigray, Ethiopia. *Environmental Systems Research*, 9, 1–20.

Birhan, D. A., Zaitchik, B. F., Fantaye, K. T., Birhanu, B. S., Damot, G. A., & Tsegaye, E. A. (2022). Observed and projected trends in climate extremes in a tropical highland region: An agroecosystem perspective. International Journal of Climatology, 42(4), 2493-2513.

Beyene, T. K., Jain, M. K., Yadav, B. K., & Agarwal, A. (2022). Multiscale investigation of precipitation extremes over Ethiopia and tele-connections to large-scale climate anomalies. *Stochastic Environmental Research and Risk Assessment*, 36, 1503–1519.

Bezu, A. (2020). Analyzing Impacts of Climate Variability and Changes in Ethiopia: *A Review. American Journal of Modern Energy*, 6, 65.

Birpınar, M. E., Kızılöz, B., & Şişman, E. (2023). Classic trend analysis methods' paradoxical results and innovative trend analysis methodology with percentile ranges. *Theoretical and Applied Climatology*, 153, 1–8.

Caloiero, T. (2020). Evaluation of rainfall trends in the South Island of New Zealand through the innovative trend analysis (ITA). *Theoretical and Applied Climatology*, 139, 493–504.

Caloiero, T., Coscarelli, R., & Ferrari, E. (2018). Application of the Innovative Trend Analysis Method for the Trend Analysis of Rainfall Anomalies in Southern Italy. *Water Resources Management*, 32, 4971–4983.

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, 89.

Datta, P., & Behera, B. (2022). What caused smallholders to change farming practices in the era of climate change? Empirical evidence from Sub-Himalayan West Bengal, India. *GeoJournal*, 87, 3621–3637.

Dawit, M., Halefom, A., Teshome, A., Sisay, E., Shewayirga, B., & Dananto, M. (2019). Changes and variability of precipitation and temperature in the Guna Tana watershed, Upper Blue Nile Basin, Ethiopia. *Modeling Earth Systems and Environment*, 5, 1395–1404.

Degefu, M. A., Tadesse, Y., & Bewket, W. (2021). Observed changes in rainfall amount and extreme events in southeastern Ethiopia, 1955–2015. *Theoretical and Applied Climatology*, 144, 967–983.

Dendir, Z., & Birhanu, B. S. (2022). Analysis of Observed Trends in Daily Temperature and Precipitation Extremes in Different Agroecologies of Gurage Zone, Southern Ethiopia. *Advances in Meteorology*, 2022.

Dinku, T. (2019). Challenges with Availability and Quality of Climate Data in Africa. Elsevier Inc.

Dinku, T., Cousin, J., del Corral, R., & Ceccato, P. (2016). The Enacts Approach. The International Research Institute for Climate and Society (IRI). Palisades, New York, USA.

Dinku, T., Thomson, M. C., Cousin, R., del Corral, J., Ceccato, P., Hansen, J., & Connor, S. J. (2018). Enhancing National Climate Services (ENACTS) for development in Africa. *Climate Development*, 10, 664–672.

Endalew, H. A., & Sen, S. (2020). Effects of climate shocks on Ethiopian rural households: An integrated livelihood vulnerability approach. *Journal of Environmental Planning and Management*, 64, 399–431.

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, 1–17.

Ferijal, T., Batelaan, O., & Shanafield, M. (2021). Rainy season drought severity trend analysis of the Indonesian maritime continent. *International Journal of Climatology*, 41, E2194–210.

Gajbhiye, S., Meshram, C., Mirabbasi, R., & Sharma, S. K. (2016). Trend analysis of rainfall time series for Sindh River basin in India. *Theoretical and Applied Climatology*, 125, 593–608.

Gebrechorkos, S. H., Hülsmann, S., & Bernhofer, C. (2019). Changes in temperature and precipitation extremes in Ethiopia, Kenya, and Tanzania. *International Journal of Climatology*, 39, 18–30.

Gebrehiwot, B., 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.

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.

Gedefaw, M., Yan, D., Wang, H., Qin, T., Girma, A., Abiyu, A., & Batsuren, D. (2018). Innovative trend analysis of annual and seasonal rainfall variability in Amhara Regional State, Ethiopia. *Atmosphere*, 9, 326.

Geremew, G. M., Mini, S., & Abegaz, A. (2020). Spatiotemporal variability and trends in rainfall extremes in Enebsie Sar Midir district, northwest Ethiopia. *Modeling Earth Systems and Environment*, 6, 1177–1187.

Gezie, M. (2019). Farmer's response to climate change and variability in Ethiopia: A review. *Cogent Food and Agriculture*, 5, 1613770.

Gummadi, S., Rao, K. P. C., Seid, J., Legesse, G., Kadiyala, M. D. M., Takele, R., et al. (2018). Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980–2010. *Theoretical and Applied Climatology*, 134, 1315–1328.

Hamed, K. H., & Ramachandra Rao, A. (1998). A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, 204, 182–196.

Harka, A. E., Jilo, N. B., & Behulu, F. (2021). Spatial-temporal rainfall trend and variability assessment in the Upper Wabe Shebelle River Basin, Ethiopia: Application of innovative trend analysis method. *Journal of Hydrology: Regional Studies*, 37, 100915.

Hurni, H., Berhe, W. A., Chadhokar, P., Daniel, D., Gete, Z., & Grunder, M. K. G. (2016). Soil and Water Conservation in Ethiopia: Guidelines for Development Agents. Volume 1. Centre for Development and Environment (CDE), University of Bern: Bern, Switzerland.

Janizadeh, S., Pal, S. C., Saha, A., Chowdhuri, I., Ahmadi, K., Mirzaei, S., Mosavi, A. H., & Tiefenbacher, J. P. (2021). Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes in the future. *Journal of Environmental Management*, 298, 113551.

Jin, H., Chen, X., Wu, P., Song, C., & Xia, W. (2021). Evaluation of spatial-temporal distribution of precipitation in mainland China by statistic and clustering methods. *Atmospheric Research*, 262, 105772.

Kendall, M. G. (1975). Rank Correlation Methods (4th ed.). Charles Griffin & Company Limited.

Kişi, Ö., Santos, C. A. G., da Silva, R. M., Zounemat-Kermani, M. (2018). Trend analysis of monthly streamflows using Şen's innovative trend method. *Geofizika*, 35, 53–68.

Kumar, S., Machiwal, D., Dayal, D. (2017). Spatial modelling of rainfall trends using satellite datasets and geographic information system. *Hydrological Sciences Journal*, 62, 1636–1653.

Kumar, S., Merwade, V., Kam, J., Thurner, K. (2009). Streamflow trends in Indiana: Effects of long-term persistence, precipitation, and subsurface drains. *Journal of Hydrology*, 374, 171–183.

Likinaw, A., Alemayehu, A., Bewket, W. (2022). Local-scale climate variability and trends in a vulnerable rural landscape, northwest Ethiopia. *Malaysian Journal of Tropical Geography*, 48, 19–44.

Mann, H. B. (1945). Nonparametric tests against trend. Econometrica: *Journal of the Econometric Society*, 13, 245–259.

Marak, J. D. K., Sarma, A. K., Bhattacharjya, R. K. (2020). Innovative trend analysis of spatial and temporal rainfall variations in Umiam and Umtru watersheds in Meghalaya, India. *Theoretical and Applied Climatology*, 142, 1397–1412.

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, e03867.

Mukherjee, S., Mishra, A. K. (2021). Cascading effect of meteorological forcing on extreme precipitation events: Role of atmospheric rivers in southeastern US. *Journal of Hydrology*, 601, 126641.

Myhre, G., Alterskjær, K., Stjern, C. W., Hodnebrog, Ø., Marelle, L., Samset, B. H., Sillmann, J., Schaller, N., Fischer, E., Schulz, M., et al. (2019). Frequency of extreme precipitation increases extensively with event rareness under global warming. *Scientific Reports*, 9, 16063.

Nicholson, S. E. (2017). Climate and climatic variability of rainfall over eastern Africa. *Reviews of Geophysics*, 55, 590–635.

Novotny, E. V., Stefan, H. G. (2007). Stream flow in Minnesota: Indicator of climate change. *Journal of Hydrology*, 334, 319–333.

Obada, E., Alamou, E. A., Biao, E. I., Zandagba, E. B. J. (2021). Interannual variability and trends of extreme rainfall indices over Benin. *Climate*, 9, 160.

Papalexiou, S. M., Montanari, A. (2019). Global and Regional Increase of Precipitation Extremes Under Global Warming. *Water Resources Research*, 55, 4901–4914.

Salameh, A. A. M., Ojeda, M. G.-V., Esteban-Parra, M. J., Castro-Díez, Y., Gámiz-Fortis, S. R. (2022). Extreme rainfall indices in southern levant and related large-scale atmospheric circulation patterns: A spatial and temporal analysis. *Wate*r, 14, 3799.

Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63, 1379–1389.

Şen, Z. (2012). Innovative trend analysis methodology. *Journal of Hydrologic Engineering*, 17, 1042–1046.

Şen, Z. (2017). Innovative trend significance test and applications. *Theoretical and Applied Climatology*, 127, 939–947.

Serencam, U. (2019). Innovative trend analysis of total annual rainfall and temperature variability case study: Yesilirmak region, Turkey. *Arabian Journal of Geosciences*, 12, 704.

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, 635–652.

Singh, R., Sah, S., Das, B., Potekar, S., Chaudhary, A., Pathak, H. (2021). Innovative trend analysis of spatio-temporal variations of rainfall in India during 1901–2019. *Theoretical and Applied Climatology*, 145, 821–838.

Şişman, E., Kizilöz, B., & Birpinar, M. E. (2022). Trend slope risk charts (TSRC) for piecewise ITA method: An application in Oxford, 1771–2020. *Theoretical and Applied Climatology*, 150, 863–879.

Srivastava, P. K., Pradhan, R. K., Petropoulos, G. P., Pandey, V., Gupta, M., Yaduvanshi, A., Jaafar, W. Z. W., Mall, R. K., & Sahai, A. K. (2021). Long-term trend analysis of precipitation and extreme events over Kosi River Basin in India. *Water*, 13, 1695.

Tank, A., Zwiers, F., & Zhang, X. (2009). Guidelines on Analysis of Extremes in a Changing Climate. World Meteorological Organization, Location: Geneva, Switzerland.

Terefe, S., Bantider, A., Teferi, E., & Abi, M. (2022). Spatiotemporal trends in mean and extreme climate variables over 1981–2020 in Meki watershed of the central rift valley basin, Ethiopia. *Heliyon*, 8, e11684.

Theil, H. (1950). A rank-invariant method of linear and polynomial regression analysis, Part I. Proceedings of the National Academy of Sciences of the USA, 53, 386–392.

Tizazu, G. Z. (2019). Food Security Status of Rural Households in Lay Gayint Woreda of South Gondar Zone, Amhara Region, Ethiopia. *International Journal of African Asian Studies*, 57, 12–26.

Vondou, D. A., Guenang, G. M., Djiotang, T. L. A., & Kamsu-Tamo, P. H. (2021). Trends and interannual variability of extreme rainfall indices over Cameroon. *Sustainability*, 13, 6803.

Wang, X. L., & Feng, Y. (2010). RHtestsV3 User Manual. Atmospheric Science Technology Directorate, Science Technology Branch, Environment Canada, 2010, 1–27.

Wang, X. L., Wen, Q. H., & Wu, Y. (2007). Penalized Maximal t Test for Detecting Undocumented Mean Change in Climate Data Series. *Journal of Applied Meteorology and Climatology*, 46, 916–931.

Wang, Y., Liu, G., & Guo, E. (2019). Spatial distribution and temporal variation of drought in Inner Mongolia during 1901–2014 using Standardized Precipitation Evapotranspiration Index. *Science of The Total Environment*, 654, 850–862.

Wang, Y., Xu, Y., Tabari, H., Wang, J., Wang, Q., Song, S., & Hu, Z. (2020). Innovative trend analysis of annual and seasonal rainfall in the Yangtze River Delta, eastern China. *Atmospheric Research*, 231, 104673.

Worku, G., Teferi, E., Bantider, A., & Dile, Y. T. (2019). Observed changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia. *Theoretical and Applied Climatology*, 135, 839–854.

World Meteorological Organization (WMO). (2021). State of the Climate in Africa 2020. World Meteorological Organization: Geneva, Switzerland.

Wu, C., Huang, G., Yu, H., Chen, Z., & Ma, J. (2013). Spatial and temporal distributions of trends in climate extremes of the Feilaixia catchment in the upstream area of the Beijiang River Basin, South China. *International Journal of Climatology*, 34, 3161–3178.

Wu, H., & Qian, H. (2017). Innovative trend analysis of annual and seasonal rainfall and extreme values in Shaanxi, China, since the 1950s. *International Journal of Climatology*, 37, 2582–2592.

Yang, Y., Gao, M., Xie, N., & Gao, Z. (2020). Relating anomalous large-scale atmospheric circulation patterns to temperature and precipitation anomalies in the East Asian monsoon region. *Atmospheric Research*, 232, 104679.

Yue, S., & Wang, C. Y. (2004). The Mann-Kendall test modified by effective sample size to detect trend in serially correlated hydrological series. *Water Resources Management*, 18, 201–218.

Yue, S., Pilon, P., Phinney, B., & Cavadias, G. (2002). The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrological Processes*, 16, 1807–1829.

Zhang, X., Yang, F., & Canada, E. (2004). RClimDex (1.0). Climate Research Division, Environment Canada. Toronto, Canada. (pp. 1–23).

Chapter Four

Smallholder farmers' vulnerability to climate change in northwest Ethiopia[3]

Abstract

The livelihoods of households in Tach Gayint, Simada and Lay Gayint districts in northwest Ethiopia are at risk due to climate variability. To better understand susceptibility of these households, a study was conducted by means of two approaches: the Livelihood Vulnerability Index (LVI) and the Socioeconomic Vulnerability Index (SeVI). The LVI encompasses 32 indicators, while the SeVI incorporates 31 indicators. The study was conducted with a survey of 352 households and focus group discussants in 6 groups in the three districts. Both methods indicate that Simada is the most vulnerable district, followed by Tach Gayint and Lay Gayint. According to the SeVI approach, Simada showed the highest level of exposure and sensitivity to climate-related threats, and the lowermost score for adaptive capacity. However, under the LVI approach, Simada was found to have the uppermost sensitivity to climate threats and exposure to climate-related threats, along with more adaptive capacity than both Tach Gayint and Lay Gayint. The study highlights the importance of promoting the adaptive capacity of households in the study area. The findings are also useful to guide policy and program development to lessen susceptibility and increase adaptive capacity of households in the study area.

Keywords Climate change, Vulnerability, Livelihoods, Socioeconomics, Smallholders, Ethiopia.

[3] Likinaw, A., Alemayehu, A., & Bewket, W. (2023). Smallholder farmers' vulnerability to climate change in northwest Ethiopia. *International Journal of Climate Change Strategies and Management* (Under review).

1. Introduction

The frequency of severe events that have negative impacts on the livelihoods of smallholder farmers in developing nations is on the rise due to the impacts of climate change (Balaganesh et al., 2020; Farid et al., 2019; GebreMichael, 2020). The vulnerability of these farmers to climate related risks is triggered by their geographical location in vulnerable landscapes, their socioeconomic characteristics, heavy reliance on natural resources, and regulatory constraints that impede their capacity to adapt to changing climate (Jamshidi et al., 2019). In regions like sub-Saharan Africa, extreme climatic occurrences like droughts present considerable challenges to agricultural activities and livestock upkeep (Pironon et al., 2019; Tofu et al., 2023). These challenges are particularly pronounced due to the region's fragile socioeconomic backdrop, which poses obstacles to the achievement of Sustainable Development Goals (SDGs) (Chirambo, 2018; Kumi, 2019).

Among the sub-Saharan African countries, Ethiopia stands out as one severely impacted by climate-induced hazards, leading to significant negative consequences for its agricultural sector (Kamali et al., 2018; Sietz et al., 2017). This vulnerability of Ethiopia's agricultural system is primarily attributed to its substantial dependance on rain-fed smallholder farming (Yalew et al., 2018). Projections indicate a continued rise in the incidence and strength of extreme climate patterns such as floods, droughts and heatwaves (Liou and Mulualem, 2019; Nikulin et al., 2018). Although climate change is a worldwide phenomenon, its impacts are specific to certain regions. Hence, researchers have suggested local assessments of vulnerability to climate variability (Ahsan and Warner, 2014; Tessema and Simane, 2021). To this end, Hahn et al. (2009) proposed evaluating vulnerability at the communal level, facilitating the comparison of vulnerability levels among societies within a region or district and enabling the prioritization of context-specific adaptation measures. Thus, understanding vulnerability within local contexts becomes crucial for implementing effective adaptation strategies tailored to specific needs, addressing factors unique to each area (Quandt, 2021).

Local-level studies also aid in addressing challenges related to the formulation of reliable criteria for evaluating vulnerability and resilience. Additionally, micro-level vulnerability assessments help identify the most vulnerable populations and livelihoods within a specific region (Dhital et al., 2023). Consequently, conducting empirical research on household vulnerability to climate is

essential. Evaluating vulnerability to climate often involves the use of indicator-based approaches (Dendir and Simane, 2019; Ebrahim et al., 2022; Gebreegziabher et al., 2019; Oo et al., 2018). These approaches allow for the creation of vulnerability indexes by combining indicators (Oo et al., 2018). However, the concept of vulnerability lacks precise and consistent definition (Masuda et al., 2019; Sam et al., 2017), to develop diverse vulnerability indexes. While some experts argue that vulnerability cannot be quantified (Ahsan and Warner, 2014; Oo et al., 2018; Tessema et al., 2019), they suggest that indicator-based approaches enable sensitivity analysis, allowing for calibration of vulnerability assessments within and among vulnerable regions through manipulation of contributing factor scores.

Vulnerability assessments play several critical roles, including tracking changes in vulnerability over time and space, identifying contributing processes, outlining practices for vulnerability lessening, and evaluating the efficacy of these practices in various natural and social contexts (Alam et al., 2017; Mulugeta et al., 2019; Salman et al., 2022). However, quantifying vulnerability is intricate due to factors such as the combined effects of multiple variables, nonlinear interactions, and uncertainties about their relative importance. In evaluating household vulnerability to climate, different methodologies like the LVI (Hahn et al., 2009) and the SeVI (Ahsan and Warner, 2014) have been utilized. Previous research indicates that no single approach is exhaustive for assessing climate change vulnerability, given that each method possesses its own strengths and limitations (Oo et al., 2018; Sam et al., 2017). For example, the LVI method assigns equal weight to all indicators, potentially failing to accurately represent the impact of climate on household susceptibility (Hahn et al., 2009; Raj et al., 2022). Conversely, certain social and economic indicators that do not align with LVI framework could be combined with SeVI technique to assess households' socioeconomic vulnerability more comprehensively (Oo et al., 2018; Sam et al., 2017).

A thorough evaluation of household livelihood profiles can offer valuable insights, provided it considers the economic and social dimensions of the specific region (Ahsan and Warner, 2014; Mekonen and Berlie, 2021; Oo et al., 2018). Such approaches equip policymakers and development organizations with crucial information regarding socio-demographic characteristics and climate-related risks that contribute to vulnerability. This information serves as a foundation for formulating effective adaptation strategies and policies within resource constraints. To holistically comprehend household vulnerability to climate in the studied area, we employ and

compare two methods: the LVI and SeVI approaches, while considering the aforementioned factors. As such, the aim of this study is to evaluate the vulnerability of farmers in northwest Ethiopia to climate variability using a livelihood vulnerability assessment, employing both the LVI and SeVI approaches.

2. Materials and Methods

2.1. The study area

The study area encompasses three districts: Simada, Lay Gayint and Tach Gayint (Figure 4.1). These districts are characterized by distinct elevation features, each belonging to a specific agro-ecological zone. Lay Gayint occupies *High Dega*, located at an altitude span extending between 3200 and 3700 m.a.s.l. Tach Gayint falls within the *Dega zone*, spanning an altitude of 2300 to 3200 m.a.s.l, while Simada is located in the *Woyna Dega* zone, which extends from 1500 to 2300 m.a.s.l (Hurni et al., 2016). Across the study area, there are variations in annual precipitation and temperature patterns. Simada receives an average annual rainfall of 788mm, whereas Lay Gayint experiences a higher average of 1096mm. In terms of mean annual temperature, Lay Gayint records 14℃, while Simada has a slightly higher mean temperature of 18℃. The rainfall distribution follows two distinct seasons. The primary rainy season, known as the *Kiremt* season, occurs from June to mid-September. In contrast, the *Belg* season, considered a minor rainy period, takes place between March and May (Endalew and Sen, 2020). The area's precipitation system allows for two harvesting seasons. The main harvest, referred to as *Meher*, coincides with the *Kiremt* season, while the secondary harvest, known as *Belg*, aligns with the *Belg* season. However, the *Belg* harvest often faces difficulties due to the short duration, high variability, and frequent inadequacy of the rainy season (Endalew and Sen, 2020).

The area is marked by recurring food insecurity, primarily caused by challenges such as prolonged delay and early termination of the rainy season, and poor performance in *Belg* season. As a result, a significant number of households struggle to meet their food needs. To address this issue, the Ethiopian government, in collaboration with development partners, has implemented the Productive Safety Nets Program (PSNP). This program aims to assist the impoverished population in building assets, enhancing their livelihoods, and ultimately achieving self-sufficiency in terms of food security. It also seeks to improve resilience to stresses and shocks in areas that face insistent food insecurity. The availability of non-farm livelihood activities is severely limited. This is due

to lack of social services. Consequently, households heavily rely on the PSNP as a crucial means of support. By addressing these challenges and promoting sustainable livelihoods, efforts can be made to alleviate food insecurity and improve the resilience of households in the study area.

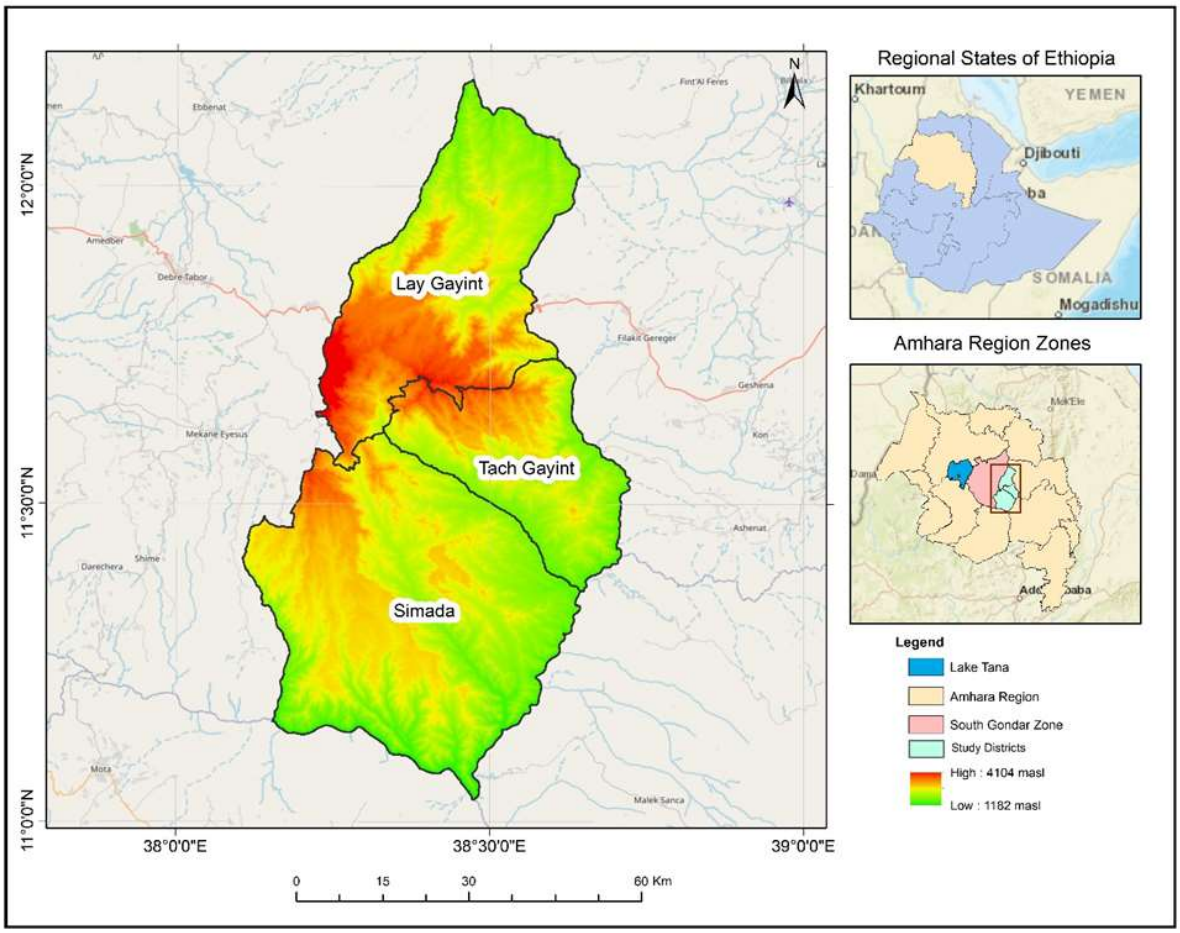

Figure 4. 1. Map of the study area

2.2. Research design

Employing a convergent mixed methods design, the study enabled the concurrent gathering of both qualitative and quantitative data. Through distinct investigation of these data, researchers then compared the outcomes to ascertain their alignment or divergence (Creswell, 2018). This strategy is rooted in the notion that qualitative and quantitative data yield distinct kinds of information - qualitative data delving into nuanced participant viewpoints, while quantitative data furnishing instrument-derived scores. Through this fusion of viewpoints, the objective is to attain harmonious outcomes. As a result, quantitative research approaches were employed to amass and scrutinize climate change risk and adaptation response perceptions within households, executed through a

household survey. Supplementary to this, qualitative research techniques like in-depth interviews with key informants (KIIs) and interactive focus group discussions (FGDs) were deployed to accumulate and evaluate households' outlooks concerning climate change risks and adaptation measures.

2.3. Sampling techniques and procedures

The study utilized a multi-stage sampling technique that combined purposive and random sampling methods to select both the study area and sample households. First, Lay Gayint, Tach Gayint, and Simada districts were purposively selected from the South Gondar Zone due to their frequent exposure to climate extremes, particularly droughts. Next, three *Kebeles* were selected at random, one from each agro-ecological zone, based on the assumptions that smallholder farmers in different zones possess varying livelihood resources, indigenous knowledge and skills. Finally, we selected a sample of households from each target *Kebeles* by obtaining sampling frames from the administrative offices of the respective sample *Kebeles*. The household heads were then chosen using a systematic sampling technique. The study's sample size was determined using the formula provided by Kothari (Kothari, 2004) as follows.

$$n = \frac{Z^2 * p * q * N}{e^2(N-1) + Z^2 * p * q}$$

The total sample size (n) was determined using the proportional-to-size formula with the following parameters: N = 4,203, p = 0.5, q = 0.5, e = 5%, and Z = 1.96 for a 95% confidence interval. The total number of households was N = 4,203, comprising 1,644 from Lay Gayint, 1,404 from Tach Gayint, and 1,155 from Simada. The resulting sample size was n = 352, with sample sizes of 138, 117, and 97 for Lay Gayint, Tach Gayint, and Simada, respectively. The sample size at each *Kebele* was determined using a simple random sampling (SRS) technique with a probability proportional to size as follows.

$$ni = \frac{n \times Ni}{\sum Ni}$$

Where ni refers to the number of households in the ith *Kebele*, while Ni represents the total number of households in the ith *Kebele*. A calculated sample size, denoted by n, was used to determine the number of households to be included in the survey. Before conducting the survey, respondents

provided informed consent, and no personally identifiable information was collected during data collection.

2.4. Sources of data and methods of collection

The study utilized two datasets: (1) quantitative data obtained from a survey of 352 households, and (2) qualitative data collected through six focus group discussions (FGDs). The quantitative data were used to develop the SeVI and the LVI by characterizing households in relation to their sensitivity, adaptive capacity and exposure to climate variability. The qualitative data were used to complement and support the quantitative analysis. FGD participants were selected based on their years of farming experience, voluntary participation, and knowledge of the influence of climate variability on their livelihoods. For this purpose, two FGDs, each with 8-12 participants were conducted in each *Kebele*. The sample included both men and women between the ages of 25 and 75 with many years of local knowledge and farm experience.

2.5. Analytical model and index formulation

Vulnerability indexes are constructed upon main components, formed by integrating diverse sub-components. When dealing with equally weighted indicators, where equivalence in importance is maintained, an imperative lie in adopting a standardization approach. This minimizes the potential for erroneous evaluations of distinct sub-components and prevents the emergence of biases stemming from selection or data gaps. Conversely, when handling indicators of varying weightings, a multitude of methodological avenues can be explored to avoid the uncertainty posed by uniform weighting, as elaborated upon by Raj et al. (2022). Several methodological strategies have been documented in prior research, encompassing the utilization of expert judgment (Jamshidi et al., 2019), principal component analysis (Datta and Das, 2019), and retrospective analysis of past catastrophic events (Tofu et al., 2023). In the context of this study, the methodology adopted involves the conceptualization, standardization, and aggregation of selected indicators, as detailed in Tables 4.1 and 4.2. Moreover, this study investigates household vulnerability to climate using two methods: the LVI, encompassing 32 indicators, and the SeVI, comprising 31 indicators. Additionally, the study quantifies and visually represents sensitivity, exposure and adaptive capacity through spider and triangular diagrams, with each facet being individually discussed. The subsequent section offers an exposition of the two methods employed to assess household vulnerability. We used different vulnerability indexes, such as LVI and SeVI, to provide a

comprehensive assessment of vulnerability, tailor the analysis to specific contexts, explore methodological differences, enable comparative analysis, and address policy-relevant questions. These indexes serve as valuable tools for understanding and addressing vulnerability in diverse socio-ecological systems, helping policymakers and stakeholders make informed decisions and design effective strategies for vulnerability reduction and adaptation.

2.5.1. Socio-economic vulnerability index (SeVI)

Ahsan and Warner (2014) employed the SeVI as a tool to evaluate household vulnerabilities through the analysis of socio-economic matters, while taking into account the three dimensions of climate change (sensitivity and exposure and adaptive capacity) as defined by (IPCC, 2001). As the individual indicators are measured on diverse scales, standardization is required for each of them.

$$\text{Indicator Index Score (IIS)}_{\mathrm{d}} = \frac{\mathrm{X_d} - \mathrm{X_{min}}}{\mathrm{X_{max}} - \mathrm{X_{min}}} \quad (1)$$

The indicator value for a district, denoted by X_d, is calculated using the highest value (X_{max}) and minimum value (X_{min}) of the pointer. After obtaining the index value, the next step is to calculate the domain vulnerability rate by combining the weighted values for all metrics in the same category. This is done by aggregating the values using Equation (2), as described by Ashan and Warner (2014), Payus et al. (2022).and Sesana et al. (2020).

$$\text{Domain Vulnerability Score } (\mathrm{DVS})_{\mathrm{d}} = \frac{\sum_{\mathrm{j=1}}^{\mathrm{n}} (\mathrm{WIS})_{\mathrm{jd}}}{\sum_{\mathrm{j=1}}^{\mathrm{n}} (\text{ Averageweight })_{\mathrm{jd}}} \quad (2)$$

In this context, $(DVS)_d$ represents the domain scores for the Vulnerability Index in district d, and j represents the count of metrics within the specified range. Once the domain values for the vulnerability indices are calculated, the various vulnerability dimensions can be obtained by dividing the amount of the domains under sensitivity, adaptive capacity and exposure by the number of domains analyzed. This calculation is denoted as:

$$\mathrm{DM_{kd}} = \frac{\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{DVS_{jd}}}{\mathrm{n}} \quad (3)$$

The number of domains under sensitivity, exposure and adaptive capacity is denoted by k. The calculation of the SeVI for district d follows the method outlined by Ahsan and Warner (2014) and can be obtained from the following equation:

$$\text{Socioeconomic Vulnerability Index (SeVI)d} = \frac{\text{DM}_{\text{acd}} + \text{DM}_{\text{sd}} + \text{DM}_{\text{ed}}}{3} \quad (4)$$

The total vulnerability index for district d is determined by the mean values of adaptive capacity, exposure and sensitivity, with the SeVI having a direct association with sensitivity and exposure but an opposite association with adaptive capacity (Asfaw et al., 2018; Ford et al., 2018). To assess household socioeconomic vulnerability, we selected 31 indicators based on previous studies (Adhav et al., 2021; Asfaw et al., 2018; Balaganesh et al., 2020), a field survey, and consultations with local experts (Table 4.1). The SeVI varies between 0 (indicating minimum vulnerability) and 1 (representing maximum vulnerability).

Table 4. 1. Main components, sub-component indexes of SeVI in the study area

IPCC dimension	Domain	Indicators/variables	Lay Gayint	Tach Gayint	Simada
Adaptive capacity	Demographic	Ratio of dependents to the working-age population	0.64	0.74	0.67
		Proportion of households led by females	0.07	0.18	0.21
		The mean number of years of farming experience.	0.46	0.48	0.45
		The weighted mean score (with standard deviation).	0.39(0.29)	0.47(0.28)	0.44(0.23)
	Social	Proportion of households not receiving aid from PSNP.	0.65	0.73	0.77
		Proportion of households without communication with neighboring farmers.	0.15	0.18	0.21
		Proportion of households without support from relatives or friends.	0.81	0.71	0.73
		Proportion of households lacking information access (radio, television).	0.96	0.92	0.89
		The weighted mean score (with standard deviation).	0.64(0.35)	0.64(0.32)	0.65(0.30)
Sensitivity	Economic	Proportion of households with no income from off-farm sources.	0.74	0.73	0.91
		Proportion of households without any income from non-farm sources.	0.69	0.76	0.89
		Proportion of households obtaining loans from informal moneylenders.	0.38	0.37	0.46

	Proportion of households taking loans from credit associations.	0.58	0.61	0.55
	Proportion of households indicating inability to independently resolve financial issues.	0.82	0.89	0.97
	The weighted mean score (with standard deviation).	0.64(0.17)	0.67(0.19)	0.76(0.23)
Physical	Proportion of households without engagement in irrigation practices.	0.86	0.82	0.81
	Proportion of households indicating low fertility of their farmland.	0.58	0.50	0.47
	Proportion of households stating that climatic shocks impacted crop production.	0.84	0.92	0.96
	Mean duration of walking to water sources (minutes).	0.60	0.66	0.72
	Proportion of households lacking paved roads in the vicinity.	0.88	0.96	0.93
	Proportion of households reporting chronic illness.	0.15	0.22	0.33
	Proportion of households not adequately utilizing fertilizer.	0.64	0.58	0.73
	Proportion of households not utilizing chemical insecticides.	0.63	0.66	0.76
	The proportion of households that do not utilize manure as fertilizer.	0.77	0.74	0.65

		The mean time taken to walk to health centers in minutes.	0.31	0.49	0.51
		The proportion of households without access to sanitary latrines.	0.88	0.90	0.94
		The weighted mean score (with standard deviation).	0.65(0.24)	0.68(0.22)	0.71(0.21)
Exposure	Exposure to climatic hazards	The proportion of households that report receiving warning information from the government.	0.07	0.23	0.29
		The proportion of households that describe experiencing farmland damage due to severe erosion.	0.45	0.59	0.49
		The proportion of households that report facing issues with agricultural production due to climate shocks.	0.74	0.96	0.98
		The mean count of droughts in the last decades.	0.36	0.49	0.59
		The mean count of flood events over the previous decade.	0.36	0.41	0.36
		The proportion of households that document damage to physical assets caused by climate uncertainties.	0.59	0.64	0.79
		The proportion of households that report livestock damage due to recurrent calamity.	0.57	0.66	0.85
		The mean rainfall perception index as a percentage.	0.70	0.92	0.97
		The weighted mean score (with standard deviation).	0.48(0.22)	0.61(0.25)	0.67(0.27)

2.5.2. Livelihood vulnerability index (LVI)

The LVI development applied the methods introduced by Hahn et al. (Hahn et al., 2009) with some modifications tailored to the study area situation. LVI indices were structured into three dimensions, namely sensitivity, exposure, and adaptive capacity, which were defined based on the IPCC's description of vulnerability. Vulnerability refers to the extent to which a structure is capable of dealing with or vulnerable to the negative impacts of climate change, including its variability and extremes. Meanwhile, adaptive capacity pertains to the system's capacity to manage and regulate to climate variation, enabling it to lessen possible damage, seize instances, or deal with the moments. Lastly, sensitivity designates the degree to which a structure is positively or negatively influenced by climate-related events.

The LVI in this study comprises of seven primary components, including social networks, livelihood strategies, socio-demographic profile, food, water, health, climate variability and associated hazards, which are standardized using the same method as the SeVI. These seven components were further subdivided into 32 sub-components (Table 4.2). The indicators were developed by reviewing existing literature (Asfaw et al., 2021; Balaganesh et al., 2020; Sahana et al., 2021) and conducting a field survey, and consulting with local experts to assess household vulnerability. To calculate vulnerability, an equally weighted approach was used, where every sub-element contributes equally, which is preferred over an unbalanced weight approach (Jamshidi et al., 2019; Oo et al., 2018; Zare-Bidaki et al., 2023). The LVI is calculated by allocating equivalent weight for each sub-components, resulting in a simpler and more accessible interpretation process for policy advisors. However, since the number of sub-elements varies across the main components, each main component contributes a different weight to the overall vulnerability score. The calculation of LVI involves standardizing the sub-components of each main component using Equation (1) and then averaging them.

$$M_d = \frac{\sum_{i=1}^{n} \text{index}S_d i}{n} \quad (5)$$

After deriving the sub-elements of district d for every one of the seven principal elements, denoted by M_d, the subcomponents could be indexed through i with n as the number of sub-components in each main component. The average LVI can then be obtained using the following formula:

$$LVI_d = \frac{\sum_{i=1}^{7} - W_{id}M_{id}}{\sum_{i=1}^{7} - W_{id}} \quad (6)$$

where LVI_d is the livelihood vulnerability index for district d, i is the index of households in district d, and W_{id} symbolizes the number of sub-components that comprising each main component. Furthermore, the contributing factors (sensitivity, adaptive capacity and exposure) can be formulated as the following equation:

$$CF_d = \frac{\sum_{i=1}^{n} W_{id}M_{id}}{\sum_{i=1}^{n} W_{id}} \quad (7)$$

The contributing factor for district 'd' is denoted by CF_d. The main components for district 'd' are represented by Mid, signified by 'i'. The weight of main element in individual contributing element is denoted by W_{id}. The LVI is a vulnerability measure that has been rescaled within the range of 0 to 1, with 0 representing the least vulnerable and 1 representing the most vulnerable. Once exposure, sensitivity and adaptive capacity have been obtained employing either vulnerability indicator method, the vulnerability index ($IPCC_d$) can be determined.

$$LVI(IPCC_d) = (e_d - a_d)^* S_d \quad (8)$$

Where, vulnerability index ($IPCC_d$) is the LVI and SeVI for district ‘d’ quantified applying the IPCC framework. The vulnerability index (IPCCd) was dissected into the computed sensitivity, adaptive capacity and exposure represented by "e," "a," and "s" respectively for district 'd'. The vulnerability index (IPCCd) was then scaled from -1 (representing the least vulnerable) to 1 (representing the most vulnerable). Additionally, this study incorporates a flow chart that delineates the methodologies utilized (Figure 4.2).

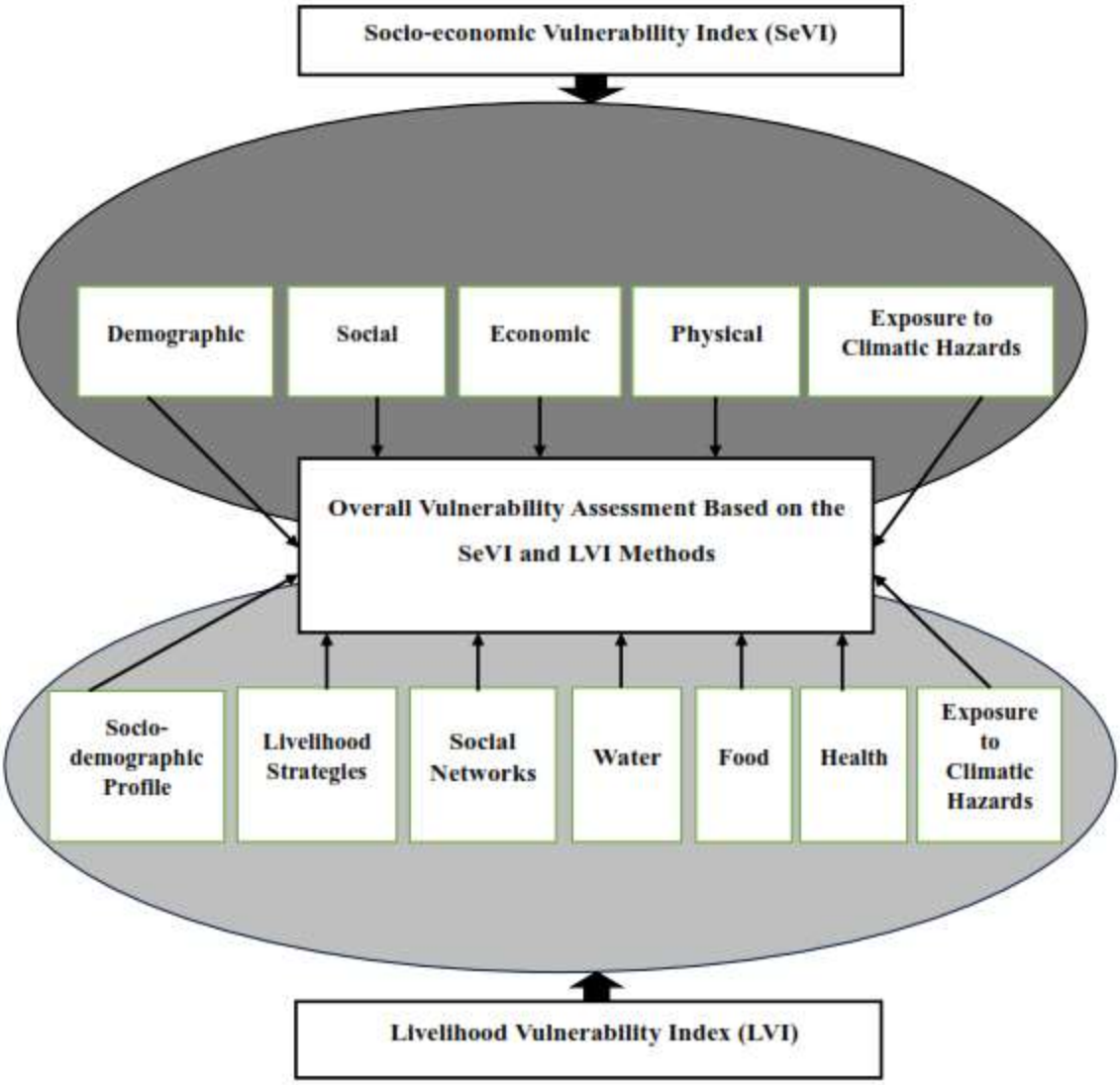

Figure 4. 2. Methodological flowchart of the study

Table 4. 2. Main components, sub-component indexes of LVI in the study area

IPCC dimension	Main components	Sub-components	Lay Gayint	Tach Gayint	Simada
Adaptive capacity	Socio-demographic profile	Proportion of households led by females	0.07	0.18	0.21
		The proportion of households containing orphaned individuals.	0.42	0.11	0.16
		Percentage of households not attending school	0.54	0.50	0.55
		Ratio of dependents to the working-age population.	0.64	0.67	0.72
		The weighted mean score (with standard deviation).	0.42(0.25)	0.37(0.26)	0.41(0.27)
	Livelihood strategies	The proportion of households for whom agriculture serves as the primary income source.	0.93	0.95	0.91
		The proportion of households that are not engaged in irrigation practices.	0.83	0.82	0.81
		The proportion of households lacking members employed in external communities.	0.76	0.87	0.89
		The reciprocal of the agricultural livelihood diversification index (1 divided by the sum of livelihoods plus 1).	0.38	0.06	0.06
		The weighted mean score (with standard deviation).	0.72(0.23)	0.68(0.41)	0.67(0.41)
	Social networks	The proportion of households without reach of extension facilities	0.33	0.34	0.13

		The percentage of households that are not participating in social groups.	0.18	0.23	0.07
		The proportion of households that have not undergone any climate change training.	0.96	0.97	0.68
		The portion of households without help from relatives or friends.	0.81	0.71	0.4
		The weighted mean score (with standard deviation).	0.57(0.37)	0.56(0.34)	0.32(0.28)
Sensitivity	Water	The mean time taken to walk to reach water sources in minutes.	0.58	0.66	0.72
		The proportion of households making use of natural water sources.	0.79	0.92	0.94
		The proportion of households that report experiencing conflicts related to water.	0.07	0.13	0.39
		The proportion of households lacking a reliable and consistent drinking water supply.	0.71	0.81	0.87
		The weighted mean score (with standard deviation).	0.54(0.32)	0.63(0.35)	0.73(0.24)
	Food	The proportion of households that did not engage in crop preservation.	0.74	0.8	0.87
		The mean count of months during which households face food scarcity.	0.37	0.39	0.41
		The percentage of households without seed storage.	0.72	0.74	0.79

		The proportion of households relying on the family farm as their food source.	0.94	0.96	0.95
		The reciprocal of the crop diversity index (1 divided by the number of crops plus 1).	0.38	0.06	0.16
		The weighted mean score (with standard deviation).	0.63(0.25)	0.59(0.36)	0.64(0.34)
	Health	The proportion of households that indicate the presence of chronic illness.	0.15	0.22	0.43
		The percentage of households where a member had to miss work or school because of illness.	0.06	0.11	0.19
		The proportion of households unable to afford recommended health services.	0.52	0.62	0.78
		The proportion of households lacking access to a sanitary latrine.	0.78	0.90	0.94
		The mean time taken to walk to health centers in minutes.	0.31	0.49	0.51
		The weighted mean score (with standard deviation).	0.36(0.29)	0.47(0.32)	0.57(0.30)
Exposure	Climate variability & related hazards	Mean standard deviation in monthly precipitation (1981–2018)	0.38	0.41	0.42
		The average standard deviation in monthly temperature during the period 1981–2018.	0.57	0.66	0.85
		The proportion of households that report livestock loss due to a recent disaster.	0.46	0.49	0.52

	The mean count of flood events over the previous 10 years.	0.36	0.49	0.59
	The mean count of drought events over the past 10 years.	0.59	0.64	0.79
	The proportion of households that document damage to physical assets caused by climate-related hazards.	0.32	0.34	0.47
	The proportion of households where family members were harmed in recent climate-related incidents.	0.45(0.22)	0.51(0.31)	0.61(0.34)

3. Results and discussion

3.1. Socioeconomic vulnerability (SeVI)

The values that constitute the SeVI for each specific indicator, disseminated across the 5 domains, are presented in Table 4.1. A brief discussion of each domain and sub-domain is provided, and the subsequent sections present the vulnerability of households as assessed through the SeVI approach.

3.1.1. Demographic vulnerability

Tach Gayint had the highest ratio of dependents to the working-age population (score: 0.74) among households, while Lay Gayint had the lowest (score: 0.64). This aligns with Oo et al. (2018) and Sowman (2020) findings that populations with higher proportions of children and elderly individuals are at higher risk from natural threats because of limited protective capacity. Notably, Simada had the highest proportion of households led by females (score: 0.21), while Lay Gayint had the lowest (score: 0.07). Overall, Tach Gayint was identified as the most vulnerable in this domain, with a weighted mean score of 0.47 (±0.28), compared to Simada and Lay Gayint with scores of 0.44 (±0.23) and 0.39 (±0.29), respectively.

3.1.2. Social vulnerability

Simada had the highest social vulnerability score of 0.65 (±0.30) compared to Lay Gayint and Tach Gayint, which had scores of 0.64 (±0.35) and 0.64 (±0.32) respectively. Intra-farmers extension support has been identified as an alternative for societal assets and farmer-to-farmer relationships, where information and farming technologies are shared among farmers (Belay et al., 2022; Oo et al., 2018). About 21% of Simada's households conveyed the absence of social relationships with nearby farmers; this exceeds the percentages of Lay Gayint (15%) and Tach Gayint (18%). In this study, the majority of households (75%) did not receive any aid from friends or relatives during difficult times. In addition, the majority of households (92%) stated that they did not receive any information from radio or television. The limited access to information and social capital increases the vulnerability of poor households to climate change- associated hazards, which underscores the need to enhance access to information and social capital (Oo et al., 2018; Tessema and Simane, 2021).

3.1.3. Economic vulnerability

Lay Gayint was revealed to have the least economically vulnerable, with mean score of 0.64 (± 0.17), while Simada was recognized as the most vulnerable. with a score of 0.76 (±0.23). In Simada, 91% of households had no off-farm income, the corresponding values in Lay Gayint and Tach Gayint were 74% and 73%, respectively. Moreover, a large portion of households (78%) informed that they do not receive any non-farm income and have limited access to credit. Lack of non-farm and off-farm incomes are the key sources for households getting supplementary revenues from relatives. Households require agricultural credit prior to the start of crop cultivation periods and often resort to borrowing from moneylenders at high interest rates throughout these periods. Higher agricultural input prices, low yield returns, and a lack of production consistency owing to climate change are the reasons for increasing debt (Oo et al., 2018).

3.1.4. Physical vulnerability

The majority of households (65%) explained that they did not apply sufficient fertilizer owing to limited access to credit and the elevated price. Moreover, the majority of households (72%) did not use manure as fertilizer due to a shortage of resources for composting. Additionally, the absence of paved roads in the area hindered the movement and interaction of households for various purposes. Sanitation was also a concern, with the highest percentage of households (90%) lacking sanitary latrines in the study area. Furthermore, households faced challenges in accessing water resources and health centers, which affected their ability to engage in farming activities. According to weighted average scores, Simada was revealed to have the highest vulnerability score of 0.71 (±0.21), followed by Tach Gayint with a score of 0.68 (±0.22), and Lay Gayint with a score of 0.65 (±0.24).

3.1.5. Climate variability and related hazards

According to the study, Simada had the highest vulnerability score of 0.67 (±0.27) in relation to climate variability and related hazards, while Lay Gayint had the lowest vulnerability score of 0.48 (±0.22). Furthermore, households in Simada reported the highest percentage (97%) of increased rainfall variability, compared to Tach Gayint (92%) and Lay Gayint (70%). The majority of households (80%) testified that early warnings and climate information from government are limited. The influences of climate variability and change, such as floods and droughts, loss of

arable land, reduction in agricultural production, and livestock deaths, were reported to have triggered household vulnerability across the study area.

3.2. Livelihood vulnerability index (LVI)

Presented in (Table 4.2) are the values for the individual indicators of the LVI, distributed across its seven components. Additionally, the subsequent sections present a vulnerability analysis of households using the LVI approach, accompanied by a concise discussion of each component.

3.2.1. Socio-demographic profile

In this study, the proportion of households led by females in Simada was found to be the highest (21%) compared to Tach Gayint (18%) and Lay Gayint (7%). In the study by Tessema et al. (2019), it was proposed that households led by women exhibit greater vulnerability in comparison to households headed by men, owing to socio-cultural barriers that limit their access to resources. Furthermore, in a study by Asmamaw et al. (2020), it was disclosed that households headed by men exhibiting both a low dependence ratio and an average family size that remains below the national average manifest reduced vulnerability to climate variability. Moreover, Simada was found to be relatively vulnerable compared to Tach Gayint and Simada in terms of dependency ratio. Consistent with this study, Khan et al. (2022) demonstrated that significant family sizes are prone to having substantial dependents, thereby increasing the household's vulnerability to climatic threats. Around 53% of the respondents in the study area were unable to read and write, making them particularly exposed to the detrimental impacts of climate change. Education enhances a household's ability to comprehend extension services and adopt alternative solutions during times of crisis, as noted by Aribi and Sghaier (2021). The research showed that Lay Gayint had the highest socio-demographic vulnerability score of 0.42 (±0.25) compared to Simada (score: 0.41 (±0.27)) and Tach Gayint (score: 0.37 (±0.26)) districts, as shown in (Table 4.2). The increased vulnerability of Lay Gayint's socio-demographic profile was mainly attributed to the higher proportion of households with orphans (42%) in comparison to Simada (16%) and Tach Gayint (11%).

3.2.2. Livelihood strategies

The study found that Lay Gayint is the most vulnerable to livelihood strategies, with a score of 0.72 (±0.23), while Simada is the least vulnerable, with a score of 0.67(±0.41). In Tach Gayint, 95% of households rely predominantly on income derived from agricultural activities, compared

to 93% in Lay Gayint and 91% in Simada. Due to the absence of substitute sources of income, households are forced to seek employment in other communities. The agricultural diversity index, which evaluates crops, livestock, agroforestry, and off-farm activities, can enhance adaptive capacity (Hahn et al., 2009; Tessema and Simane, 2021). The study highlights that single-source income households are more exposed to risks, leading to reduced ability to fulfill their needs in times of crises. Several studies have demonstrated that households relying solely on a singular revenue stream (i.e., agriculture) are susceptible to risks and less capable of fulfilling their wants during catastrophes (Adu et al., 2018; Alam et al., 2017; Belay et al., 2017; Oo et al., 2018). However, Dendir and Simane (2019) and Dendir and Birhanu (2022) found that diversifying livelihoods is not a guaranteed strategy for reducing vulnerability. This is because various cross-cutting factors, such as the market, availability of credit facilities and technological access., affect the entire livelihood activities. Given its sensitivity to climatic conditions, rain-fed agriculture is notably vulnerable to extreme weather events. Unfortunately, an overwhelming 82% of households within the study area experience a shortage of irrigation water access, thereby intensifying their reliance on rain-fed agricultural practices.

3.2.3. Social networks

Lay Gayint exhibited the highest vulnerability score of 0.57(±0.37) in relation to social network components, followed by Tach Gayint with the second-highest score of 0.56 (±0.34), while Simada had the lowest score of 0.32 (±0.28). The study found that social support programs, such as the PSNP, could help mitigate food security challenges, but approximately 33% of respondents in the study area were not PSNP beneficiaries. Additionally, households' involvement in social groups was not strong enough to reduce the impact of climate-related hazards. However, indigenous social networks such as "Equib," "Idir," and "Wonfel" played a crucial role in agricultural activities, information exchange, and crisis management, and were important inputs for improving the economic performance of smallholder farmers. Focus group discussants (FGDs) reported a recent decrease in their social networks, which increases their vulnerability to climate variability and instability. Existing literature suggests that social networks can enhance local communities' adaptive capability and reduce their susceptibility to climate variability (Dapilah et al., 2020; Guerrero Lara et al., 2023; Son and Kingsbury, 2020). Nearly all households (97%) were not recipients of climate change training, which is crucial for improving their knowledge and

anticipation of natural disasters (Venus et al., 2022). Exposure to climate change training opportunities is also key for enhancing productivity and rural betterment (Alam et al., 2017).

3.2.4. Water

Simada has been identified as the topmost vulnerability, indicated by a weighted mean score of 0.73 (±0.24) based on water indicators. Tach Gayint follows with a score of 0.63 (±0.35), whereas Lay Gayint is considered as the least exposed, with a value of 0.54 (±0.32). In the study area, a significant number of households (88%) rely on natural water sources, and about 80% of households face inconsistent availability of drinking water. Furthermore, in Simada, a significant percentage of households (39%) have reported conflicts over water resources, in contrast to Tach Gayint (13%) and Lay Gayint (7%). The availability of water significantly affects vulnerability. (Khadka et al., 2022). In Simada, the time required to reach a water source is greater than in Lay Gayint and Tach Gayint, further imposing additional responsibilities on women and children tasked with collecting water for household needs. As per the discussions in the FGDs, individuals depend on rivers and streams to fulfill their daily requirements for drinking and household water.

3.2.5. Food

The food vulnerability of Simada, Lay Gayint, and Tach Gayint was evaluated, with Simada found to be the most vulnerable (score: 0.64 ±0.34)), while Tach Gayint had a lower vulnerability score of 0.59 (±0.36). The study revealed that farming served as the predominant occupation for households, with an average of 96% in Tach Gayint relying on agriculture, compared to 95% in Simada and 94% in Lay Gayint. Households reported challenges in acquiring food, with those in Simada facing an average of 2.9 months each year of difficulty in ensuring sufficient food. Similarly, Tach Gayint and Lay Gayint encountered 2.7 months and 2.6 months, respectively, of food scarcity. The challenging periods for obtaining food were reported to occur mainly during the *Kiremt* season (June to September), and households that didn't store food or preserve seeds were found to be the most vulnerable. In this study, nearly 80% and 75% of households did not save crop and seed due to the subsistence nature of agriculture.

3.2.6. Health

The health vulnerability of the study area was assessed, with Simada being the utmost vulnerable, having an average score of 0.57 (±0.30). However, Tach Gayint was found to have an increased vulnerability to health issues with a score of 0.47 (±0.32), compared to Lay Gayint which had a

score of 0.36 (±0.29). The greatest distance to health facilities was identified in Simada, taking an average of 190 minutes, followed by Tach Gayint at 180 minutes and Lay Gayint at 120 minutes. Insufficient access to health services diminishes the health status of households, rendering them more vulnerable to severe climatic conditions (Adu et al., 2018). Macusi et al (2021) and Pironon et al. (2019) have suggested that the increased vulnerability of farmers to climate variability could be linked to health problems. About 87% of households lacked sanitary latrines. This situation is concerning because poor sanitation practices can increase the risk of child mortality and diarrheal diseases., and fatalities. Simada was also found to be more vulnerable to having households with family members suffering from chronic illnesses (43%), compared to Tach Gayint (22%) and Lay Gayint (15%). Furthermore, households in Simada reported relatively higher rates of family members' days off from school or work due to being sick (19%), compared to Tach Gayint (11%) and Lay Gayint (6%).

3.2.7. Climate variability and related-hazards

Simada was found to be the most vulnerable (score: 0.61 (±0.34)) in terms of climate variability and related hazards, followed by Tach Gayint (score: 0.51 (±0.31)) as the second most vulnerable and Lay Gayint (score: 0.45 (±0.22)) as the least vulnerable. Livelihoods of households were impacted by loss of cattle and physical assets, with drought and flooding affecting 48% and 49% of households, respectively. FGDs revealed that persistent drought and unpredictable rainfall patterns are significant challenges that hinder farmers' livelihoods. Prevalent among the issues are the lack of climate awareness within the local population, the government's unpreparedness preceding natural catastrophes, and insufficient procedures for rehabilitation and resettlement, all of which were cited as reasons for the loss of livestock and physical assets (Ahsan and Warner, 2014; Oo et al., 2018). Given the circumstances, it is imperative to prioritize the implementation of climate change awareness programs, preventive measures, and strategies aimed at mitigating and adapting to climate change within the study area.

3.3. Overall vulnerability assessment based on the SeVI and LVI methods

Figure 4.3 illustrates the derived outcomes of the LVI and SeVI's key constituents and sectors through spider diagrams, while the triangular diagram depicts the scores of contributing factors. We compare and briefly discuss the vulnerability of households using both the SeVI and LVI methods. Our findings, based on the weighted averages show that indicators such as water, food,

health, and climate-related hazards are determining indicators of sensitivity and exposure in the Simada as compared to the Lay Gayint and Tach Gayint based on the LVI method. Likewise, based on the SeVI method, Simada is more sensitive and exposed than Lay Gayint and Tach Gayint in terms of social, economic, physical, and climate-related hazards. This means that there could be higher socio-economic and livelihood vulnerabilities in Simada. The study reveals that Simada has lower scores for health and water indicators compared to Lay Gayint and Tach Gayint due to weaker sanitation facilities, physical infrastructure, and health services, as well as persistent water availability problems. In both methods, the overall IPCC vulnerability scores underscore that households in Simada exhibit higher vulnerability compared to those in Lay Gayint and Tach Gayint due to greater exposure to climate-related hazards. Conversely, the overall IPCC vulnerability index scores indicate Lay Gayint's comparatively lower vulnerability. Furthermore, Figure 4.4 illustrates the overall vulnerability scores emphasizing Simada's vulnerability.

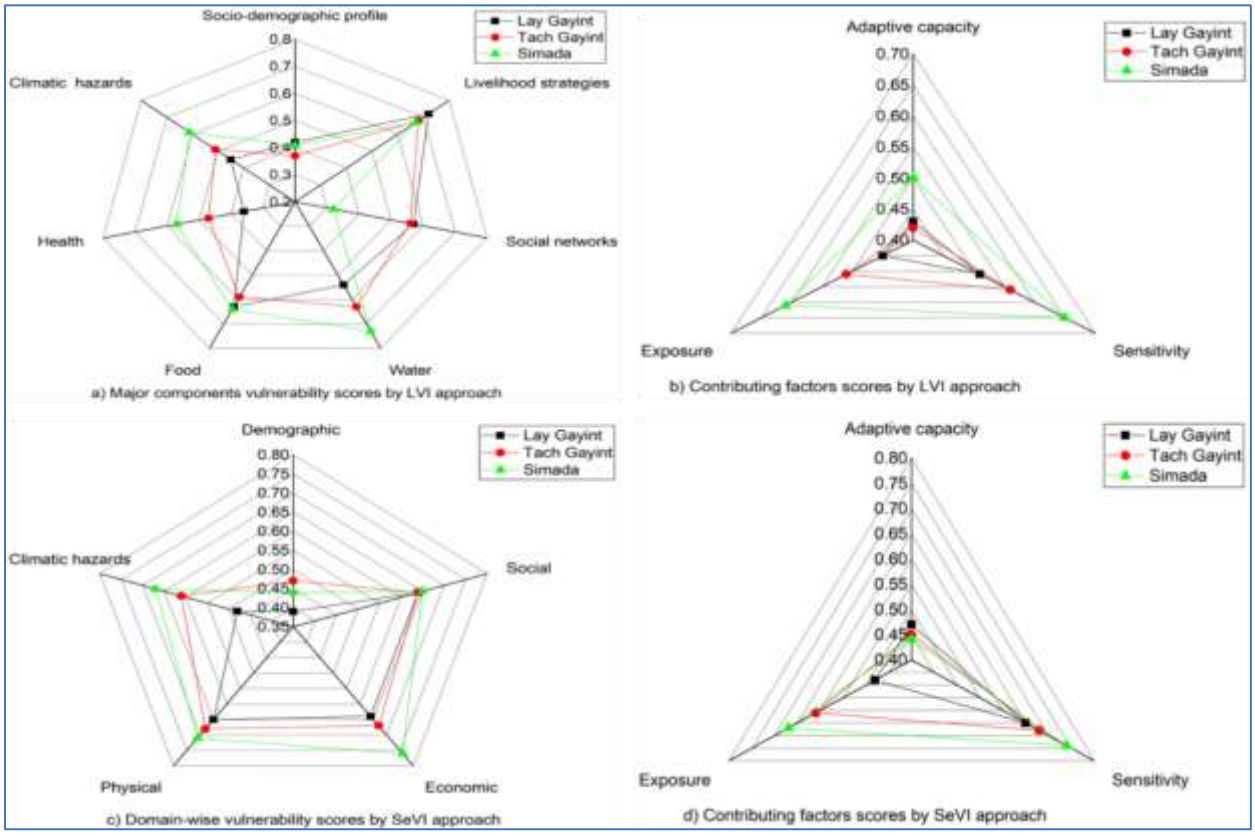

Figure 4. 3. Main constituents (depicted as a spider diagram) and contributing factors (represented through a triangle diagram) of LVI (a and b) and SeVI (c and d) in the study area.

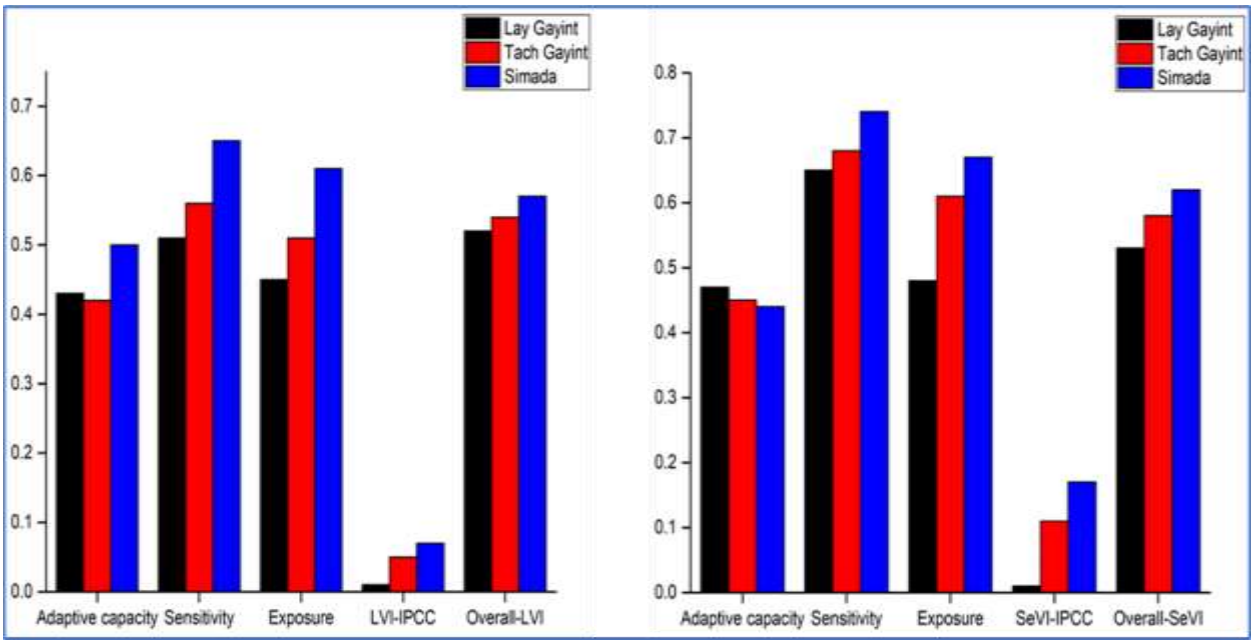

Figure 4. 4. Comprehensive vulnerability scores along with the major component scores for both the SeVI and LVI approaches in the study area.

Overall, the study districts (Simada, Tach Gayint and Lay Gayint) are among the most climate related drought-prone areas in South Gondar zone. In this study, we classified the degree of SeVI and LVI vulnerability as "very high," "high," "medium," and "low" (Oo et al., 2018) (Table 4.3). Among the three districts, Simada displays the highest vulnerability and exposure to climate-related risks, combined with a moderate adaptive capacity, resulting in greater vulnerability equated to Lay Gayint and Tach Gayint. In contrast, Lay Gayint stands out as the least vulnerable, as evidenced by both the LVI and SeVI indices, indicating a moderate level of exposure to climate-related threats.

Table 4. 3. Comparative analysis of the SeVI and LVI vulnerability scores in the study area.

LVI	Adaptive capacity[a]	Sensitivity[b]	Exposure[c]	Overall LVI score[d]
Lay Gayint	Medium	High	Medium	High
Tach Gayint	Medium	High	High	High
Simada	High	Very High	Very High	High
SeVI				Overall SeVI score
Lay Gayint	Medium	Very High	Medium	High
Tach Gayint	Medium	Very High	Very High	High
Simada	Low	Very High	Very High	Very High

[a] Very high (> 0.55), High (> 0.5 and< 0.55), Medium (> 0.4) and (< 0.5), and Low (< 0.4).
[b] Very high (> 0.6), High (> 0.5 and< 0.6), Medium (> 0.5) and (< 0.4), and Low (< 0.4).
[c] Very high (> 0.6), High (> 0.5 and< 0.6), Medium (> 0.4) and (< 0.5), and Low (< 0.4).
[d] Very high (> 0.6), High (> 0.5 and< 0.6), Medium (> 0.4) and (< 0.5), and Low (< 0.4).

4. Conclusions

The aim of this research was to evaluate the vulnerability of households in Simada, Tach Gayint and Lay Gayint to the influences of climate variability. To do this, two vulnerability methods, LVI and SeVI, were applied and compared. Although individual indicators revealed varying results among the districts, the overall findings showed that households in Simada were highly vulnerable. Both assessment methods concurred that the lack of access to basic amenities, absence of alternate sources of revenue, and overdependence on the agricultural sector, made these households extremely exposed to the negative impacts of climate variability. As such, this study recommends that decision-makers and developmental strategists take action to implement disaster prevention and management, promote adaptation strategies, and enhance the adaptive capacity of households. It should be noted that the shortage of adaptive capacity (such as socio-demographic characteristics, social ties and livelihood systems) was identified as a significant factor leading to the high vulnerability to climate variability. Hence, investing in education and diversifying income sources is encouraged. The study proposes that households' adaptive capacity to climate variability might be increased by providing them with seeds and fertilizers, more extension services, and off-farm and non-farm income opportunities.

References

Adhav, C.A., Chandel, B.S., Bhandari, G., Ponnusamy, K., & Ram, H. (2021). Socio-economic vulnerability to climate change–Index development and mapping for districts in Maharashtra, India.

Adu, D.T., Kuwornu, J.K., Anim-Somuah, H., & Sasaki, N. (2018). Application of livelihood vulnerability index in assessing smallholder maize farming households' vulnerability to climate change in Brong-Ahafo region of Ghana. *Kasetsart Journal of Social Sciences*, 39(1), 22-32.

Ahsan, M.N., & Warner, J. (2014). The socioeconomic vulnerability index: A pragmatic approach for assessing climate change led risks–A case study in the south-western coastal Bangladesh. *International Journal of Disaster Risk Reduction*, 8, 32-49.

Alam, G.M., Alam, K., Mushtaq, S., & Clarke, M.L. (2017). Vulnerability to climatic change in riparian char and river-bank households in Bangladesh: Implication for policy, livelihoods and social development. *Ecological Indicators*, 72, 23-32.

Aribi, F., & Sghaier, M. (2021). Livelihood vulnerability assessment to climate change and variability: The case of farm households in South-East Tunisia. Environment, Development and Sustainability, 23(8), 12631-12658.

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), 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.

Asmamaw, M., Mereta, S.T., Beyene, E.M., & Ambelu, A. (2020). Multidimensional livelihood vulnerability analysis in Dinki watershed, central highlands of Ethiopia. *Climate and Development*, 12(9), 814-826.

Balaganesh, G., Malhotra, R., Sendhil, R., Sirohi, S., Maiti, S., Ponnusamy, K., & Sharma, A.K. (2020). Development of composite vulnerability index and district level mapping of climate change induced drought in Tamil Nadu, India. *Ecological Indicators*, 113, 106197.

Belay, A., Oludhe, C., Mirzabaev, A., Recha, J. W., Berhane, Z., Osano, P. M., ... & Solomon, D. (2022). Knowledge of climate change and adaptation by smallholder farmers: evidence from southern Ethiopia. Heliyon, 8(12).

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.

Chirambo, D. (2018). Towards the achievement of SDG 7 in sub-Saharan Africa: Creating synergies between Power Africa, Sustainable Energy for All and climate finance in-order to achieve universal energy access before 2030. *Renewable and Sustainable Energy Reviews*, 94, 600-608.

Creswell, W. J., & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. SAGE Publications, Inc.

Dapilah, F., Nielsen, J.Ø., & Friis, C. (2020). The role of social networks in building adaptive capacity and resilience to climate change: A case study from northern Ghana. *Climate and Development*, 12(1), 42-56.

Datta, P., & Das, S. (2019). Analysis of long-term precipitation changes in West Bengal, India: an approach to detect monotonic trends influenced by autocorrelations. *Dynamics of Atmospheres and Oceans*, 88, 101118.

Dendir, Z., & Birhanu, B.S. (2022). Analysis of Observed Trends in Daily Temperature and Precipitation Extremes in Different Agroecologies of Gurage Zone, Southern Ethiopia. *Advances in Meteorology*, 2022.

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.

Dhital, Y. P., Jia, S., Tang, J., Liu, X., Zhang, X., Pant, R. R., & Dawadi, B. (2023). Recent warming and its risk assessment on ecological and societal implications in Nepal. Environmental Research Communications, 5(3), 031010.

Ebrahim, A. A., Miheretu, B. A., & Alemayehu, A. (2022). Vulnerability of smallholder farmers to climate variability and change across different agro-ecological Zones in Oromo Nationality Administration (ONA), North east Ethiopia. *Plos one*, 17(6), e0268094.

Endalew, H. A., & Sen, S. (2020). Effects of climate shocks on Ethiopian rural households: An integrated livelihood vulnerability approach. *Journal of Environmental Planning and Management*, 64(3), 399-431.

Farid, K. S., Tanny, N. Z., & Rahman, M. W. (2019). Determinants of drought risk coping mechanisms among the farmers of Northern region of Bangladesh: Drought risk coping mechanisms. *Journal of the Bangladesh Agricultural University*, 17(1), 58-64.

Ford, J. D., Pearce, T., McDowell, G., Berrang-Ford, L., Sayles, J. S., & Belfer, E. (2018). Vulnerability and its discontents: the past, present, and future of climate change vulnerability research. Climatic change, 151, 189-203.

Gebreegziabher, Z., Mekonnen, A., Bekele, R. D., Bane, J., & Zewdie, S. A. (2019). Mapping vulnerability to climate change of the farming sector in the Nile Basin of Ethiopia: a micro-level perspective. In *Agricultural Adaptation to Climate Change in Africa* (pp. 28-54). Routledge.

GebreMichael, Y. (2020). Climate change, vulnerability, and adaption under the small farming households of Konso Community, Southern Ethiopia. In Handbook of Climate Change Resilience; Springer: Cham, Switzerland.

Guerrero Lara, L., van Oers, L., Smessaert, J., Spanier, J., Raj, G., & Feola, G. (2023). Degrowth and agri-food systems: A research agenda for the critical social sciences. Sustainability Science, 1-16.

Hahn, M. B., Riederer, A. M., & Foster, S. O. (2009). The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Global environmental change*, 19(1), 74-88.

Hurni, H., Berhe, W. A., Chadhokar, P., Daniel, D., Gete, Z., & Grunder, M. K. G. (2016). Soil and Water Conservation in Ethiopia: Guidelines for Development Agents. Volume 1. Centre for Development and Environment (CDE), University of Bern: Bern, Switzerland.

IPCC, (2001). Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change (Vol. 2). Cambridge University Press.

Jamshidi, O., Asadi, A., Kalantari, K., & Azadi, H. (2019). Perception, Knowledge, and Behavior towards Climate Change: A Survey among Agricultural Professionals in Hamadan Province, Iran. *Journal of Agricultural Science and Technology*, 20(7), 1369-1382.

Jamshidi, O., Asadi, A., Kalantari, K., Azadi, H., & Scheffran, J. (2019). Vulnerability to climate change of smallholder farmers in the Hamadan province, Iran. Climate Risk Management, 23, 146-159.

Kamali, B., Abbaspour, K. C., Lehmann, A., Wehrli, B., & Yang, H. (2018). Spatial assessment of maize physical drought vulnerability in sub-Saharan Africa: Linking drought exposure with crop failure. *Environmental Research Letters*, 13(7), 074010.

Khadka, C., Upadhyaya, A., Edwards-Jonášová, M., Dhungana, N., Baral, S., & Cudlin, P. (2022). Differential Impact Analysis for Climate Change Adaptation: A Case Study from Nepal. Sustainability, 14(16), 9825.

Khan, M. A., Hasan, K., & Kabir, K. H. (2022). Determinants of households' livelihood vulnerability due to climate induced disaster in southwest coastal region of Bangladesh. Progress in Disaster Science, 15, 100243.

Kothari, C. R. (2004). Research Methodology: Methods and Techniques. New Age International Publisher.

Kumi, E. (2019). Advancing the sustainable development goals: An analysis of the potential role of philanthropy in Ghana. *Journal of Asian and African Studies*, 54(7), 1084-1104.

Liou, Y. A., & Mulualem, G. M. (2019). Spatio–temporal assessment of drought in Ethiopia and the impact of recent intense droughts. *Remote Sensing*, 11(15), 1828.

Macusi, E. D., Camaso, K. L., Barboza, A., & Macusi, E. S. (2021). Perceived vulnerability and climate change impacts on small-scale fisheries in Davao gulf, Philippines. Frontiers in Marine Science, 8, 597385.

Masuda, Y.J., Castro, B., Aggraeni, I., Wolff, N.H., Ebi, K., Garg, T., Game, E.T., Krenz, J., & Spector, J. (2019). How are healthy, working populations affected by increasing temperatures in the tropics? Implications for climate change adaptation policies. *Global Environmental Change*, 56, 29-40.

Mekonen, A.A., & Berlie, A.B. (2021). Rural households' livelihood vulnerability to climate variability and extremes: a livelihood zone-based approach in the Northeastern Highlands of Ethiopia. *Ecological Processes*, 10, 1-23.

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.

Nikulin, G., Lennard, C., Dosio, A., Kjellström, E., Chen, Y., Hänsler, A., Kupiainen, M., Laprise, R., Mariotti, L., Maule, C.F., & van Meijgaard, E. (2018). The effects of 1.5 and 2 degrees of global warming on Africa in the CORDEX ensemble. *Environmental Research Letters*, 13(6), 065003.

Oo, A.T., Van Huylenbroeck, G., & Speelman, S. (2018). Assessment of climate change vulnerability of farm households in Pyapon District, a delta region in Myanmar. *International Journal of Disaster Risk Reduction*, 28, 10-21.

Payus, C. M., Herman, F., & Sentian, J. (2022). Combined climate impacts and vulnerability index on coastal ecosystems in prediction of future scenarios: extended sustainable indicator tool for adaptive strategy. SN Applied Sciences, 4(8), 222.

Pironon, S., Etherington, T.R., Borrell, J.S., Kühn, N., Macias-Fauria, M., Ondo, I., Tovar, C., Wilkin, P., & Willis, K.J. (2019). Potential adaptive strategies for 29 sub-Saharan crops under future climate change. *Nature Climate Change*, 9(10), 758-763.

Quandt, A. (2021). Coping with drought: Narratives from smallholder farmers in semi-arid Kenya. International Journal of Disaster Risk Reduction, 57, 102168.

Raj, S., Roodbar, S., Brinkley, C., & Wolfe, D. W. (2022). Food Security and climate change: Differences in impacts and adaptation strategies for rural communities in the Global South and North. Frontiers in Sustainable Food Systems, 5.

Sahana, M., Rehman, S., Paul, A.K., & Sajjad, H. (2021). Assessing socio-economic vulnerability to climate change-induced disasters: evidence from Sundarban Biosphere Reserve, India. *Geology, Ecology, and Landscapes*, 5(1), 40-52.

Salman, D., Yassi, A., & Demmallino, E.B. (2022). Livelihood vulnerability of smallholder farmers to climate change: A comparative analysis based on irrigation access in South Sulawesi, Indonesia. *Regional Sustainability*, 3(3), 244-253.

Sam, A.S., Kumar, R., Kächele, H., & Müller, K. (2017). Vulnerabilities to flood hazards among rural households in India. *Natural Hazards*, 88, 1133-1153.

Sesana, E., Gagnon, A. S., Bonazza, A., & Hughes, J. J. (2020). An integrated approach for assessing the vulnerability of World Heritage Sites to climate change impacts. Journal of cultural heritage, 41, 211-224.

Sietz, D., Ordoñez, J.C., Kok, M.T.J., Janssen, P., Hilderink, H.B., Tittonell, P., & Van Dijk, H. (2017). Nested archetypes of vulnerability in African drylands: where lies potential for sustainable agricultural intensification? *Environmental Research Letters*, 12(9), 095006.

Son, H., & Kingsbury, A. (2020). Community adaptation and climate change in the Northern Mountainous Region of Vietnam: A case study of ethnic minority people in Bac Kan Province. *Asian Geographer*, 37(1), 33-51.

Sowman, M. (2020). Participatory and rapid vulnerability assessments to support adaptation planning in small-scale fishing communities of the Benguela Current Large Marine Ecosystem. Environmental Development, 36, 100578.

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.

Tessema, Y. A., Joerin, J., & Patt, A. (2019). Crop switching as an adaptation strategy to climate change: The case of Semien Shewa Zone of Ethiopia. *International Journal of Climate Change Strategies and Management*, 11(3), 358-371.

Tofu, D. A., Fana, C., Dilbato, T., Dirbaba, N. B., & Tesso, G. (2023). Pastoralists' and agro-pastoralists' livelihood resilience to climate change-induced risks in the Borana zone, south Ethiopia: Using resilience index measurement approach. Pastoralism, 13(1), 4.

Venus, T. E., Bilgram, S., Sauer, J., & Khatri-Chettri, A. (2022). Livelihood vulnerability and climate change: a comparative analysis of smallholders in the Indo-Gangetic plains. Environment, Development and Sustainability, 1-29.

Yalew, A. W., Hirte, G., Lotze-Campen, H., & Tscharaktschiew, S. (2018). Climate change, agriculture, and economic development in Ethiopia. *Sustainability*, 10(10), 3464.

Zare-Bidaki, R., Pouyandeh, M., & Zamani-Ahmadmahmoodi, R. (2023). Applying the enhanced Water Poverty Index (eWPI) to analyze water scarcity and income poverty relation in Beheshtabad Basin, Iran. Applied Water Science, 13(2), 53.

Chapter Five

Smallholder farmers' perceptions and adaptation strategies to climate change risks in northwest Ethiopia [4]

Abstract

This paper explores the perceptions of climate change risks and adaptation responses among smallholder farmers in South Gondar, Ethiopia. It investigates the relationship between adaptation strategies and the perceived and experienced climate change risks. A convergent mixed methods design was employed, allowing for the simultaneous collection of quantitative and qualitative data. A total of 352 households participated in the survey, with the sample stratified into three districts: Lay Gayint (138 households, 39%), Tach Gayint (117 households, 33%), and Simada (97 households, 28%). The use of a four-point Likert scale facilitated the creation of a standardized risk perception index for fourteen climate events. Additionally, a one-way analysis of variance (ANOVA) was conducted to assess statistical differences in the selection of adaptation strategies among the three districts. A post hoc analysis was performed to identify the specific sources of variation. Qualitative data complemented the findings obtained from focus group discussions and key informant interviews conducted with randomly selected households. Based on the standardized climate change risk perception index, the study revealed that persistent drought, delayed onset of rainfall, early termination of rainfall, and food insecurity were the most significant climate change risks perceived by households in the study area. In response to these risks, households employed various adaptation strategies, including adjusting crop planting dates, crop diversification, terracing, tree planting, cultivating drought-tolerant crop varieties, and engaging in off-farm activities. The results of a Tukey's post hoc test indicated a significant difference in off-farm activities, crop diversification, and the cultivation of drought-tolerant crop types among the adaptation strategies in the study area between the Lay Gayint and Simada districts (p <0.05). This disparity confirms the location-specific nature of adaptation strategies. The findings of this study have practical implications for policymakers and development practitioners in designing context-specific adaptation options that address both current and future climate change risks.

Keywords Climate change risk perception, adaptation strategies, smallholders, South Gondar, Ethiopia

[4] Likinaw, A., Alemayehu, A., & Bewket, W. (2022). Smallholder farmers' perceptions and adaptation strategies to climate change risks in northwest Ethiopia. International Journal of Climate Change Strategies and Management. https://doi.org/10.1108/IJCCSM-01-2022-0001

.

1. Introduction

Worldwide climate change risks are increasing, and agriculture remains one of the most vulnerable sectors (Ado et al., 2019; Alves et al., 2020; Getahun et al., 2021), causing stress on food supply systems in different parts of the world (Gebru et al., 2020). Smallholder farmers are particularly vulnerable to climate change impacts (Antwi-Agyei and Nyantakyi-Frimpong, 2021; Berger et al., 2017; Fahad and Wang, 2018; Marie et al., 2020; Mulwa et al., 2017). Climate change has the most significant impact on the developing world due to its low adaptive capacity and lack of access to alternative means of livelihood (Ali and Erenstein, 2017; Fahad and Jing, 2018). "In the context of the assessment of climate impacts, the term risk is often used to refer to the potential for adverse consequences of a climate-related hazard, or of adaptation or mitigation responses to such a hazard, on lives, livelihoods, health and well-being, ecosystems and species, economic, social, and cultural assets, services (including ecosystem services), and infrastructure (IPCC, 2018)."

Ethiopia has been identified as one of the most vulnerable developing countries to climate change risks (Paul et al., 2018). Ethiopia's vulnerability stems from the country's heavy reliance on rainfed agriculture (Paul et al., 2018), and the sector's performance is strongly linked to the rainfall pattern (Gebru et al., 2020). In the worst-case scenarios, food shortages and famines result from rainfall shortages or changes in seasonal patterns. Climate-related disasters such as droughts, floods, and rainfall variability have contributed to the country's reliance on food aid.

The South Gonder Zone (the present study area) in the northwest highlands of Ethiopia is highly vulnerable to climate change and variability. In contrast to the overall decrease in rainfall, Likinaw et al. (2022) noted that the mean seasonal and annual minimum and maximum temperatures in Lay Gayint, Tach Gayint, and Simada districts showed a significant increasing trend. A recent study has revealed that climate variability considerably negatively affects crop production in this area (Getachew, 2018). Moreover, Bewket and Alemu (2011) observed a considerable reduction in crop production and the length of the growing period due to the late onset and early cessation of rainfall in Ethiopia's Abay and Baro-Akobo River Basins. Several studies have highlighted the importance of understanding risk perceptions and adaptation measures used at the household level to facilitate planned adaptation interventions (Abid et al., 2016; Ahmed et al., 2021). Adaptation practices are essential to farmers' climate risk management strategies and are closely linked to their risk perceptions (Dorward et al., 2020; Khanal et al., 2018; Khanal et al., 2021).

However, the linkage between climate change risk perceptions and adaptation responses is complex because it combines behavioural elements from belief formation with outcome assessments resulting from actions and weather events (Van der Linden, 2017). It is critical to understand and identify the climatic factors that farmers consider when framing their views on climate change (Tripathi and Mishra, 2017; Zamasiya et al., 2017). A study conducted by Tesfaye and Seifu (2016) identified six major adaptation strategies in the eastern Hararghe Zone (eastern part of Ethiopia), such as adjusting crop planting dates and using drought-tolerant crop types, among others. Another study found that the most common adaptation measures in the central highlands of Ethiopia included adjusting crop planting dates, soil and water conservation, crop diversification, tree planting, and soil fertility management (Alemayehu and Bewket, 2017). Gebru et al. (2020) found adaptation strategies in eastern Tigray include soil and water conservation, water harvesting, compost preparation to increase soil fertility, tree planting, and changing the quantity of land under cultivation. Likewise, Bewket (2012) revealed that adaptation measures employed in crop production comprise diversification of crops, changes in the types and varieties of crops produced, and adjusting the agricultural calendar in the central Highlands of Ethiopia. A previous study in the Gonder Zuria district, northwest Ethiopia, found that mixed farming, mixed cropping, adjusting crop planting dates, using drought-resistant crop varieties, and applying soil and water conservation measures were the most commonly used adaptation strategies (Marie et al., 2020).

Most of the available studies are focused on coping and adaptation strategies, giving little or no attention to the linkages between climate change risk perceptions and farmers' coping and adaptation responses. Unlike the previous studies, this study attempts to assess the linkages between climate change risk perceptions and adaptation responses of households in the study area. Also, we used a standardized index-based metric to assess households' views of climate change risk and their adaptation practices. The general objective of this study was to explore climate change risk perceptions and adaptation strategies practiced by smallholder farmers in the northwest highlands of Ethiopia. The specific objectives were to: (1) assess climate change risk perceptions of households, (2) describe adaptation strategies used by the households and (3) examine the linkage between adaptation strategies and perceived or experienced climate change risks. In the following section, we present a description of the study area, materials, and methods, followed by the results and discussion section. The final section contains the conclusion.

2. Materials and methods

2.1. The study area

The study area covers three districts (woredas in Amharic): Lay Gayint, Tach Gayint, and Simada in the South Gondar Administration Zone of the Amhara National Regional State of Ethiopia (Figure 5.1). Lay Gayint is in the *High Dega* (3200-3700 m a.s.l) agroecological zone, and Tach Gayint and Simada are in the *Dega* (2300-3200 m a.s.l) and *Woyna Dega* (1500-2300 m a.s.l) agroecological zones, respectively (Hurni et al., 2016). According to information obtained from the district administration offices, about 32% of the total area of the three districts is mountainous, 53% is rugged topography, 10% is plain land, and 5% is dissected valley. Based on the FAO soil classification system, Vertisols, Nitosols, and Chernozems cover about 32%, 29%, and 28% of the districts, respectively. Other soil types cover the remaining 11%. The study area is a highly deforested part of the country due to a long history of settlement and cultivation, overgrazing, and other socioeconomic and policy-related factors (Getachew, 2018). Extensive cultivation and shrublands dominate the current land cover. Simada and Tach Gayint have annual rainfall averages of 788 and 820mm, respectively, while Lay Gayint's average is 1096mm. The average annual temperature in Lay Gayint is 14℃, 18℃ in Simada, and 14℃ in Tach Gayint.

The farming system is mixed crop livestock, characterized by continuous and intensive cropping. Barley (*Hordium vulgare*), wheat (*Triticum aestivum*), tef (*Eragrostis tef*), and maize (*Zea mays*) are the main cereals grown in the area. Cattle, goats, sheep, and equines are the livestock raised. The contribution of livestock to the people's livelihood is constrained partly by the prevalence of livestock diseases (Getachew, 2018). Agricultural productivity is affected by its dependence on unreliable rainfall, among other factors.

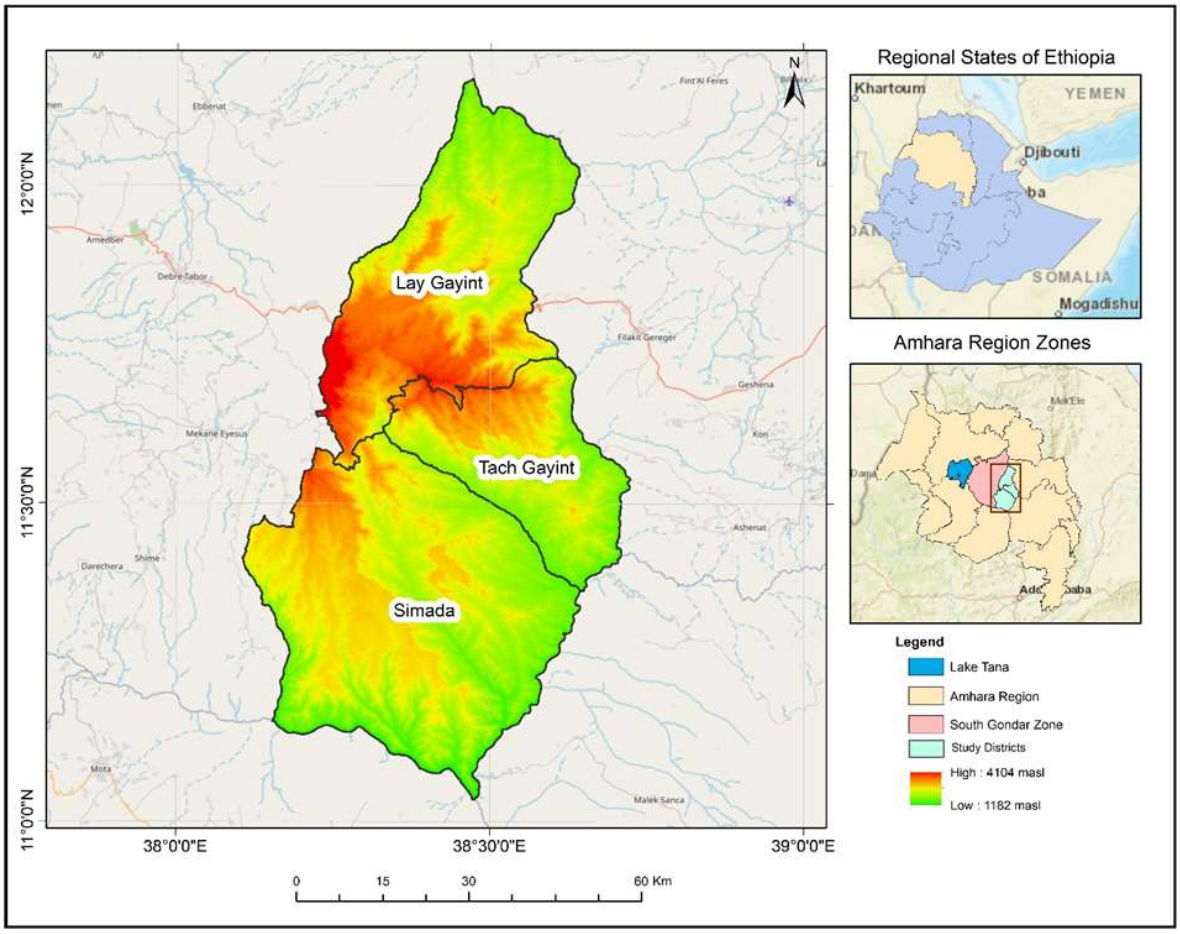

Figure 5. 1. Location map of the study area.

2.2. Research design

The study adopted a convergent mixed methods design. The design enables researchers to concurrently collect quantitative and qualitative data, analyze them separately, and then compare the findings to determine whether they corroborate or contradict one another (Creswell, 2018). The critical assumption of this method is that qualitative and quantitative data provide different types of information- often detailed views of participants qualitatively and scores on instruments quantitatively- and together, they provide results that should be the same. Hence, quantitative research methods were used to collect and analyze households' perceptions of climate change risks and adaptation responses using a household survey. Moreover, perceptions of households related to climate change risks and adaptation responses were also collected and analysed by qualitative research methods using key informant interviews (KIIs) and focus group discussions (FGDs).

2.3. Sampling procedure and sample size

We used a multi-stage sampling technique, where a combination of purposive and random sampling techniques was applied to select the study area and sample households. First, Lay Gayint, Tach Gayint, and Simada districts were selected purposively from the South Gondar Zone districts. These three districts represent some areas most frequently affected by climate extremes in the South Gondar and Amhara regions. They also represent the three important agroecological zones in the country, i.e., the *High Dega, Dega,* and *Woina Dega*, respectively.

In the second stage, three *Kebeles* (one from each district and agroecological zone) were selected randomly with the assumption that households in each agroecological zone will have differences in their livelihood assets and strategies, traditional knowledge and skills and that this will result in different perceptions and adaptation responses to climate change and variability. Because climate change will have different effects in different agroecological zones, farmers in different zones often use different adaptation strategies (Belay et al., 2017).

In the third stage, sample households from each sampled *Kebele* were identified. The sampling frame or lists of households were obtained from the sample *Kebele* Administration offices. Finally, we selected a sample of households from each target *Kebeles* by obtaining sampling frames from the administrative offices of the respective sample *Kebeles*. The household heads were then chosen using a systematic sampling technique. The sample size of the study was determined by Kothari (2004) as follows:

$$n = \frac{Z^2 * p * q * N}{e^2(N-1) + Z^2 * p * q}$$

The total sample size (n) was determined using the proportional-to-size formula with the following parameters: N = 4,203, p = 0.5, q = 0.5, e = 5%, and Z = 1.96 for a 95% confidence interval. The total number of households was N = 4,203, comprising 1,644 from Lay Gayint, 1,404 from Tach Gayint, and 1,155 from Simada. The resulting sample size was n = 352, with sample sizes of 138, 117, and 97 for Lay Gayint, Tach Gayint, and Simada, respectively. The sample size at each *Kebele* was determined using a simple random sampling (SRS) technique with a probability proportional to size as follows.

$$ni = \frac{n \times Ni}{\sum Ni}$$

Where ni refers to the number of households in the ith kebele, while *Ni* represents the total number of households there, a calculated sample size, denoted by n, was used to determine the number of households to be included in the survey. Before conducting the survey, respondents provided informed consent, and no personally identifiable information was collected during data collection.

2.4. Sources of data and methods of collection

Data for the study was collected from both primary and secondary sources. Primary data was gathered through household surveys, FGDs, and KIIs. The primary data consists of socio-demographic characteristics of households, perceptions of households about climate-related risks, and adaptation strategies. The study also used secondary data from Meteorological Stations (rainfall and temperature datasets) from 1981–2018 to triangulate and compare findings with households' perceptions of climate change risks in the study area. We consider the long experience in farming, voluntary participation in the discussion, and knowledge about the impact of climate-related risks in selecting KIIs and FGDs participants. In this regard, two FGDs, each with eight to twelve members, and four KIIs were conducted in each kebele. The FGD participants varied in terms of sex and age. Four KIIs were selected from each kebele purposively. Consulting district experts maintained the diversity of households in the FGDs and KIIs. They were chosen through purposive sampling, including males and females aged between 25 and 75 with long-term knowledge of the area. Qualitative information from FGDs and key informant interviews were conducted to supplement the survey results. Unstructured interview guide checklists were prepared to frame the interview focused on the objectives of the study and allow flexibility for interviewees to talk freely as they wish. The information gathered comprises households' adaptation strategies against climate change risks in their farming activities.

The FGDs and in-depth interviews were guided by checklists that included topics on:

- How did they describe climate change risk?
- What were their thoughts on the role(s) of climate change risk adaptation responses?

The interview questions were pre-tested with some participants, and minor changes were made to adapt to local circumstances. The interviews continued until saturation was attained, topics were conveyed repeatedly, and no new information was mentioned (Skovdal and Cornish, 2015). The

qualitative data analysis included coding, searching for underlying concepts, developing themes, and addressing significant themes related to climate change risks and adaptation responses.

2.5. Methods of data analysis

Descriptive statistics such as mean and percentage were used to summarize households' socioeconomic and demographic characteristics and adaptation strategies. Measuring climate change risk perception is a complicated process influenced by social, cultural, economic, and demographic factors (Hasibuan et al., 2020). Households ' climate change risk perceptions are unique in that they allow for a distinction between actual real-world hazards, such as climate change, and an intuitive evaluation of those dangers (Lai et al., 2021; Schneiderbauer et al., 2021). Several methods are used to understand climate change risk perceptions in the literature. The climate change risk perception index (SCCRPI) is widely used in studies on climate change risk perceptions (Ahmed et al., 2021; Iqbal et al., 2016; Sullivan-Wiley and Gianotti, 2017). The SCCRPI is a metric or index created by combining the probability or likelihood of risk events with the severity of risk event consequences (Aven, 2016; Li et al., 2018). Since risk perception is different from real or objective risk (Ahmed et al., 2021; Sullivan-Wiley and Gianotti, 2017), data in risk perception studies are mainly obtained by asking respondent's perceptions regarding risks using ordered qualitative scales where they can express their subjective views on the incidence of climate change risk, and also their concern regarding the magnitude of the gain/loss caused by the risk rather than a detailed measurement of probability or consequences (Cullen et al., 2018; Frondel et al., 2017).

The households were asked to give their views on ten climate change risks to understand their relative perceptions of the ten chosen climate change risks. Similar methods have been used to assess climate change risk perception (Alam et al., 2017; Sarker et al., 2020). This study used a similar Likert scale to assess respondents' risk perceptions of climate change. Hence, a 4-point Likert scale was adopted to estimate households' perception levels. Usually, the Likert scales are leveled as odd rather than even (they usually include five- or 7-point scales), but owing to limited resources and the household's low educational attainment, we decided to limit the household's responses to a 4-point Likert scale.

Furthermore, we included a 4-point scale to avoid having too many responses with a neutral response on personal risk assessment. However, our findings can still be used to understand

households' views of climate-related risks better. Similar studies used a four-point Likert scale (e.g., Ahmed et al., 2021; Cortes et al., 2021; Ndamani and Watanabe, 2017). The Climate Change Risk Perception Score (CCRPS) and SCCRPI were calculated to understand better how char dwellers perceive climate change risks.

We assigned values to each perception scale in increasing order for ease of analysis, such as 0 for "no perception," 1 for "low perception," 2 for "medium perception," and 3 for "high perception." Households were asked to rate their opinions on fourteen climatic event statements. The following equation was used to calculate a CCRPS:

Climate Change Risk Perception Score (CCRPS)

= CCRPn*0+CCRPl*1+CRPm*2+CCRPh*3

Where CCRPn is the number of households with no risk perception, CCRPl is the number of households with a low-risk perception, CCRPm is the number of households with a medium risk perception, and CCRPh is the number of households with a high-risk perception. The low-risk perception was assigned to households with little concern for climate change and low perceived exposure to its effects, whereas high-risk perception was assigned to households with high concern and high perceived exposure to its impacts. In moderate-risk perception, more measured statements about the severity and urgency of climate change were included.

Since our sample was 138, 117, and 97 households for Lay Gayint, Tach Gayint, and Simada districts, respectively, the CCRPS for any given climatic event could range from 0 to 414, 0 to 351, and 0 to 291, respectively; this means the lower boundary would be a minimum of 0, and the higher boundary would be a maximum of 414, 351 and 291 where 0 indicates a minimum level of risk perception and 414, 351 and 291 indicate a maximum level of risk perception. The CCRPS was then converted into a standardized index to interpret the results more quickly. To standardize the CCRPS, we used the following equation:

Standardized Climate Change Risk Perception Index (SCCRPI)

= (" Total CCRPS Value ")/ (" Respective Highest CCRPS Value “) *100

The Total CCRPS value was calculated by multiplying individual perception values by the total perception frequency for each climatic event, and the highest CCRPS value was calculated by

dividing the total CCRPS value by the highest maximum boundary value and multiplying by 100. SCCRPI is a tool for understanding and categorizing climate change risk perceptions (Ahmed et al., 2021). The SCCRPI value can range from 0 to 100, with 0 representing the lowest level of risk perception and 100 representing the highest level of risk perceived by households. Moreover, descriptive statistics were used to summarize information on adaptation responses to climate change risk. A one-way analysis of variance (ANOVA) was used to assess if there were statistically significant differences in the selection of adaptation strategies between the districts. Differences between the districts were considered significant if they were statistically significant at the 0.05 level. The ANOVA test reveals the total difference between districts; it does not reveal which districts varied from one another. Hence, a post-hoc analysis, Tukey's test, was conducted to identify the location of the difference. The meteorological data (rainfall and temperature) were analyzed using linear regression to show the rainfall and temperature data variability. In addition, the Mann-Kendall trend test was computed to test for a trend in rainfall and temperature data over the period 1981–2018. The MK test analysis of the climatic data was performed using R-software version 3.6.1.

3. Results and discussion

3.1. Characteristics of sample households

Table 5.1 presents the socio-demographic characteristics of the sample households in terms of sex, age, household size, and education. The average age of the households was 43 years (range was 18–76 years). The average household size was 5, equal to the national average. Data on education indicated that 43%, 45%, 11%, and 1% of households were illiterate in primary education (Grades 1–8), secondary (Grades 9–12), and college level, respectively.

Table 5. 1. Socio-demographic characteristics of households in the study area.

Household characteristics (n = 352)	Lay Gayint	Tach Gayint	Simada	Mean
Household heads proportion (%)	39	33	28	
Sex (%)				
Male	93	82	79	85
Female	7	18	21	15
The average age of respondents (years)	44	44	40	43
Average household /family (persons)	5	5	5	5
Education (%)				
Illiterate	29	35	66	43
Primary education (1-8)	59	52	23	45
Secondary education (9-12)	12	13	8	11
College and above	-	-	3	1

3.2. Households' perception of climate change

To assess how households perceive climate change, we asked them if they believed the temperature and rainfall in the area during the previous years had increased, decreased, or had no change. The result indicates that most households in the study area believed that the temperature and rainfall had increased and decreased in previous years. In Lay Gayint, Tach Gayint, and Simada, respectively, 91%, 93%, and 95% of households reported increased temperature. On the other hand, 73 %, 81 %, and 86 % of Lay Gayint, Tach Gayint, and Simada, respectively, believed that rainfall was decreasing (Figures 5.2 and 5.3).

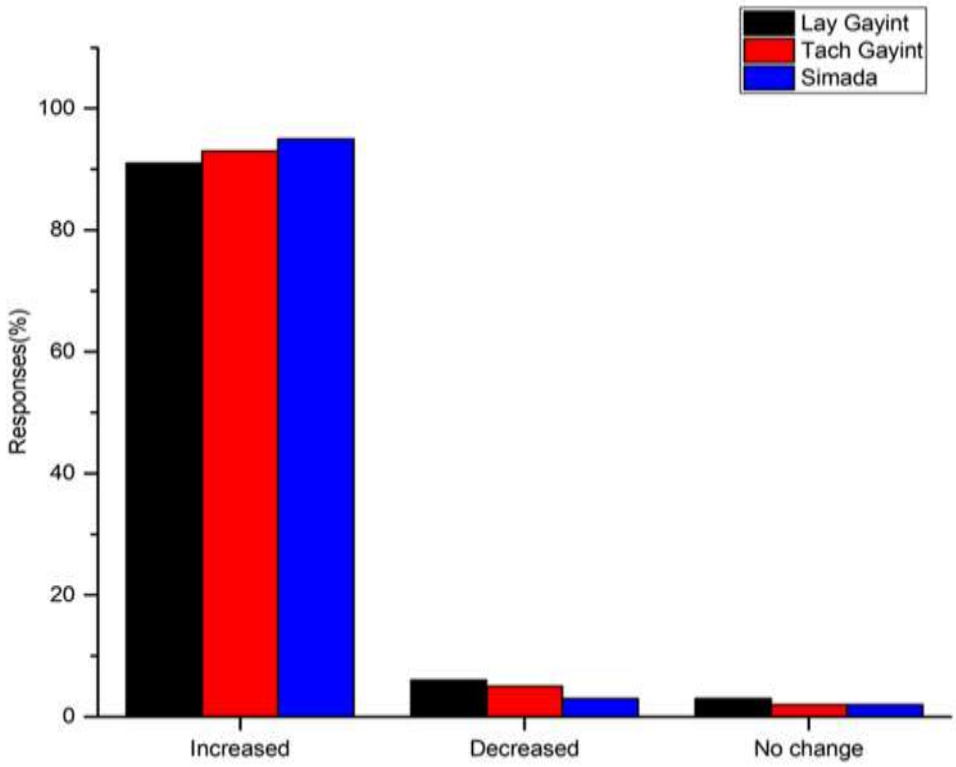

Figure 5. 2. Households' perceptions of temperature in the study area.

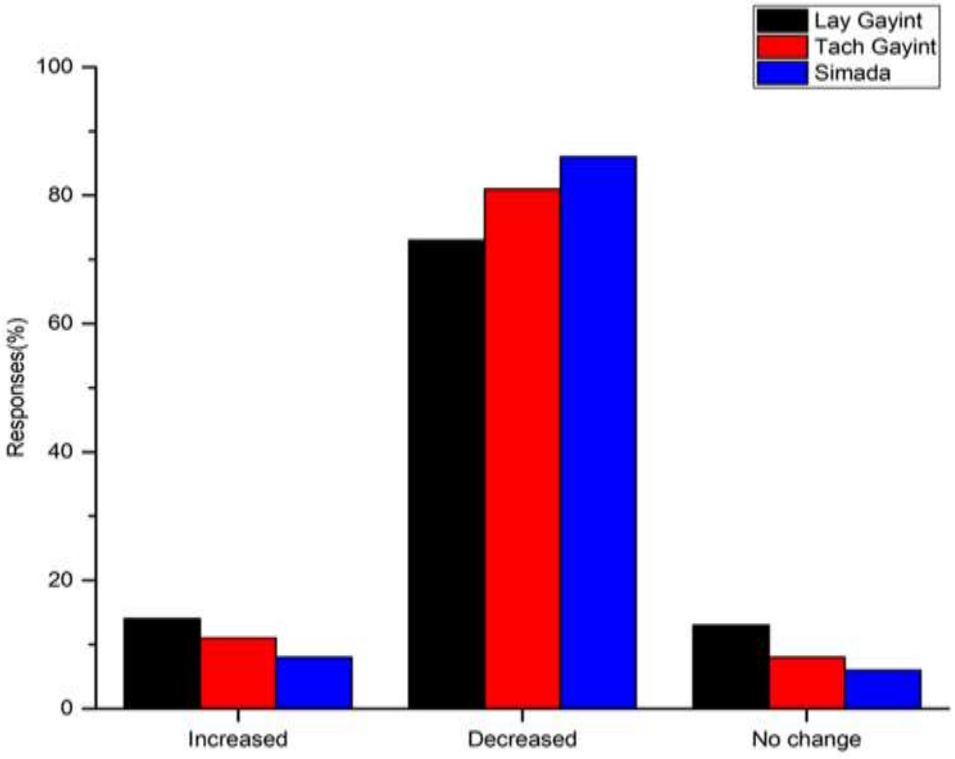

Figure 5. 3. Households' perceptions of rainfall in the study area.

According to the findings of the FGDs and KIIs, households specifically reported temperature and rainfall variability, an increase in minimum (nighttime) and maximum (daytime) temperatures, and a decrease in *Belg* rainfall (the minor rainy season). As a result, it has been found that households' perceptions of climate variability and trends are consistent with variations in minimum and maximum temperatures and rainfall in the *Belg* season. However, the annual and *Kiremt* rainfall (the major rainy season) revealed a discrepancy between household perceptions and meteorological analysis. The inconsistency of households' observation and meteorological data analysis is also reported by some studies (e.g., Behailu et al., 2021; Mertz et al., 2009; Sofoluwe et al., 2011). In these studies, households observed a decrease in rainfall, while meteorological records showed increasing trends. The discrepancy might be due to households' extreme value opinions and the constraint of average value analysis in meteorological data.

The observed meteorological data analysis confirmed how the households' perceived changes in temperature and rainfall. As a result, the observed datasets indicated that the minimum and maximum temperatures showed an increasing trend at 0.04 and 0.05°C/year, respectively, for Lay Gayint at a $p < 0.05$ level. At the $p < 0.05$ level, the regression coefficient in Simada revealed an upward trend at a rate of 0.02 and 0.06°C/year for the minimum and maximum temperatures, respectively. Moreover, the minimum and maximum temperatures showed an increasing trend at a rate of 0.04°C/year in Tach Gayint at a $p < 0.05$ level (Figure 5.4). The slope of the regression line for the *Belg* rainfall (minor rainy season) declined at a rate of 0.08, 0.11, and 0.13mm/year for Lay Gayint, Tach Gayint, and Simada, respectively, at a $p < 0.05$ level. On the other hand, annual and *Kiremt* rainfall (primary rainy season) showed increasing trends in all the study districts but with high variability (Figures 5.4–5.7).

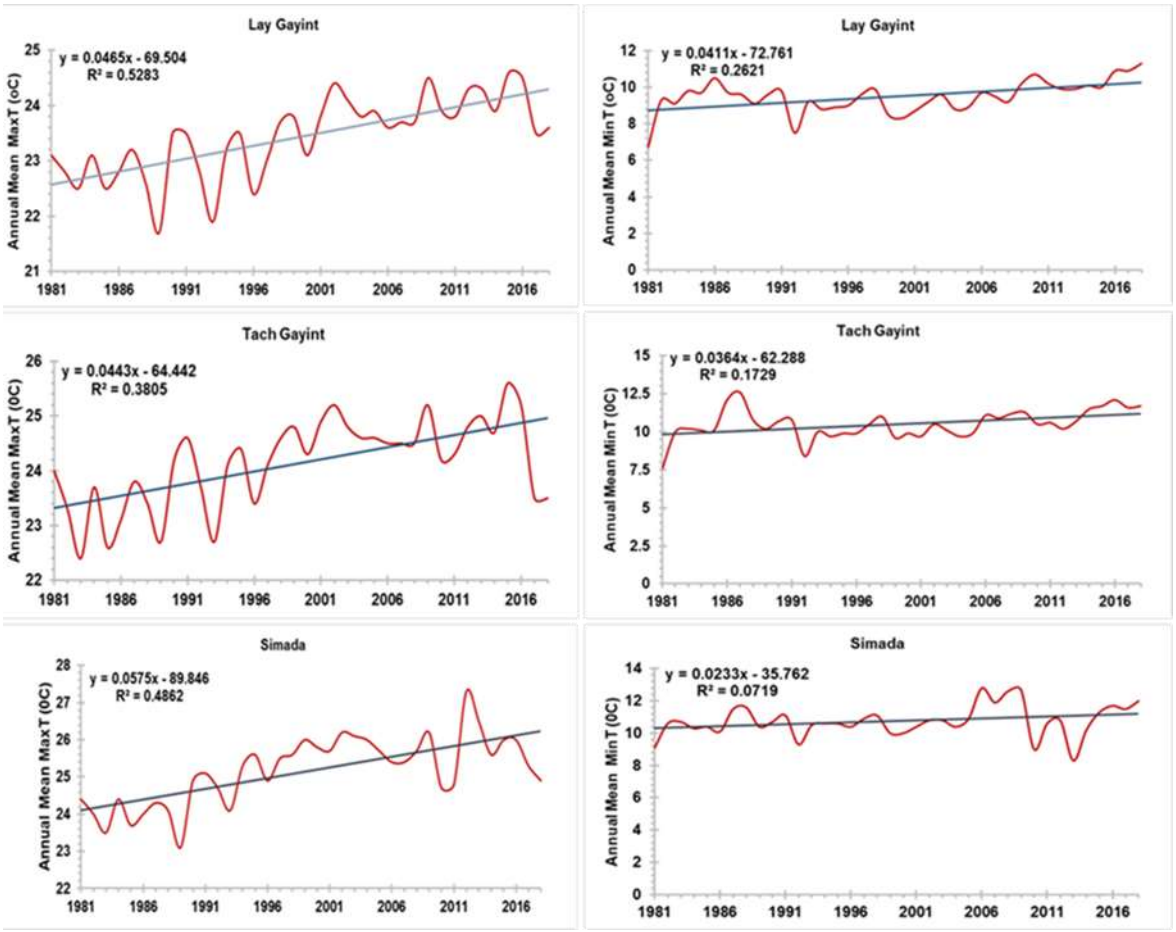

Figure 5. 4.Temperature patterns of Maximum (left) and Minimum (right) in the study area.

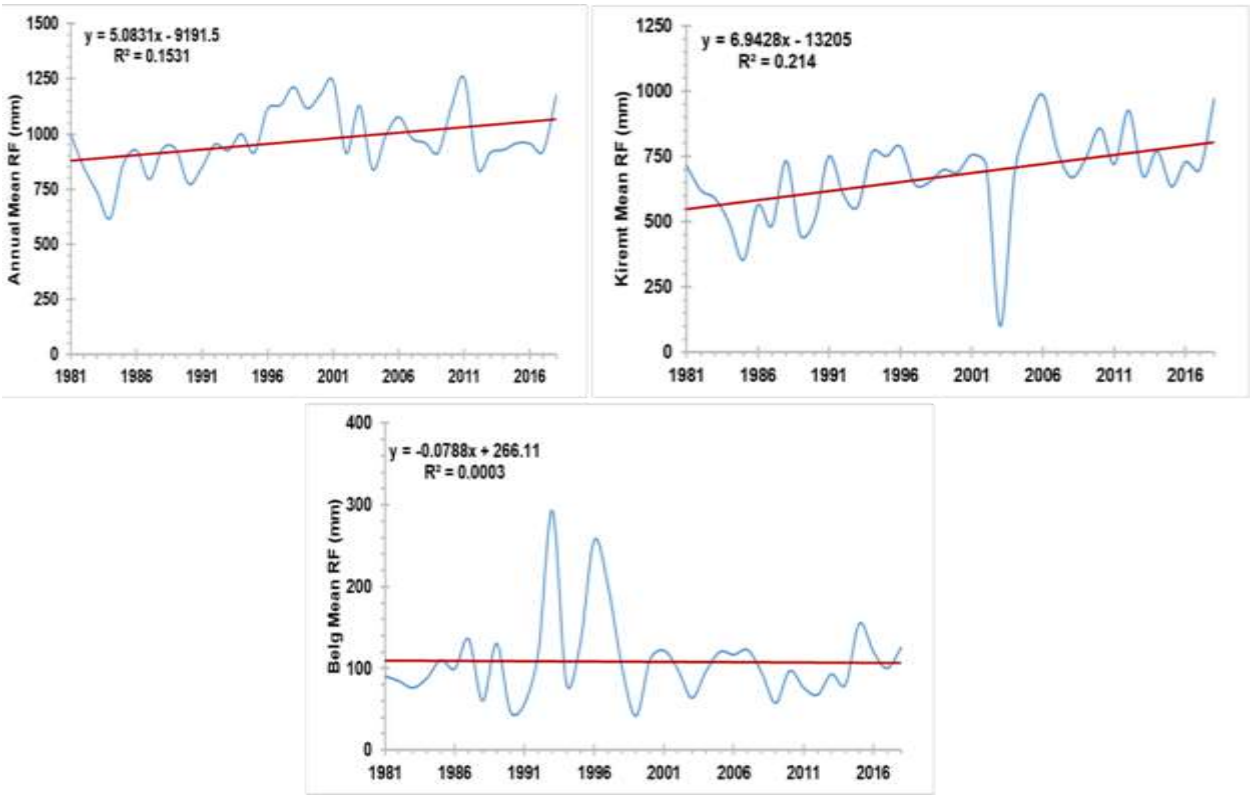

Figure 5 5. Rainfall patterns of (Annual, Kiremt, and Belg) in Lay Gayint

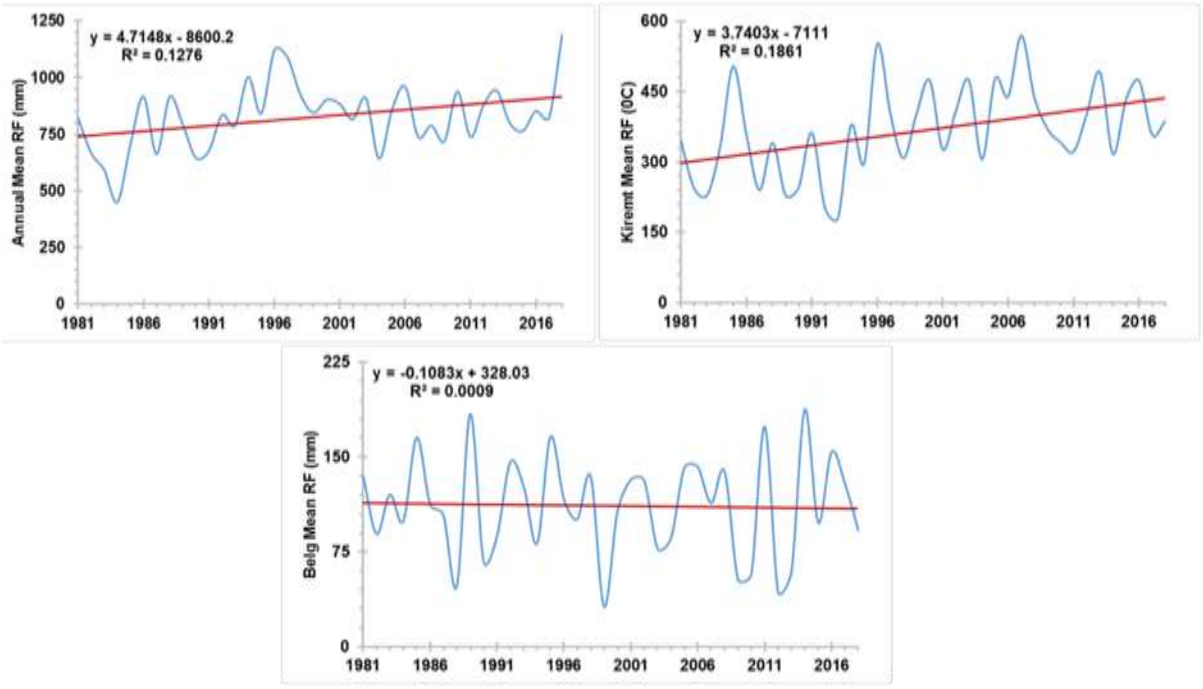

Figure 5. 6.Rainfall patterns of (Annual, Kiremt, and Belg) in Tach Gayint.

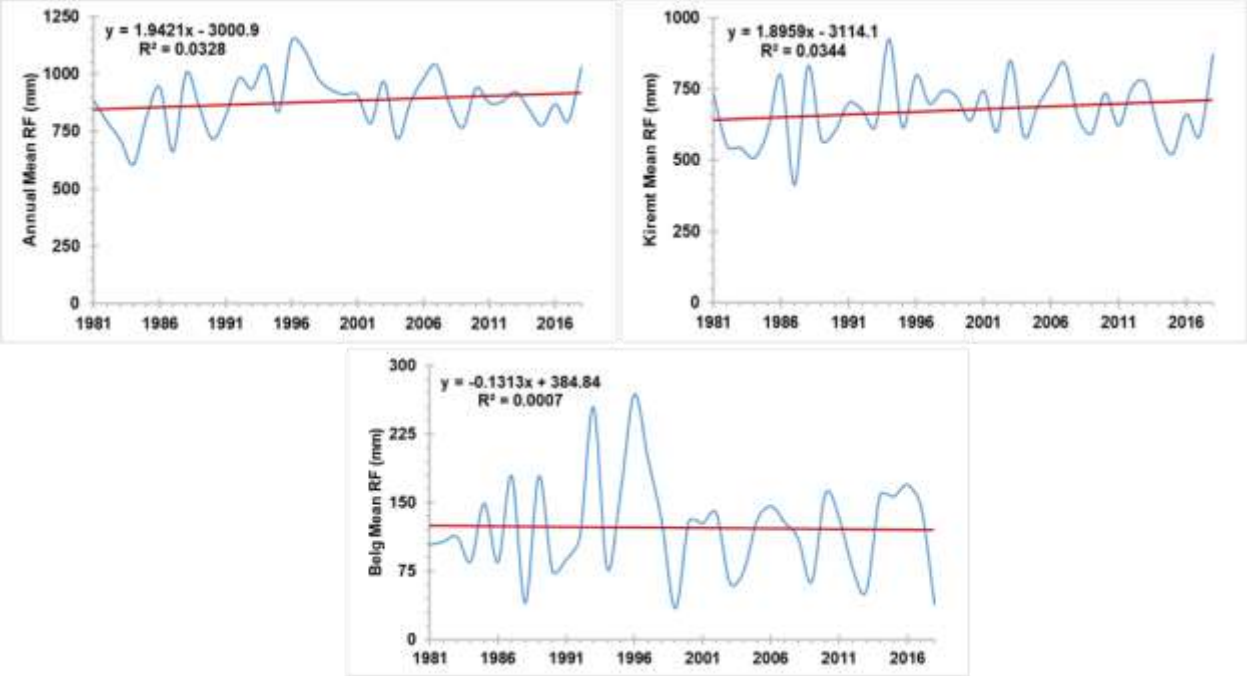

Figure 5. 7. Rainfall patterns of (Annual, Kiremt, and Belg) in Simada.

Moreover, the MK test examines seasonal and annual rainfall trends over the study area (Table 5.2). Based on the MK test, annual rainfall exhibited a significant increasing trend (7.89 mm/year) in Lay Gayint at $p < 0.01$ level and an increasing trend (7.00 mm/year) in Tach Gayint at $p < 0.1$ level, but a non-significant downward trend in annual rainfall was observed in Simada. *Kiremt* and *Belg* rainfall at the seasonal level revealed a non-significant upward trend in Lay Gayint and Tach Gayint. On the other hand, *Kiremt* and *Belg* rainfall revealed a non-significant downward trend in Simada.

Table 5. 2. The MK test values of rainfall at seasonal and annual timescales.

	Lay Gayint		Tach Gayint		Simada	
Season and annual rainfall	Z_{MK}	β	Z_{MK}	β	Z_{MK}	β
Belg	1.43	1.56	-0.20	0.12	0.21	-0.77
Kiremt	1.88	7.45	1.72	0.77	1.95	-0.57
Annual	2.73	7.89***	1.02	2.47	7.00**	1.13

Note: **, and *** are significant at 0.05, and 0.01 alpha levels, respectively.

Abbreviations: Z_{MK}, standardized statistics of Mann-Kendal trend test; β, Sen's slope estimator.

Like rainfall trend analysis, mean annual minimum and maximum temperature trends were calculated using MK test techniques. The MK test showed mean annual minimum temperature exhibited significant warming trends in Simada and Lay Gayint at $p < 0.1$ level but a non-significant increasing trend in Tach Gayint. Similarly, the trend of mean annual maximum temperatures exhibited significant warming trends at a $p < 0.01$ level in the study area (Table 5.3).

Table 5. 3. The MK test values of mean minimum and maximum annual temperatures.

	Lay Gayint		Tach Gayint		Simada	
Temperature	Z_{MK}	β	Z_{MK}	β	Z_{MK}	β
Mean minimum annual temperature	1.56	0.01**	1.19	0.01	2.01	0.02**
Mean maximum annual temperature	4.09	0.03***	1.56	0.01	2.31	0.02**

Note: **, and *** are significant at 0.05 and 0.01 alpha levels, respectively.
Abbreviations: Z_{MK}, standardized statistics of Mann-Kendal trend test; β, Sen's slope estimator.

3.3. Climate change risk perception of households

Tables 5.4–5.6 show climate change risk perceptions of households in the study area. In the Lay Gayint district, the likelihood of potentially dangerous climate change risks is most likely linked to persistent drought, delayed onset of rainfall, early termination of rainfall, and food insecurity, as reported by households (Table 5.4). As shown in Table 5.5, households in the Tach Gayint district perceived recurrent drought, food insecurity, delayed rainfall onset, and early rainfall termination as potentially dangerous climate change risks. Moreover, recurrent drought, food insecurity, delayed onset of rainfall, and early termination of rainfall were perceived as significant potentially dangerous climate change risks by households in the Simada district (Table 5.6).

The variation of CCRPI for each climate event implies that households have heterogeneous perceptions of risk arising from the different climate events, which could be associated with variations in socio-demographic and external factors. This finding is consistent with the literature, which shows that households' perceptions are influenced by individual risk aversion and socio-economic characteristics (Frondel et al., 2017; Sullivan-Wiley and Gianotti, 2017). Accordingly, from the CCRPI, the values varied, ranging from 2.65 to 92.99 (Lay Gayint), 3.41 to 92.02 (Tach Gayint), and 4.46 to 94.50 (Simada), which demonstrates that households' perceptions were heterogeneous. Households living in Simada (*Woyna Dega* agroecology) and Tach Gayint (*Dega* agroecology) perceived more climate change risks than households in Lay Gayint (*High Dega*

agroecology). This could be associated with the probability of potentially dangerous climate change risks in the area. However, most of the households belonged to medium to high perception index values in Lay Gayint (48.06 to 92.99), in Tach Gayint (48.71 to 92.02), and in Simada (49.14 to 94.50), and fewer belonged to low and medium perception index values (2.65 to 31.40 for Lay Gayint, 3.41 to 44.44 for Tach Gayint and 4.46 to 35.05 for Simada). Moreover, the results of KIIs and FGDs also revealed that household aggregated responses matched the estimated index values for each climate change risk.

Table 5. 4. Climate change risk perception of households in Lay Gayint.

Climatic events	3	2	1	0	CCRPS	SCCRPI	Rank
Recurrent drought	101	33	16	0	385	92.99	1
Delayed onset of rainfall	100	28	17	0	373	90.09	2
Early termination of rainfall	97	30	12	0	363	87.68	3
Food insecurity	94	28	13	0	351	84.78	4
Flood	62	25	13	2	249	60.14	5
Soil fertility loss	61	24	11	1	242	58.45	6
Drinking water scarcity	57	19	25	4	234	56.52	7
Gulley formation	59	22	10	0	231	55.79	8
Crop pests	48	4	47	2	199	48.06	9
Frost	27	4	41	29	130	31.40	10
Human &livestock diseases	22	5	34	37	110	26.57	11
Resource-based conflict	18	3	32	36	92	22.22	12
Cultivated and grazing land encroachment	11	2	29	35	66	15.94	13
Landslide	1	2	4	76	11	2.65	14

Note: 0: No perception; 1: Low perception; 2: Medium perception; and 3: High perception.

Table 5. 5. Climate change risk perception of households in Tach Gayint.

Climatic events	3	2	1	0	CCRPS	SCCRPI	Rank
Recurrent drought	91	20	10	0	323	92.02	1
Delayed onset of rainfall	86	19	22	0	318	90.59	2
Food insecurity	89	19	9	0	314	89.46	3
Early termination of rainfall	85	16	23	3	310	88.31	4
Flood	56	14	23	2	219	62.39	5
Soil fertility loss	56	13	21	3	215	61.25	6
Drinking water scarcity	57	11	17	4	210	59.82	7
Gulley formation	54	12	21	1	207	58.97	8
Resource-based conflict	53	12	14	3	197	56.13	9
Crop pests	43	13	16	2	171	48.71	10
Cultivated and grazing land encroachment	41	10	13	2	156	44.44	11
Human & livestock diseases	30	4	20	5	118	33.61	12
Frost	31	5	13	2	116	33.04	13
Landslide	1	2	5	78	12	3.41	14

Note: 0: No perception; 1: Low perception; 2: Medium perception; and 3: High perception.

Table 5. 6. Climate change risk perception of households in Simada.

Climatic events	3	2	1	0	CCRPS	SCCRPI	Rank
Recurrent drought	60	40	15	0	275	94.50	1
Food insecurity	59	39	16	0	271	93.13	2
Delayed onset of rainfall	59	41	9	0	268	92.09	3
Early termination of rainfall	58	42	2	0	260	89.34	4
Cultivated and grazing land encroachment	56	41	3	0	253	86.94	5
Flood	27	46	13	2	186	63.91	6
Soil fertility loss	26	45	11	2	179	61.51	7
Drinking water scarcity	29	38	11	1	174	59.79	8
Gulley formation	24	41	13	3	167	57.39	9
Crop pests	30	8	37	27	143	49.14	10
Resource-based conflict	17	9	33	39	102	35.05	11
Human & livestock diseases	17	7	30	37	95	32.64	12
Frost	17	4	25	49	84	28.86	13
Landslide	1	2	6	90	13	4.46	14

Note: 0: No perception; 1: Low perception; 2: Medium perception; and 3: High perception.

3.4. Households' adaptation strategies

The study found eight adaptation strategies practiced by households in the study area (Table 5.7). Adjusting crop planting, dates was farmers most widely used (84% households) adaptation strategy in the study area. This is perhaps because adjusting crop planting dates is cheaper than other adaptation strategies. A similar result was reported by Alemayehu and Bewket (2017), Kahsay et al. (2019), and Getahun et al. (2021) in different parts of Ethiopia. Terracing was farmers' second most adopted strategy (82% of households), ranging between 76% in Simada and 83% in Tach Gayint, and 87% in Lay Gayint. This is partly a result of the government-led conservation activities in the country as a whole. Crop diversification was the third most (78% of households) adopted strategy by farmers; it was used by 70% of households in Lay Gayint, 77% of households in Tach Gayint, and 87% in Simada. The other strategies were tree planting (75% of households), the use of improved crop seeds (67% of households), and the use of drought-tolerant crop varieties (51% of households). Off-farm activities (26% of households) and water harvesting/ irrigation (12% of households) were the least used adaptation strategies by households in the study area. Participants in the FGD noted that despite irrigation being one of the most crucial adaptation measures for managing the risks of climate change, low irrigation potential and a lack of financial resources are two of the significant obstacles to adaptation.

Table 5. 7. Adaptation strategies used by households in the study area.

Adaptation strategies	Respondents (%) in respective districts				F	Sig.
	Lay Gayint	Tach Gayint	Simada	Mean		
Crop diversification	70	77	87	78	4.3	0.014*
Off-farm activities	34	23	21	26	3.2	0.040*
Terracing	87	83	76	82	2.3	0.104
Improved seed	65	68	69	67	0.2	0.820
Tree planting	76	74	75	75	0.6	0.545
Adjusting crop planting dates	84	81	88	84	0,8	0.443
Water harvesting/Irrigation	9	13	13	12	0.8	0.447
Drought tolerant crop	43	50	60	51	3.3	0.036*

* Significant at α 0.1 level

A significant difference was found between districts in the following adaptation strategies: off-farm activities ($F(2,349) = 3.2$, $p < 0.1$), crop diversification ($F(2,349) = 4.3$, $p < 0.1$), and drought tolerant crop ($F(2,349) = 3.3$, $p < 0.1$). A Tukey's post hoc test revealed a statistically significant difference in off-farm activities, crop diversification, and planting drought-tolerant crop types among the adaptation strategies in the study area between Lay Gayint and Simada districts ($p < 0.1$) compared to the Tach Gayint district. This difference reconfirms that adaptation strategies are location-specific and thus differ between localities (Dendir and Simane, 2021).

3.5. Links between adaptation strategies and perceived/ experienced climate risks

Adjusting crop planting dates

Early sowing dates increase crop production compared to the baseline planting dates, and a delayed sowing date with rainfed or irrigation (Getachew et al. 2021). However, early sowing dates were more effective when applied with irrigation than when applied with rain. A similar study found that early sowing dates are essential for early-maturing crops (Akinseye et al., 2020).

According to a focus group discussion participant, onset and offset dates for both the primary rainy season (June to September, called *Kiremt*) and the short rainy season (March to May, called *Belg*) had become highly variable in recent years, especially with remarkable delays in the onset times. Participants noted that the *Belg* production season had been lost, and the *Kiremt* rainfall had become insufficient for their agricultural production. The *Belg* rains are critical for *Belg* season production and land preparation for the primary season crops (also known as *Meher* season). Hence, the decline in *Belg* rains impacts *Belg* and *Meher* season production, especially long-cycle crops. As a result of the changes in rainfall patterns, participants reported that crop planting dates had been adjusted and land ploughing frequency had been reduced. The reduction of ploughing frequency often leads to an increased occurrence of weeds. The timing of farmland preparation and sowing is adjusted to coincide with the arrival of sufficient rainfall. Land preparation for all *Meher* season crops and planting dates for long-cycle crops like maize and sorghum had been set for May from the earlier usual planting dates of April. Similarly, planting dates for tef (*Eragrotis teff*) had been shifted to late June from its earlier usual planting date in the study area of early June. However, FGDs and KIIs participants indicated that adjusting crop planting dates has become more challenging in recent years because the rainy season is unpredictable.

Terracing

A study conducted by Alemayehu and Bewket (2017) and Bewket (2012) revealed that the government mainly undertakes soil and water conservation measures through its annual community mobilization for watershed management program, in which each household contributed 30-60 days of free labour in different parts of Ethiopia. In the study area, terracing was the second most crucial adaptation strategy, as indicated by the number of households who reported to have used it. Terraces provide various ecological services, such as reducing runoff and silt and increasing grain yields and soil moisture content. Furthermore, terracing can help to conserve plant biodiversity on a local scale. Hence, its use mitigates the negative impacts of rainfall variability, a growing challenge in the study area due to climate change. However, as terraces age, a variety of drawbacks emerge, including water circulation interference and the development of major environmental problems caused by poorly built or unmanaged terraces, where average runoff and soil loss can be 1–5 times that of well-managed terraces (Deng et al., 2021).

Crop diversification

Several studies suggest convincing evidence of how the efficient use of agrobiodiversity can result in improved livelihood outcomes using various strategies that can be used in any combination. For instance, Raseduzzaman and Jensen (2017) confirmed that intercropping lowers the possibility of a complete crop failure, can diversify small-scale farmers' diets and increase their food security, and can help crop production adapt to climate change. Moreover, different cultivars of the same crop can be mixed to reduce pest and disease impacts on crops and increase production in space and over time (Nankya et al., 2017; Vernooy, 2022).

According to findings from focus group discussions and key informant interviews, households in the study area received advice from extension agents to diversify their crops. For instance, farmers in Simada were reportedly encouraged to grow Mung bean (*Vigna radiate*), locally known as Masho. Mung bean is a self-pollinated, short-duration diploid legume crop with high nutritional properties, nitrogen-fixing potential, and a cash crop that pays better than cereals. Farmers in the area were also encouraged to adopt new varieties of sorghum (known as *Girana-1*) and tef (known as *Cross-37*), both of which are said to be early maturing and adapted to moisture-deficit conditions. Quncho, an improved variety of tef that has good tolerance to drought and waterlogging conditions and suffers relatively little from diseases and pests, has grown by nearly

half of the farmers in Simada. *Quncho* is an improved variety of tef with a good tolerance for drought and waterlogging conditions as well as diseases and pests.

Tree planting

As described above, planting trees was one of the adaptation strategies used in the study area. Eucalyptus was the area's most planted tree type, an important cash crop. Besides its climate adaptation benefits, tree planting is preferred for its lower labour demand, mainly once planted. A study conducted by Alemayehu and Bewket (2018) confirmed that households are transforming their farmlands into eucalyptus trees despite some reservations from local experts that eucalyptus planting may have an impact on future crop production in the central highlands of Ethiopia. Moreover, in the Raya Azebo district of Ethiopia, Sertse et al. (2021) noted that households use tree planting as an agroforestry practice and can sell the trees in times of climate change shocks. FGDs and KIIs participants reported that eucalyptus trees offer protection against the negative impacts of climate variability and support them in managing shocks to their way of life.

4. Conclusions

This study assessed farmers' perceptions of climate change risks and their adaptation strategies in the northwest highlands of Ethiopia. We found that recurrent drought, a delayed onset and early cessation of rainfall, and food insecurity were the major climate change risks perceived by households. Adaptation strategies used by the households included adjusting crop planting dates, crop diversification, terracing, tree planting, and cultivating drought-tolerant crop varieties, among others. A statistically significant difference was found between the districts in their use of adaptation strategies, the difference being in the use of off-farm activities, crop diversification, and planting drought-tolerant crop types between Lay Gayint and Simada compared to Tach Gayint. The results from this study are essential for local decision-makers as they seek to support adaptation strategies that improve the livelihoods of households while the local climate changes. There is an opportunity to enhance households' climate change risk perception and adaptation strategies to climate-related issues in the study area. Households with fewer adaptation strategies may be more exposed to climatic threats and require further attention to strengthen their adaptation responses. We recommend that (a) future policy initiatives both by government and non-governmental organizations should be agroecology-specific and incorporate the study area during policy design given the peculiar environmental conditions faced by these households; (b) decision-

makers should integrate households' perceptions of climate change risks and locally used adaptation strategies to facilitate their transition to improve adaptation and sustainability; (c) adaptation plans and risk communication techniques need to be developed to increase the risk perception and adaptation responses of climate change in the study area; and (d) there is a need for further research on climatic change risk perception and adaptation strategies among demographic and socioeconomic characteristics in the study area, such as gender, age, education level, and income.

Acknowledgments

The authors would like to thank Addis Ababa University and Dilla University for providing financial support for the data collection and write-up of the manuscript. The authors also extend their sincere thanks to all the data collectors and farmers who took part in the surveys for the study. The authors are also very grateful to the National Meteorological Agency of Ethiopia for providing rainfall and temperature data.

References

Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F. (2016). Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment*, 35, 447-460.

Ado, A. M., Savadogo, P., Pervez, A. K. M. K., & Mudimu, G. T. (2019). Farmers' perceptions and adaptation strategies to climate risks and their determinants: insights from a farming community of Aguie district in Niger. *GeoJournal*, 85(4), 1075-1095.

Ahmed, Z., Guha, G. S., Shew, A. M., & Alam, G. M. (2021). Climate change risk perceptions and agricultural adaptation strategies in vulnerable riverine char islands of Bangladesh. *Land Use Policy*, 103, 105295.

Akinseye, F. M., Ajeigbe, H. A., Traore, P. C., Agele, S. O., Zemadim, B., & Whitbread, A. (2020). Improving sorghum productivity under changing climatic conditions: a modelling approach. *Field Crops Research*, 246, 107685.

Alam, G. M., Alam, K., & Mushtaq, S. (2017). Climate change perceptions and local adaptation strategies of hazard-prone rural households in Bangladesh. *Climate Risk Management*, 17, 52-63.

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

Alemayehu, A., & Bewket, W. (2018). Trees and rural households' adaptation to local environmental change in the central highlands of Ethiopia. *Journal of Land Use Science*, 13(1-2), 130-145.

Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183-194.

Alves, F., Leal Filho, W., Casaleiro, P., Nagy, G. J., Diaz, H., Al-Amin, A. Q., de Andrade, J. B. S. O., Hurlbert, M., Farooq, H., Klavins, M., & Saroar, M. (2020). Climate change policies and agendas: facing implementation challenges and guiding responses. *Environmental Science and Policy*, 104, 190-198.

Antwi-Agyei, P., & Nyantakyi-Frimpong, H. (2021). Evidence of climate change coping and adaptation practices by smallholder farmers in northern Ghana. *Sustainability*, 13(3), 1308.

Aven, T. (2016). Risk assessment and risk management: review of recent advances on their foundation. *European Journal of Operational Research*, 253(1), 1-13.

Behailu, G., Ayal, D. Y., Zeleke, T. T., Ture, K., & Bantider, A. (2021). Comparative analysis of meteorological records of climate variability and farmers' perceptions in Sekota Woreda, Ethiopia. *Climate Services*, 23, 100239.

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 and Food Security*, 6(1), 1-13.

Berger, T., Troost, C., Wossen, T., Latynskiy, E., Tesfaye, K., & Gbegbelegbe, S. (2017). Can smallholder farmers adapt to climate variability, and how effective are policy interventions? Agent-based simulation results for Ethiopia. *Agricultural Economics*, 48(6), 693-706.

Bewket, W. (2012). Climate change perceptions and adaptive responses of smallholder farmers in the central highlands of Ethiopia. *International Journal of Environmental Studies*, 69(3), 507-523.

Bewket, W., & Alemu, D. (2011). Farmers' perceptions of climate change and its agricultural impacts in the Abay and Baro-Akobo River Basins, Ethiopia. *Ethiopian Journal of Development Research*, 33(1), 1-28.

Cortés, S., Burgos, S., Adaros, H., Lucero, B., & Quirós-Alcalá, L. (2021). Environmental health risk perception: adaptation of a population-based questionnaire from Latin America. *International Journal of Environmental Research and Public Health*, 18(16), 8600.

Creswell, W. J., & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. SAGE Publications, Inc.

Cullen, A. C., Anderson, C. L., Biscaye, P., & Reynolds, T. W. (2018). Variability in cross-domain risk perception among smallholder farmers in Mali by gender and other demographic and attitudinal characteristics. *Risk Analysis*, 38(7), 1361-1377.

Dendir, Z., & Simane, B. (2021). Farmers' perceptions about changes in climate variables: perceived risks and household responses in different agroecological communities, Southern Ethiopia. *Climate Services*, 22, 100236.

Deng, C., Zhang, G., Liu, Y., Nie, X., Li, Z., Liu, J., & Zhu, D. (2021). Advantages and disadvantages of terracing: a comprehensive review. *International Soil and Water Conservation Research*, 9, 344-359.

Dorward, P., Osbahr, H., Sutcliffe, C., & Mbeche, R. (2020). Supporting climate change adaptation using historical climate analysis. *Climate and Development*, 12(5), 469-480.

Fahad, S., & Jing, W. (2018). Evaluation of Pakistani farmers' willingness to pay for crop insurance using contingent valuation method: the case of Khyber Pakhtunkhwa province. *Land Use Policy*, 72, 570-577.

Fahad, S., & Wang, J. (2018). Farmers' risk perception, vulnerability, and adaptation to climate change in rural Pakistan. *Land Use Policy*, 79, 301-309.

Frondel, M., Simora, M., & Sommer, S. (2017). Risk perception of climate change: Empirical evidence for Germany. *Ecological Economics*, 137, 173-183.

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.

Getachew, B. (2018). Trend analysis of temperature and rainfall in south Gonder zone, Amhara Ethiopia. *Journal of Degraded and Mining Lands Management*, 5(2), 1111-1125.

Getachew, F., Bayabil, H. K., Hoogenboom, G., Teshome, F. T., & Zewdu, E. (2021). Irrigation and shifting planting date as climate change adaptation strategies for sorghum. *Agricultural Water Management*, 255, 106988.

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.

Hasibuan, A. M., Gregg, D., & Stringer, R. (2020). Accounting for diverse risk attitudes in measures of risk perceptions: a case study of climate change risk for small-scale citrus farmers in Indonesia. *Land Use Policy*, 95, 104252.

Hurni, H., Berhe, W. A., Chadhokar, P., Daniel, D., Gete, Z., & Grunder, M. K. G. (2016). Soil and Water Conservation in Ethiopia: Guidelines for Development Agents. Volume 1. Centre for Development and Environment (CDE), University of Bern: Bern, Switzerland.

IPCC, (2018). Annex I: Glossary [Matthews, J. B. R. (ed.)]. In: Global Warming of 1.5°C. 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 (pp. 541-562). Cambridge University Press, Cambridge, UK and New York, NY, USA.

Iqbal, M. A., Ping, Q., Abid, M., Kazmi, S. M. M., & Rizwan, M. (2016). Assessing risk perceptions and attitude among cotton farmers: a case of Punjab province, Pakistan. *International Journal of Disaster Risk Reduction*, 16, 68-74.

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*, 1-13.

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.

Khanal, U., Wilson, C., Rahman, S., Lee, B. L., & Hoang, V. N. (2021). Smallholder farmers' adaptation to climate change and its potential contribution to UN's sustainable development goals of zero hunger and no poverty. *Journal of Cleaner Production*, 281, 124999.

Kothari, C. R. (2004). Research Methodology: Methods and Techniques (2nd ed.). New Age International Publishers, Jaipur.

Lai, C. H., Liao, P. C., Chen, S. H., Wang, Y. C., Cheng, C., & Wu, C. F. (2021). Risk Perception and Adaptation of Climate Change: an assessment of community resilience in rural Taiwan. *Sustainability*, 13(7), 3651.

Li, J., Bao, C., & Wu, D. (2018). How to design rating schemes of risk matrices: A sequential updating approach. *Risk Analysis*, 38(1), 99-117.

Likinaw, A., Alemayehu, A., & Bewket, W. (2022). Local-scale climate variability and trends in a vulnerable rural landscape, northwest Ethiopia. *Malaysian Journal of Tropical Geography*, 48(1), 19-44.

Marie, M., Yirga, F., Haile, M., & Tquabo, F. (2020). Farmers' choices and factors affecting adoption of climate change adaptation strategies: Evidence from north-western Ethiopia. *Heliyon*, 6(4), e03867.

Mertz, O., Mbow, C., Reenberg, A., & Diouf, A. (2009). Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. *Environmental Management*, 43(5), 804-816.

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.

Nankya, R., Mulumba, J. W., Caracciolo, F., Raimondo, M., Schiavello, F., Gotor, E., ... & Jarvis, D. I. (2017). Yield perceptions, determinants, and adoption impact of on-farm varietal mixtures for common bean and banana in Uganda. *Sustainability*, 9(8), 1321.

Ndamani, F., & Watanabe, T. (2017). Determinants of farmers' climate risk perceptions in agriculture: A rural Ghana perspective. *Water*, 9(3), 210.

Paul, C. J., Jeuland, M. A., Godebo, T. R., & Weinthal, E. (2018). Communities coping with risks: Household water choice and environmental health in the Ethiopian Rift Valley. *Environmental Science and Policy*, 86, 85-94.

Raseduzzaman, M. D., & Jensen, E. S. (2017). Does intercropping enhance yield stability in arable crop production? A meta-analysis. *European Journal of Agronomy*, 91, 25-33.

Sarker, M. N. I., Wu, M., Alam, G. M., & Shouse, R. C. (2020). Life in riverine islands in Bangladesh: Local adaptation strategies of climate-vulnerable riverine island dwellers for livelihood resilience. *Land Use Policy*, 94, 104574.

Schneiderbauer, S., Pisa, P. F., Delves, J. L., Pedoth, L., Rufat, S., Erschbamer, M., Thaler, T., Carnelli, F., & Granados-Chahin, S. (2021). Risk perception of climate change and natural hazards in global mountain regions: A critical review. *Science of the Total Environment*, 784, 146957.

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.

Skovdal, M., & Cornish, F. (2015). Qualitative research for development: A guide for practitioners. Practical Action Publishing, Rugby, UK.

Sofoluwe, N. A., Tijani, A. A., & Baruwa, O. I. (2011). Farmers' perception and adaptation to climate change in Osun State, Nigeria. *African Journal of Agricultural Research*, 6(20), 4789-4794.

Sullivan-Wiley, K. A., & Gianotti, A. G. S. (2017). Risk perception in a multi-hazard environment. *World Development*, 97, 138-152.

Tesfaye, W., & Seifu, L. (2016). Climate change perception and choice of adaptation strategies: Empirical evidence from smallholder farmers in east Ethiopia. *International Journal of Climate Change Strategies and Management*, 8(2), 253-270.

Tripathi, A., & Mishra, A. K. (2017). Knowledge and passive adaptation to climate change: An example from Indian farmers. *Climate Risk Management*, 16, 195-207.

Van der Linden, S. (2017). Determinants and measurement of climate change risk perception, worry, and concern. In The Oxford Encyclopedia of Climate Change Communication (pp. 1-53). Oxford University Press, Oxford, UK.

Vernooy, R. (2022). Does crop diversification lead to climate-related resilience? Improving the theory through insights on practice. *Agroecology and Sustainable Food Systems*, 46(6), 877-901.

Zamasiya, B., Nyikahadzoi, K., & Mukamuri, B. B. (2017). Factors influencing smallholder farmers' behavioral intention towards adaptation to climate change in transitional climatic zones: A case study of Hwedza district in Zimbabwe. *Journal of Environmental Management*, 198, 233-239.

Chapter Six
Summary, conclusions and recommendations

1. Summary

The principal goal of this study was to gain insights into the climate dynamics of three food-insecure and vulnerable districts in Northwest Ethiopia, namely Simada, Lay Gayint, and Tach Gayint. To achieve this, the study focused on investigating climate dynamics and trends on a local scale. The analysis involved examining rainfall and temperature data across 4 × 4 km grids. The coefficient of variation and standardized anomaly index were utilized to assess the extent of variability in these districts. The data analysis revealed that both seasonal and annual rainfall revealed pronounced inter-annual variability, with the *Kiremt* season displaying a medium coefficient of variation. Throughout the observation period, negative irregularities were observed, ranging from 39% to 65%.

To analyze the trends, the MK and ITA methods were employed. The results indicated significant upward trends in annual rainfall for Tach Gayint and Lay Gayint, while Simada showed downward trends. Comparable upward trends were detected in annual and seasonal temperatures. These findings offer valuable insights for local development planning, considering current and future climate patterns. Additionally, this study investigated long-term extreme precipitation metrics, utilizing the gridded datasets from 1981 to 2018 and employing ITA and MK methods. Tach Gayint and Lay Gayint demonstrated substantial upward trends in extreme precipitation according to ITA, whereas Simada exhibited decreasing trends. The MK test results indicated varying trends across the districts. The study highlighted the effectiveness of ITA in identifying significant trends that MK might miss, providing valuable insights into extreme precipitation patterns. Additionally, this study examined climate change risk perceptions and adaptation responses. To achieve this, a convergent mixed methods design was employed, combining both quantitative and qualitative data collection techniques.

The study identified significant climate change threats and various adjustment measures, with variations observed among the districts. Standardized risk perception indexes and statistical analyses provided valuable information for designing context-specific strategies for addressing climate risks through adaptation measures. In addition, the vulnerability of households to climate variability was evaluated in this study. The assessment was conducted using the LVI and SeVI

methods. The study found Simada to be the most vulnerable district, followed by Tach Gayint and Lay Gayint. It emphasized the importance of improving the adaptive capacity of households and provides valuable insights for policymaking and program development to minimize vulnerability and promote adaptability

2. Conclusions

The study area has been negatively affected by climate change. This implies that the region has experienced changes in weather patterns and global temperatures that are harmful to the local environment and communities. Climate change has led to an increase in extreme weather events such as storms, droughts, or floods. These events have disrupted the regular patterns of rainfall in the study area, affecting the availability and distribution of water resources. The disrupted precipitation patterns and extreme weather events have significantly affected the growth of crops in the region. As a result, agricultural productivity has been compromised, leading to food insecurity. This suggests that farmers are facing challenges in producing enough food to meet their needs and sustain their communities.

Farmers in the study area are highly vulnerable due to their dependence on weather-dependent agriculture and natural resources. Their livelihoods and socio-economic status are at risk because of the impacts of climate change. This vulnerability implies that farmers are more prone to experiencing negative consequences and difficulties in adapting to the changing climate. The paragraph states that farmers have become increasingly aware of the repercussions of climate change on their livelihoods. This indicates that they recognize the connection between climate change and the challenges they face in agriculture and food security. Farmers perceive climate-related risks and extreme climate events as significant threats to agricultural productivity and food security. This means that they view these factors as having a major negative impact on their ability to produce crops and ensure a stable food supply.

Overall, the results highlight the adverse effects of climate change on the study area, particularly in relation to agriculture, food security, and the vulnerability of farmers. It emphasizes the need for understanding and addressing these challenges to support the resilience and well-being of the local community. Despite these challenges, farmers have made efforts to adapt by adopting various adaptation strategies. These strategies encompass changes in cropping patterns, the adoption of climate-tolerant crops, implementation of water and soil conservation measures, tree planting, and

diversification of crops and income sources. Farmers' perceptions and adaptation strategies are influenced by multiple factors, including access to information and technology, education, socio-economic status, and cultural beliefs. To address their vulnerability effectively, it is crucial to implement adaptive measures that enhance the resilience of farming systems to climate-related risks. This includes promoting drought-resistant crop varieties, improving irrigation and water management practices, adopting conservation agriculture techniques, and facilitating diversification of crops and income streams. Furthermore, supporting farmers in accessing vital resources such as weather forecasts, credit facilities, and training in sustainable agricultural practices is essential for successful adaptation.

Formulating impactful climate change adaptation programs and policies demands a comprehensive understanding of local contexts and must be customized to the specific requirements and situations of farming communities. Addressing the livelihood and socio-economic vulnerability of farmers to climate variability necessitates a multi-sectoral method, involving not only the agriculture sector but also water, health, and finance sectors. To enhance resilience and sustainable future for farming communities, coordinated efforts from governments, civil society, and the private sector are indispensable. By supporting farmers in adopting and scaling up climate-resilient practices, we can collectively tackle the difficulties brought about by climate change, and foster a more secure future for all.

3. Recommendations and the way forward

Climate change exerts a direct and substantial influence on the livelihoods of farmers, especially those whose sustenance depends on natural reserves like water and soil. To decrease their vulnerability and ensure adaptability of agriculture to climate variability, it is vital to consider the following recommendations:

- Improve access to weather and climate knowledge: Farmers require reliable information to make informed decisions about planting, harvesting, and managing their crops. There is a need to invest in improving weather forecasting and monitoring systems and enable farmers to access this information in a timely and user-friendly manner.
- Promote the adoption of climate-adaptive agricultural practices: Climate-adaptive agricultural practices, such as agroforestry, conservation agriculture, and integrated crop-livestock systems, can help farmers adapt to climate variability while minimizing

greenhouse gas releases. Concerned organizations should support the adoption of these practices through training programs, financial incentives, and the sharing of information on their benefits.

- Offer financial assistance: Local governments should establish financial support programs that are tailored to the needs of farmers and deliver them with affordable access to credit, which can be a barrier to adopting new technologies and practices that would help them adapt to climate change.
- Reinforce local organizations and governance: Effective governance and strong local institutions can enable farmers to adapt to climate by ensuring that their needs and priorities are considered in decision-making procedures. Local governments should work to strengthen local institutions and ensure that they have the capacity to represent the interests of farmers in policy and decision-making processes.
- Facilitate farmer participation in policy development: Local governments should involve farmers in the development of policies and programs that affect their livelihoods, ensuring that policies are relevant, effective, and address the needs and concerns of farmers.

Finally, this research provides valuable insights into the livelihood and socio-economic vulnerability of households to climate variability. However, it lacks a comprehensive assessment of agricultural vulnerability, which is crucial for addressing reduced vulnerability and ensuring increased livelihood sustainability within the background of economic and sustainable development agendas. The study focused on households as the unit of analysis to investigate the perception and adaptation responses of farmers to climate variability. However, it did not explore the perception, adaptation, and vulnerability of different subgroups of farmers, who may experience varying levels of vulnerability to climate variability. Consequently, it is vital to examine the vulnerability, adaptation, and perception of households across different social groups.

To address this gap, further research is recommended to critically examine the vulnerability, adaptation, and perception of households among various social groups, including those classified as poor, medium, and rich households. Such an approach would provide a more detailed understanding of the challenges faced by different subgroups of farmers and support the design of targeted interventions that proficiently address the concerns of vulnerable households. Moreover,

it is imperative to investigate how gender affects the perception, adaptation, and vulnerability of households to climate variability. Hence, future studies will examine, the impact of climate variability on gender groups and how gender-sensitive approaches can be incorporated into climate change adaptation practices. By doing so, gender inequalities can be addressed, and women's specific requirements and experiences can be considered in the development of interventions aimed at enhancing the resilience of rural communities to climate change and variability.

Appendices

Appendix A: Questionnaire

Addis Ababa University

College of Social Sciences

Department of Geography and Environmental Studies

Households Survey Questionnaire

Dear respondents,

This questionnaire is designed to collect data about **"Climate Change, Vulnerability and Adaptation of Rural Households in Northwest Ethiopia"** for the study being carried out as a fulfillment of doctorial study at Addis Ababa University. The objectives of this questionnaire is to collect data on exposure of smallholder farmers' to climate change-related shocks and stresses, farmers' perception and adaptation practices to climate change, extent of vulnerability of smallholder farmers to climate variability and change and vulnerability of crop production to drought.

N.B: Dear respondents: This research survey questionnaire is purely for academic purposes. You are assured of confidentiality of any view expressed in relation to this research. I therefore request you to provide information as accurate as possible for true results.

Thank you for your co-operation

I. Basic Information

1. House code: _____
2. District: _____ Kebele: _____
3. Household head's gender: 1. Male 2. Female
4. Age of the household head: _____ years.
5. Marital Status: 1. Married 2. Single 3. Widow/Widower 4. Divorced/Separated
6. Religion 1. Christian Orthodox 2. Muslim 3. Protestant 4. Others _____
7. Educational status:
    1. Illiterate 3. Primary school (grade 1- 8) 5. Higher education
    2. Can read and write 4. Secondary school (grade 9 - 12)

8. Size of the Household:

No	Age	Number of Family Members by Gender		
		Male	Female	Total
1	<15 years			
2	15-65 years			
3	>65 years			
Total				

9. Farming experiences _____ years.

II. Crop Production, Land Resources, and Livestock Ownership

1. Do you possess land in your name?1. Yes 2. No

2. If your response is yes, what is the extent of your land in hectares (Timad)?

- Rainfed-cultivated land _____
- Irrigated land _____
- Grass and woodland _____
- Homestead _____
- Forest land _____
- Total _____

3. How many land parcels do you currently own? Please indicate the number of parcels (plots).

4. Please use the numbers to describe the attributes of your agricultural land in the table provided below.

Description	Plot 1	Plot 2	Plot 3	Plot 4	Plot 5
Plot area (hectares)					
Degree of soil erosion: 1. High 2. Medium 3. Low					
Plot slope: 1. Very steep 2. Steep 3. Medium 4. Gentle 5. Flat					
Plot fertility: 1. Very poor 2. Poor 3. Medium 4. Rich 5. Very rich					
Application of at least one type of conservation structure 1. Yes 2. No					
Number of years since the plot has been in use:					

5. If you possess irrigated land, what serves as the water source for your irrigation?1. Spring 2. Micro Pond 3. Hand dung well 4. Stream/rivers

6. How frequently do you engage in crop production each year on your irrigated land? __

7. Which varieties of crops do you cultivate on your irrigated plot? ____

8. Do you face any limitations when it comes to utilizing agricultural inputs? 1. Yes 2. No

9. If you encounter any challenges in utilizing agricultural inputs, could you please specify the issues you face? (Multiple responses are possible) 1. Lack of finance 2. High prices of inputs 3. Lack of supply 4. Untimely input distribution 5. Others _____

10. Considering the overall circumstances, how would you characterize the trend of crop production over the past 15 years? 1. Decreasing 2. Increasing 3. No change 4. Didn't noticed

11. If there has been an increase in the productivity of your cultivated land, what factors do you attribute to this improvement? (Multiple responses are possible) 1. Strong extension services 2. Water conservation practices 3. Suitable weather conditions 4. Use of improved inputs 5. Increase in soil fertility 6. Increase in labor forces

12. If you have observed a decrease in the productivity of your cultivated land, what factors do you believe have contributed to this decline? (Multiple responses are possible) 1. Lack of timely input supply 3. Rainfall variability 5. Pests and crop diseases 2. Decrease in soil fertility 4. Drought 6. Lack of extension services

13. What are the primary challenges that have an impact on both crop and livestock productivity? (Multiple responses are possible) 1. Labor shortage 2. Erratic rainfall 3. Drought 4. Less access to input 5. Soil erosion 6. Land shortage 7. Others (specify) _____

14. What are the primary issues of land degradation that you have observed? 1. Deforestation 2. Soil erosion 3. Soil nutrient depletion 4. Others (specify) _____

15. Does your food production adequately meet the annual requirements of your household? 1. Yes 2. No

16. If not, over what duration of months are you able to fulfill your household's food requirements?

17. How do you address the months when your household faces a food deficit? (Multiple responses are possible) 1. Selling animals 2. Food Aid 3. Buying 4. Borrowing 5. Casual labor 6. Selling Forest products 7. Others (specify) _____

III. Information Access

1. Are you able to access information related to climate change, variability, and associated risks? 1. Yes 2. No
2. If your answer is affirmative, could you please specify your sources of information? (Multiple responses are possible)1. Neighbors 2. Radio 3. Training 4. Agriculture experts/Das 5. Other _____
3. How frequently do you interact with and receive information from agricultural experts or Development Agencies (DAs)? 1. Once in a month 2. Irregularly 3. Weekly 4. Daily 5. Once in two weeks

IV. Climate change and variability

1. What alterations have occurred in the realm of daily precipitation extremes over the last decade? 1. Decrease 2. Increase 3. No change 4. Don't know
2. Has the climate in your local area remained consistent with conditions from a decade ago? 1. Yes 2. No
3. What local indicators demonstrate the fluctuations or alterations in rainfall and temperature patterns within your vicinity?
    1. The appearance of novel animal and plant species within the area.
    2. Shifts in the local crop calendar over time.
    3. Incidence of novel human and animal diseases previously unseen in the area.
    4. Changes in the clothing styles of the communities.
    5. Others (specify)
4. What changes have there been in rainfall over the past 10 years?
    1. Increase 2. Decrease 3. Don't know 4. No change
5. What are the local indicators of variability or change in rainfall over time in your locality? / Multiple responses are possible/ 1. Shift in crop types 2. Alteration in cropping seasons 3. Rise in the frequency of droughts 4. Crop yield loss 5. Shift in the commencement and conclusion of the rainy season 5. Rise in the frequency of floods 6. Others (specify)
6. Have you observed any instances of extreme climate events or hazards in the past 10 years? 1. Yes 2. No

7. If yes, what types of extreme climate events or hazards have you encountered? /Multiple responses are possible/

   1. Flood 2. Drought 3. Hailstorm 4. Land slide 5 Others (specify)

V. Perceptions on Climate Variability and Change

1. Do you hold the belief that the climate is undergoing change? 1. Yes 2. No
2. If the answer is yes, how have you come to differentiate the changes in the climate? 1. Personal experience 2. From school 3. From mass media 4. From government and non-governmental organizations 5. Others (specify) __
3. What are the local indicators that show the variability or change in temperature? /Multiple responses are possible/ 1. The emergence of new plant and animal species 2. Occurrences of diseases that have not been seen before 3. Changes in clothing styles of the community 4. Shifts in the local crop calendar over time 5. Others (specify) _____
4. What are the local indicators that show the variability or change in rainfall over time? /Multiple responses are possible/ 1. Alterations in cropping seasons 2. Shifts in crop types 3. Increase in the frequency of droughts 4. Crop yield loss 5. Shifts in the starting and ending times of the rainy season 6. Rise in the frequency of floods 7. Others (specify) _

VI. Climate Related Extremes/Disasters

1. Have you observed climate extremes or hazards in the past 15 years?1. Yes 2. No
2. If yes, please specify the types of climate extremes or disasters.? /Multiple responses are possible/ 1. Hailstorm 2. Landslide 3. Drought 4. Flood
3. How would you assess the frequencies of climate-related extreme events in the past 10 years?1. every year 2. Once in 2 years 3. once in every 3 years 4. once every in 4 years 5. Once every 5 years

No	Extreme events	Frequency
1	Drought	
2	Flood	
3	Hailstorms	
4	Landslide	

VII. Strategies for Climate Change Adaptation

1. Choose the Climate Change Adaptation Strategies in Your Area.

No	Strategy	1. Yes 2. No
1	Adjusting crop calendars	
2	Utilizing varied crop types and varieties	
3	Implementing water harvesting and irrigation techniques	
4	Engaging in tree planting initiatives	
5	Practicing soil and water conservation methods	
6	Embracing crop diversification strategies	
7	Employing improved seeds	
8	Managing soil fertility effectively	
9	Cultivating drought-tolerant crops	
10	Enforcing crop rotation practices	
11	Participating in off-farm activities	
12	Establishing terracing systems	
13	Exploring non-farm activities	

VIII. Risks of Climate Change

1. Identify the Principal Climate Change Risks in Your Area.

Climatic events	3	2	1	0
Persistent drought				
Inadequate food supply				
Delayed commencement of rainfall				
Premature cessation of rainfall				
Encroachment on cultivated and grazing lands				
Flooding				
Depletion of soil fertility				
Shortage of potable water				
Erosion and gulley formation				
Crop infestations by pests				
Conflicts related to resources				
Incidence of human and livestock illnesses				
Frost events				
Landslides				

Note: 0: No perception; 1: Low perception; 2: Medium perception and 3: High perception.

IX. Vulnerability to Climate Change

A. Indicators/Variables for Domains of the Socio-economic Vulnerability Index (SeVI)

Social	
Have you previously benefited from support under the PSNP program?	1. Yes 2. No
Do you maintain regular communication with neighboring farmers?	1. Yes 2. No
Have you received aid from relatives or friends during challenging periods?	1. Yes 2. No
Do you possess access to mediums such as radio or television?	1. Yes 2. No
Economic	
Have you obtained income from sources other than farming?	1. Yes 2. No
Did you receive income from non-agricultural activities?	1. Yes 2. No
In the last month, did you take out loans from informal moneylenders?	1. Yes 2. No
In the last month, did you borrow money from a credit association?	1. Yes 2. No
Do you possess the capability to independently resolve financial challenges?	1. Yes 2. No
Physical	
Are you involved in irrigation practices?	1. Yes 2. No
Do you possess arable land with good fertility?	1. Yes 2. No
Do you perceive climatic shocks have impacted your crop yields?	1. Yes 2. No
What is the duration of your journey to water sources (in minutes)?	1. Yes 2. No
Are there well-constructed roads in your vicinity?	1. Yes 2. No
Does any member of your family experience persistent health issues?	1. Yes 2. No
Do you apply an adequate amount of fertilizer for your crops?	1. Yes 2. No
Do you make use of chemical insecticides?	1. Yes 2. No
Do you utilize manure as a form of fertilizer?	1. Yes 2. No
How much time does it take you to reach healthcare facilities (in minutes)?	1. Yes 2. No
Do you have access to a hygienic latrine?	1. Yes 2. No
Exposure to climatic hazards	
Were you provided with advance notice regarding the impending flood or drought?	1. Yes 2. No
Is soil erosion a significant issue in your area?	1. Yes 2. No

Do you encounter challenges in agricultural production due to climate-related shocks?	1. Yes 2. No
How frequently has this region encountered droughts in the past 30 years?	_____
How frequently has this locality been subjected to flooding incidents in the past 30 years?	_____
Have you incurred damage to your physical assets as a result of climate-related events?	1. Yes 2. No
Have you recently suffered any livestock losses due to disaster events?	1. Yes 2. No

B. Indicators/Variables for Components of the Livelihood Vulnerability Index (LVI)

Livelihood strategies	
Was agriculture your primary source of income?	1. Yes 2. No
Were you involved in irrigation practices?	1. Yes 2. No
Was there a family member employed in a different community?	1. Yes 2. No
Social networks	
Were you provided with extension services?	1. Yes 2. No
Are you affiliated with any social groups?	1. Yes 2. No
Have you undergone any training related to climate change?	1. Yes 2. No
Have you received support from relatives or friends?	1. Yes 2. No
Water	
What is the duration of your journey to access water sources (measured in minutes)?	1. Yes 2. No
Did you make use of natural water sources for your household water needs?	1. Yes 2. No
Have you experienced any conflicts related to water within your local community?	1. Yes 2. No
Is your access to a reliable drinking water supply consistent?	1. Yes 2. No
Food	
Does your family set aside a portion of the harvested crops for consumption during other periods of the year?	1. Yes 2. No

In the past 12 months, were there any months during which your family faced food scarcity and didn't have sufficient provisions?	1. Yes 2. No
Does your family preserve seed for planting in the upcoming year's crop cycle?	1. Yes 2. No
Did your family rely on the household farm as a primary source of food?	1. Yes 2. No
Health	
Does anyone in your family experience frequent and persistent illness?	1. Yes 2. No
Has any member of your family been unwell to the extent that they had to miss work or school in the past 2 weeks?	1. Yes 2. No
Is your family capable of affording prescribed healthcare services?	1. Yes 2. No
Do you have access to a hygienic latrine?	1. Yes 2. No
What is the duration of your journey to reach health centers, measured in minutes?	1. Yes 2. No
Climate variability & related hazards	
Have you faced livestock losses as a result of recent disasters?	1. Yes 2. No
How frequently has this region been impacted by floods over the past 30 years?	_____
How frequently has this locality experienced droughts in the last 30 years?	_____
Have you incurred damage to physical assets due to climate-related incidents?	1. Yes 2. No
Has any member of your family sustained injuries due to recent climate-related events?	1. Yes 2. No

Appendix B: Questions for the Interview Guide

Key Informant Interviews and Focus Group Discussions Guidelines for the study area:

1. Can you describe your awareness of the current climatic conditions in your area?
2. In your opinion, have there been noticeable changes in temperature, rainfall patterns, and occurrences of drought in your community?
3. How have rising temperatures, unpredictable rainfall, and recurrent droughts affected crop production? Could you elaborate on the specific impacts you've observed?

4. What strategies have you employed to mitigate the adverse effects of climate change and variability on your livelihood?
5. Regarding soil and water conservation practices, do you believe they play a role in reducing the impacts of climate change and variability on crop production?
6. Could you share any personal experiences with climate-related risks that you or your community have faced?
7. How easily accessible is information about climate change and its influence on your way of life?
8. Please provide your assessment of the quality and utility of the technological and educational support offered by government experts and agricultural development agencies (DAs).
9. In your opinion, how effective are these DAs in equipping you with the necessary knowledge and skills relevant to your livelihood circumstances?
10. From your perspective, how well do government policies and strategies address climate-related concerns and contribute to maximizing crop and livestock yields?
11. Are the coping strategies you independently implement proving to be effective in dealing with climate-related challenges?
12. Could you discuss your access to various crop and livestock species? How do you perceive their significance and relevance in your context?