ASSESSING CROP SUITABILITY, SOIL MOISTURE DYNAMICS, AND RESIDUAL SOIL MOISTURE EFFECTS IN A CHANGING CLIMATE FOR SUSTAINABLE AGRICULTURE IN ETHIOPIA

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This declaration attests to the thesis authored by Tamirat Bekele Jimma, entitled **Assessing Crop Suitability, Soil Moisture Dynamics, and Residual Soil Moisture Effects in a Changing Climate for Sustainable Agriculture in Ethiopia**. It is submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Environmental Science, in accordance with the regulations stipulated by the University. The thesis adheres to acknowledged criteria for originality and scholarly excellence.

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Dedication

To my innocent little girl Yohanan Tamirat, who struggles a lot and passes through many ups and downs with me throughout my study.

Declaration

I hereby declare that the research outlined in this Ph.D. thesis is original and was conducted independently by myself, Tamirat Bekele Jimma, under the guidance of my advisers. This Ph.D. thesis has not been presented for the purpose of obtaining any other academic degree or professional qualification. Proper attribution is provided for all cited sources, with comprehensive references included.

Acronyms and Abbreviations

ACIAR	Australian Center for International Agricultural Research
AEZ	Agro-Ecology Zones
AICCRA	Accelerating Impacts of CGIAR Climate Research for Africa
AMI-WS	Active Microwave Instrument-Windsat
AMSR-E	Advanced Microwave Scanning Radiometer-Earth Observing System
ASAP	Anomaly Hotspots of Agricultural Production
ASCAT	Advanced Scatterometer
B-EPICC	Brazil-East Africa Peru India Climate Capacities
C3S	Copernicus Climate Change Services
CCAFS	Climate Change, Agriculture and Food Security
CCI	Climate Change Initiative
CDS	Climate Data Store
CGIAR	Consortium of International Agricultural Research Centers
CHIRPS	Climate Hazard Group InfraRed Precipitation with Station
CMCA	Complex Maximum Covariance Analysis
CMIP	Coupled Models Intercomparison Project
DEM	Digital Elevation Model
DMI	Dipole Mode Index
ECMWF	European Center for Medium-Range Weather Forecasts
ECOCROP	Ecological Crop Screening System
ECV	Essential Climate Variable
EMI	Ethiopian Meteorological Institute
ENSO	El Niño-Southern Oscillation
EOF	Empirical Orthogonal Function
ERA5	Fifth generation ECMWF Atmospheric Reanalysis
ESA	European Space Agency

ET	Evapotranspiration
FAO	Food and Agriculture Organization
FEWS NET	Famine Early Warning Systems Network
FLDAS	FEWS NET Land Data Assimilation System
GAEZ	Global AgroEcological Zones
GBIF	Global Biodiversity Information Facility
GCM	Global Climate Model
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GLDAS	Global Land Data Assimilation System
GMTED2010	Global Multi-resolution Terrain Elevation Data 2010
GTOPO30	Global Topographic 30 arc DEM
IOD	Indian Ocean Dipole
ISRIC	International Soil Reference and Information Center
JJAS	June-July-August-September
KDE	Kernel Density Estimation
LEG4DEV	Legume for Development
LSM	Land Surface Model
MAM	March-April-May
MCA	Maximum Covariance Analysis
MDPI	Multidisciplinary Digital Publishing Institute
MERRA	Modern-Era Retrospective analysis for Research and Application
MoA	Ministry of Agriculture
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
OND	October-November-December
ONI	Oceanic Nino Index
PACWARMPOOL	Pacific Warm Pool

PC	Principal Component
PDO	Pacific Decadal Oscillation
PIK	Potsdam Institute for Climate Impact Research
POWER	Prediction Of Worldwide Energy Resources
PSL	NOAA Physical Laboratory
RF	Rainfall
RMSD	Root-Mean-Square-Difference
SM	Soil Moisture
SMMR	Scanning Multichannel Microwave Radiometer
SSM/I	Special Sensor Microwave Imager
SSP	Shared Socioeconomic Pathway
SST	Sea Surface Temperature
TEJ	Tropical Easterly Jet
TMI	TRMM Microwave Imager
TRMM	Tropical Rainfall Measuring Mission
UBNB	Upper Blue Nile Basin
USGS	United States Geological Survey
WindSat	WindSat Spaceborne Polarimetric Microwave Radiometer

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Abstract

Challenges to enhancing agricultural productivity in sub-Saharan Africa, particularly in Ethiopia where rain-fed agriculture is vital, are versatile. Human activities that alter the environment, combined with climate variability, soil degradation, and limited adoption of climate-smart technologies, exacerbate these challenges. This dissertation adopts an interdisciplinary approach, integrating climate science, soil science, and agronomy, to address some of these critical issues. It aims to identify soil moisture dynamics and its drivers, key food crops suitability, and the role of residual soil moisture to legume-based cropping systems in Ethiopia. A particular focus is given to soil moisture, a fundamental climate variable influencing local climate variability, soil properties, and agricultural productivity. Despite its significance, studies on soil moisture characteristics in Ethiopia are relatively sparse. Changes in crop suitability extents at the intersection of climate change and soil acidity are not sufficiently addressed. Moreover, the potential of residual soil moisture for post-harvest cropping remains under-explored. Therefore, this research assesses the spatiotemporal characteristics of soil moisture across Ethiopia and investigates the local and remote drivers influencing it. The study also examines the contributions of soil moisture to post-rainy season cropping by focusing on selected legume-based crops such as chickpeas (*Cicer arietinum*), field peas (*Pisum sativum*), common beans (*Phaseolus vulgaris*), soybeans (*Glycine max*), and alfalfa (*Medicago sativa*). Additionally, it evaluates the current and future suitability of key food crops like teff (*Eragrostis tef*), maize (*Zea mays L.*), barley (*Hordeum vulgare L.*), and common wheat (*Triticum aestivum L.*) under changing climate and soil conditions from 1970 to 2020 and projected climate changes by 2050. The research employs several statistical methodologies, including Empirical Orthogonal Functions (EOF), Complex Maximum Covariance Analysis (CMCA), Kmeans clustering algorithm, crop models, and the Penman-Monteith equation, to investigate the spatiotemporal dynamics of soil moisture, crop suitability, and crop water demands. The analysis reveals significant variability in soil moisture across Ethiopia, with a distinct gradient between the eastern and western regions. Interannual variability of the soil moisture is primarily driven by rainfall patterns, while evapotranspiration significantly influences soil moisture dynamics in the east. Global oceanic indices such as the Oceanic Niño Index (ONI, r = 0.72), Indian Ocean Dipole (IOD, r = 0.43), Pacific warm pool (PACWARMPOOL, r = 0.48), and Pacific Decadal Oscillations (PDO, r = -0.52) are closely associated with local soil moisture anomalies. The combined impacts of climate change and soil acidity on key food crops indicate that while climate change alone may not drastically affect crop suitability, its superimposition with soil acidity leads to adverse effects, reducing suitability for all crops (e.g., -26.7% for teff, -8.7% for maize, -30.9% for barley, and -34.3% for wheat). While the post-rainy season (OND) is not the same across the country, residual soil moisture analysis during the post-rainy season shows adequate moisture reserves in the western, central, and southwestern regions of Ethiopia. In these regions, crop water demand is adequately met by residual soil moisture during the initial and late growing stages of the crops; however, residual soil moisture is insufficient to meet crop water demands during the mid-season crops development stage. Conversely, the northern and southeastern tips of the country face unreliable residual moisture levels due to adverse climate conditions and prolonged dry periods (> 150 days), resulting in insufficient residual soil moisture to meet crop water demand in these regions. Findings from this dissertation provides valuable insights into the spatiotemporal dynamics of soil moisture and its critical role in post-rainy season cropping and crop suitability under the changing climate and soil conditions in Ethiopia. Furthermore, the findings contribute to the overarching goal of agricultural sustainability, providing insights for long-term climate resilient cropping systems while maintaining minimal disruption to the environment.

Keywords: soil moisture, teleconnections, oceanic indices, soil pH, crop suitability, post-rainy season, legumes, agricultural sustainability, climate adaptation, residual moisture, post-harvest cropping, EOF, CMCA, EcoCrop

Chapter 1

Introduction

1.1 Background

Agriculture, the foundation of global food production, is encountering unprecedented challenges in the 21st century. These challenges require a shift towards sustainable and resilient practices (Kassam and Kassam 2021; Alexandratos and Bruinsma 2012; Howden et al. 2007). Climate change introduces uncertainties in weather patterns, resulting in altered precipitation levels, temperature extremes, and an increased frequency of extreme events (IPCC 2014). These climatic changes significantly impact crop yields by altering the length of growing seasons and causing heat and water stress (Anwar et al. 2013; Evangelista et al. 2013; Hatfield et al. 2011). In addition, adverse changes in soil properties, such as low soil fertility and increased soil acidity, create deficiencies in essential nutrients. These nutrients include phosphorus (P), molybdenum (Mo), calcium (Ca), magnesium (Mg), and potassium (K). Such deficiencies contribute to substantial crop losses (Trunhe and Yli-Halla 2016; Debaeke and Aboudrare 2004). These climatic and soil property changes threaten the future of crop suitability and food security by reducing soil fertility, increasing soil acidity, and altering weather patterns (Alotaibi 2023; Ahmed et al. 2019). One approach to understanding these diverse impacts on crop suitability involves identifying the primary contributing factors and examining their effects through modeling. Crop suitability modeling, which considers crop environmental requirements and soil properties, can provide valuable insights into how climatic factors, soil properties, or both affect crop suitability. Therefore, studies on the combined impacts of climate change and soil conditions on cropping systems are essential to examine these interconnected challenges.

Ethiopian cropping systems experience significant hurdles due to the variability of soil moisture, rising soil acidity, and the need to optimize residual soil moisture for post-rainy season cropping (Korbu et al. 2022; Wubetu 2017; Wubie 2015) among others. Soil moisture variability leads to prolonged droughts, disrupting crop cycles; thus reducing crop yield or resulting in total crop failure (Upadhyaya et al. 2012). Concurrently, intensive farming practices and deforestation have increased land degradation (Desta et al. 2021; Srinivasarao et al. 2019; Singh and Ryan 2015). These effects are due to the fact that fertilizer application, while boosting crop yields, releases hydrogen ions into the soil during nitrification, leading to a decrease in soil pH and subsequent acidification (Gidda et al. 2015). Deforestation removes the vegetative cover that protects the soil and contributes to organic matter content. When forests are cleared, the organic matter, which helps neutralize soil acidity, is rapidly depleted. This leads to increased soil erosion and leaching of basic cations, further contributing to soil acidification (Abate et al. 2017). Across these challenges, using residual soil moisture to cultivate legume crops during the post-rainy season offers a promising approach to boost agricultural productivity and soil fertility (Mwila et al. 2021). Addressing these interconnected issues is crucial for developing resilient and sustainable farming systems in Ethiopia, supporting the livelihoods of smallholder farmers, and ensuring long-term resilient cropping systems.

Ethiopia's seasonality of rainfall is influenced by the Intertropical Convergence Zone (ITCZ), which causes an altering wet and dry seasons (Diro et al. 2008a; Segele and Lamb 2005). However, climate change and variability have exacerbated the irregularity of the seasonal patterns, leading to variable rainfall and extended droughts (Zeleke et al. 2017). This variability impacts soil moisture levels, crucial for crop growth and agricultural productivity. The erratic nature of soil moisture affects not only the timing of planting and harvesting but also the overall yield and health of crops (Zveryaev et al. 2019; Lal 2009). Consequently, this moisture variability poses a substantial threat to Ethiopian cropping systems and the broader economy, emphasizing the urgent need for adaptive strategies in agricultural practices and water management.

Understanding the spatiotemporal dynamics and distribution of soil moisture characteristics across Ethiopia is essential. This knowledge will help prepare adaptation plans based on the amount and distribution of soil moisture and determine where and when to allocate resources for intervention. However, studies addressing the spatiotemporal variability of soil moisture in Ethiopia are generally limited to specific watersheds (Ayehu et al. 2020, 2019; Mekonnen 2009). These studies primarily focus on monitoring, validating, and estimating soil moisture variability for applications, which limits their applicability in a broader country scale. Despite these efforts, it remains challenging to find research examining the spatial and temporal dynamics of soil moisture and its influential climatic drivers nationwide.

On the other hand, the rise in soil acidity in Ethiopia is a growing concern with far-reaching implications for crop suitability. Soil acidification arises from both natural phenomena and human activities. Nonetheless, studies (Gedamu 2020; Chimdi et al. 2012a) indicate that intensive farming practices, excessive use of chemical fertilizers, and deforestation have significantly contributed to the increase in soil acidity across various regions of Ethiopia. Several studies (Alemu et al. 2022; Desta et al. 2021; Abate et al. 2017) also highlight that regions such as the Ethiopian highlands are particularly affected, where soil pH levels have dropped, making the soil less suitable for staple crops like teff and maize. Acidic soils hinder the availability of essential nutrients to plants (e.g., binding phosphorous); thus reducing crop yields (Chimdi et al. 2012b; The et al. 2006; Ramankutty et al. 2002). Concurrently, variability in rainfall patterns and increasing temperature, attributed to climate change, are primary drivers of droughts and crop failures across Ethiopia (Zeleke et al. 2017; Araya and Stroosnijder 2011; Segele and Lamb 2005). Notably, there has been an observed shift in suitable crop areas from one agroecological zone to another due to these soil and climatic changes (Evangelista et al. 2013).

Hence, the ongoing rise in soil acidity and the changing climate threaten Ethiopia's agricultural sustainability and food security, posing a significant challenge to its economic development and the well-being of its population. Several studies (Girmay et al. 2018; Yohannes and Soromessa 2018; G.Selassie et al. 2014) have attempted to understand the shift in crop suitability by independently focusing on the significance of climatic factors or soil quality. This fragmented approach impedes comprehending the combined effects of climate and soil conditions on crop suitability. To address this gap, examining the coupled impacts of climatic factors (such as temperature, rainfall, or soil moisture) and soil properties (like soil pH) on crop suitability in

Ethiopia is paramount. This approach provides a comprehensive understanding that could give broad insights for policymakers, land managers, and farmers to make informed decisions.

Another aspect to consider is the potential of residual soil moisture for post-rainy season cropping of legume crops in Ethiopia. This practice shows great promise for improving agricultural productivity and ensuring resilient cropping systems. Studies (Agegnehu 2018; Feyissa et al. 2018; Agegnehu et al. 2006) have shown that residual soil moisture, retained after the main rainy season, can support the cultivation of legume crops such as chickpeas, lentils, and cowpeas. These crops are well-suited to the relatively dry conditions following the rainy season due to their deep root systems and drought tolerance (Korbu et al. 2022). Legume crops benefit from the available moisture and improve soil fertility through nitrogen fixation, providing long-term benefits to subsequent crops (Kebede 2020; Bationo et al. 2011; Mapfumo 2011). In Ethiopia, where rainfall variability and drought are persistent challenges (Araya and Stroosnijder 2011; Segele and Lamb 2005), utilizing residual soil moisture for post-rainy season cropping can maximize land use and increase crop yields. This practice can reduce the risk of food shortages and enhance the resilience of smallholder farmers to climate variability. Therefore, considering residual soil moisture for legume cultivation in Ethiopia could be a strategic approach to enhance sustainable crop productivity in the face of climatic challenges.

In this regard, a few studies (Korbu et al. 2022; Yang et al. 2021a; Chimdessa et al. 2019) have demonstrated crop water-stress response and yield improvement for selected cultivars of legume crops using post-rainy season soil moisture at specific locations and research centers. It is essential to expand these efforts to regional and countrywide scales, including a greater variety of crops, to understand the availability of residual moisture to support crop water demands. Examining the potential of residual soil moisture to meet crop water demands across Ethiopia's arable croplands could contribute to sustainable soil water utilization, enhance crop resilience, and promote adaptive management strategies.

In this dissertation, three comprehensive studies have been conducted to enhance crop productivity in Ethiopia. The three core chapters of this dissertation are summarized as follows:

Chapter 2: Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers

The second chapter explores the complex dynamics and distribution of soil moisture, investigating its local and remote driving factors across Ethiopia. We have collected soil moisture datasets from various sources, including the Ethiopian Meteorological Institute (in-situ), FEWS NET Land Data Assimilation System (FLDAS), Copernicus Climate Change Services (ERA5Land), Global Land Data Assimilation System (GLDAS), and the European Space Agency (Combined). After validating these reanalysis and satellite datasets against in-situ observation, the study aims to characterize the spatiotemporal variability of soil moisture and identify the local and remote drivers influencing soil moisture anomalies across Ethiopia. We employed advanced statistical techniques such as Empirical Orthogonal Functions (EOFs), K-means clustering, and Complex Maximum Covariance Analysis (CMCA) to investigate the spatiotemporal dynamics of soil moisture systematically. Additionally, we considered the nonlinear interactions between soil moisture and two fundamental climate variables, rainfall and evapotranspiration, using composite analysis to unravel their roles in soil moisture anomalies. The results indicated that soil moisture is highly variable and influenced by other climatic variables, such as rainfall, evapotranspiration, and sea surface temperature anomalies across Ethiopia.

The following two chapters build on the validated soil moisture dataset and the direct relationship between rainfall and soil moisture established in this chapter. Chapter 2 is the foundation for the modeling and empirical analysis conducted in the subsequent chapters.

Chapter 3: Coupled impacts of climate change and soil acidification on future crop suitability in Ethiopia

While Chapter 2 extensively addresses the spatial and temporal dynamics of soil moisture across Ethiopia, it also identifies the direct relationship between rainfall and soil moisture, highlighting their high correlations. Building on these fundamental relationships, Chapter 3 uses rainfall instead of soil moisture as a critical variable in the crop suitability modeling approach for climate change analysis.

Chapter 3 examines the combined impacts of climate change and soil acidification on future crop suitability in Ethiopia. We studied the suitability of four staple food crops in Ethiopia: teff, maize, barley, and common wheat. Data from seven Global Climate Models (GCMs)—CMCC-ESM2, GFDL-ESM4, INM-CM5-0, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL—outputs for rainfall and temperature variables were extracted for both historical (1970-2000) and future projections (2050). In addition, soil acidity (pH) data was sourced from ISRIC-World Soil Information. We have considered the decadal declining trend in soil pH and set three threshold values corresponding to changes in soil acidity by 0.5, 1.0, and 1.5 from current distributions of soil pH over Ethiopia. By integrating soil acidity assessments and climate change projections with advanced crop modeling techniques, this research seeks to elucidate the potential repercussions of climate change and soil acidification on crop suitability in Ethiopia. We showed that the combined impacts of climate change and soil acidity significantly affect the suitability of the mentioned staple food crops in Ethiopia. The central western region of Ethiopia is likely to experience a significant decline in soil pH, rendering the mentioned crops unsuitable in this area.

Chapter 4: Spatiotemporal dynamics of residual soil moisture and its role in legume-based cropping systems in Ethiopia

The forth chapter assesses the potential of residual soil moisture to support post-rainy season cropping in Ethiopia using the highly accurate GLDAS soil moisture dataset. This dataset is employed due to its higher temporal resolution than the FLDAS dataset, as identified in Chapter 2.

This chapter emphasizes the critical importance of optimizing post-rainy season cropping practices to strengthen resilience and maximize crop yields. By investigating the dynamic relationship between soil moisture and crop water demands, it aims to demonstrate the potential of residual moisture to sustain post-rainy season cropping across homogeneous climate regions in Ethiopia. The research focuses on enhancing post-rainy season cropping by analyzing residual soil moisture and crop water requirements using advanced statistical techniques and the Penman-

Monteith equation. We evaluated the potential of residual soil moisture to support the water demands of five selected legume crops: chickpeas, field peas, common beans, soybeans, and alfalfa. The findings indicated that there is significant potential for residual soil moisture to support second cropping in the western, central, and southwestern regions of Ethiopia. Conversely, it was observed that residual soil moisture in the northern and southeastern tips of the country is insufficient to meet crop water demands.

1.2 Statement of the problem

In the pursuit of agricultural sustainability, several critical challenges demand attention and resolution. One significant challenge revolves around the spatiotemporal variability of soil moisture, which is crucial for efficient water management in agriculture. However, in-situ soil moisture measurements are generally very scarce, with only a few available across Ethiopia. Consequently, researchers rely on satellite estimates or atmospheric reanalysis simulation outputs (Dorigo et al. 2017). In Ethiopia, there are few studies (Ayehu et al. 2020, 2019; Mekonnen 2009) that have attempted to monitor and estimate soil moisture amounts and variability for specific basins. Therefore, it is necessary to understand the degree of agreement among satellite estimates of soil moisture, reanalysis products, and in-situ measurements to use reanalysis or satellite datasets for impact assessment effectively. Additionally, although a few studies (Liu et al. 2022b; Zhu et al. 2020; Nicolai-Shaw et al. 2016; Feng and Liu 2015; Gaur and Mohanty 2013) have indicated the influence of rainfall, evapotranspiration, and sea surface temperature on global soil moisture persistence, similar studies for East Africa are lacking. Understanding the levels and distribution of soil moisture and its local and remote drivers, such as rainfall, evapotranspiration, and sea surface temperature, is essential for various reasons. Firstly, maintaining optimal soil moisture levels protects against drought and water stress, thereby reducing the susceptibility of agricultural systems to climate variability (Srivastav et al. 2021). Secondly, soil moisture is vital in mediating other soil properties, such as soil acidity, microbial activity, and nutrient availability (Blake 2005; Bolan et al. 2005). Therefore, carefully considering and optimizing available soil moisture for plants can boost crop productivity and help us understand its role in influencing other soil properties, like soil acidity.

A second challenge arises from changes in crop suitability due to climate change and soil degradation. Soil degradation can be exacerbated by intensive agricultural practices driven by population growth and changing consumption patterns. Agricultural practitioners often recommend intensification through the use of industrial chemical inputs, such as fertilizers, to maximize crop yields and enhance food security needs. However, it is crucial to recognize that such intensification measures can lead to undesired outcomes and potential maladaptation (Alemu et al. 2022; Abate et al. 2015; Fageria et al. 2010; Stumpe and Vlek 1991), thereby putting agricultural sustainability into question. For instance, Fageria et al. (2010) discussed the consequences of intensive soil nutrient management, which can lead to nutrient imbalances and soil degradation, ultimately affecting crop yields and sustainability. Several studies have attempted to assess crop suitability changes at the watershed (Girmay et al. 2018; Yohannes and Soromessa 2018; G.Selassie et al. 2014) and countrywide (Evangelista et al. 2013) scales, emphasizing the significance of climate factors and soil quality in determining crop yields and production potential in Ethiopia. However, there is a lack of research addressing the combined effects of climate change (e.g., changes in temperature and rainfall or soil moisture) and soil acidity on future crop suitability. Therefore, it is essential to examine the coupled impacts of climate change and soil acidification on future crop suitability in Ethiopia. This understanding is crucial for achieving a balance between meeting the increasing demand for food production and preserving the ecological resilience of agroecosystems.

The third challenge lies in enhancing the productivity of post-rainy season cropping, a period marked by significant soil moisture variability. Several studies (Gurmessa 2021; Golla 2019; Takala 2019; Abate et al. 2017) have attempted to address agricultural productivity by focusing on the amount and distribution of rainfall, temperature patterns, and soil types to gain insights into crop yields and assess agricultural production in Ethiopia. A few studies (Desta et al. 2017; Soulis et al. 2015) have addressed the efficient use of soil moisture to enhance crop productivity, but these studies are limited to specific basin scales. Moreover, some studies (Korbu et al.

2022; Yang et al. 2021a; Chimdessa et al. 2019) have evaluated soil moisture availability for post-rainy season cropping at research centers and watershed levels. However, there is a need to assess the potential of residual soil moisture for post-harvest cropping on a country-wide scale to identify potential arable lands for second cropping. Evaluating the potential of residual soil moisture for double cropping within a single calendar year is crucial for enhancing crop production, strengthening agricultural resilience, and ensuring long-term sustainability.

In light of these challenges, it is imperative to conduct a comprehensive investigation into the spatiotemporal variability of soil moisture, the impacts of climate change and soil acidification on future crop suitability, and the optimization of post-rainy season cropping practices through residual soil moisture potential analysis in Ethiopia. Addressing these challenges is essential for improving crop productivity and contributing to the broader goal of agricultural sustainability under changing climate conditions and evolving land use patterns. This effort is indispensable for meeting the nutritional needs of both the growing Ethiopian and global populations.

1.3 Research questions

This dissertation aims to address existing gaps (mentioned in Section 1.2) in understanding soil moisture characteristics, the impacts of climate change and soil acidity on crop suitability, and the relevance of residual soil moisture for post-rainy season cropping. Therefore, the research is guided by the following key questions:

i. **Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers:**

   - Which soil moisture datasets are available to effectively characterize the spatiotemporal variability of soil moisture across Ethiopia?
   - What are the key characteristics of soil moisture variability in the country?
   - What are the local and remote drivers influencing soil moisture dynamics in Ethiopia?

ii. **Coupled impacts of climate change and soil acidification on future crop suitability in Ethiopia:**

    - What is the present suitability of four key food crops—teff, maize, barley, and wheat—in Ethiopia?
    - Which regions in Ethiopia experience the highest signs of soil acidification and crop failure under the changing climate?
    - Which crops are most likely to be affected by changes in soil acidity in terms of their suitability?

iii. **Spatiotemporal dynamics of residual soil moisture and its role in legume-based cropping systems in Ethiopia:**

    - What is the extent of residual soil moisture after the main rainy season?
    - How does the level of soil moisture vary across homogeneous climate regions in time and space?
    - What is the potential of this residual soil moisture to support crop water demands?

These research questions are formulated to guide the investigation into the spatiotemporal variability of soil moisture, the effects of climate change and soil acidification on future crop suitability, and the potential of residual soil moisture to support post-rainy season cropping in Ethiopia.

1.4 Objectives

1.4.1 General objective:

The general objective of this dissertation is to investigate soil moisture dynamics, assess the impact of climate change and soil acidification on the future suitability of key food crops, and evaluate the potential of residual soil moisture for post-rainy season cropping in Ethiopia through empirical analysis and modeling.

1.4.2 Specific objectives:

i. **Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers:**
    a. Inter-compare satellite, reanalysis, and in-situ soil moisture datasets to determine the level of agreement and evaluate the spatiotemporal variability of soil moisture across Ethiopia.
    b. Assess the characteristics of spatiotemporal dynamics of soil moisture and infer its local and remote influential drivers.

ii. **Coupled impacts of climate change and soil acidification on future crop suitability in Ethiopia:**
    a. Determine the suitability extent of four key food crops—teff (*Eragrostis tef*), maize (*Zea mays*), barley (*Hordeum vulgare*), and wheat (*Triticum aestivum*)—in Ethiopia.
    b. Examine the impacts of climate change on these food crops suitability by the middle of the century (2050).
    c. Evaluate the effect of soil acidification on changes in crop suitability for each food crop under the changing climate.

iii. **Spatiotemporal dynamics of residual soil moisture and its role in legume-based cropping systems in Ethiopia:**
    a. Examine residual soil moisture levels and variability across the country following the main rainy season.
    b. Assess the feasibility of cultivating selected drought-resistant crops—chickpea (*Cicer arietinum*), field peas (*Pisum sativum*), common bean (*Phaseolus vulgaris*), soybean (*Glycine max*) and alfalfa (*Medicago sativa*)—during the post-rainy season.

1.5 Significance of the study

This dissertation holds manifold significance in contributing to agricultural sustainability, encompassing integrated policy implications and adaptive strategy management. First, investigating the spatiotemporal variability of soil moisture contributes significantly to agricultural precision water management. Understanding how soil moisture levels fluctuate over time and space enables farmers and water managers to implement targeted irrigation strategies. This precision approach optimizes water use efficiency, mitigates water stress on crops, and promotes sustainable agricultural practices.

Second, the research on the impact of climate change and soil acidification on future crop suitability is crucial for informed decision-making. Policymakers, land managers, and agricultural stakeholders can use the insights gained to anticipate shifts in crop suitability, guiding land-use planning and resource allocation. For instance, this knowledge is vital for balancing the need to intensify agriculture to meet food demands with the need to preserve the long-term health of agroecosystems.

Third, optimizing post-rainy season cropping through residual soil moisture analysis directly addresses the challenges posed by fluctuating soil moisture levels. By providing actionable insights into the potential of residual soil moisture for post-rainy cropping, this study empowers farmers to enhance resilience during a critical phase in the agricultural calendar. The significance lies in mitigating the risks associated with water scarcity and ensuring sustainable crop yields.

The collective significance of this dissertation extends to the broader domain of sustainable agriculture. These studies contribute valuable knowledge by advancing our understanding of soil moisture dynamics, predicting shifts in crop suitability, and optimizing cropping practices during the post-rainy season. These contributions support the global effort to develop resilient, eco-friendly, and socially equitable agricultural systems.

1.6 Scope of the study

The scope of this dissertation is expansive, encompassing diverse geographical regions, temporal scales, crops, and cross-disciplinary approaches. Its overarching goal is to provide valuable insights addressing the challenges of enhancing crop productivity and suitability in the ever-changing environment of Ethiopia.

i. **Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers**

The study on spatiotemporal variability of soil moisture aims to explore soil moisture dynamics across diverse topographies in Ethiopia, including highlands and lowlands. We utilized statistical methods such as Empirical Orthogonal Functions (EOF) and Complex Maximum Covariance Analysis (CMCA) to analyze soil moisture dynamics from 1982 to 2020. Our analysis includes longitudinal assessments to capture seasonal and annual variations. Additionally, we examine critical variables like rainfall, evapotranspiration, and sea surface temperature to understand local and remote drivers influencing soil moisture dynamics.

ii. **Coupled impacts of climate change and soil acidification on future crop suitability in Ethiopia**

The study examines the impact of climate change and soil acidification on the future suitability of key food crops across Ethiopia. It analyzes two crucial environmental factors, rainfall and temperature, and soil pH, spanning historical periods (1970-2000) and future projections (2050). This research evaluates crop suitability across Ethiopia for both current and future scenarios using a crop suitability EcoCrop model. Building on earlier findings outlined in Chapter 2, which highlight a direct correlation between soil moisture and rainfall, this study utilizes rainfall as a climatic factor instead of soil moisture, aligning with the requirements of the crop model. Staple food crops like teff, maize, barley, and wheat are thoroughly analyzed to understand how climate change and soil acidification impact their suitability in Ethiopia's future climate.

iii. **Spatiotemporal dynamics of residual soil moisture and its role in legume-based crop-**

ping systems in Ethiopia

The study aims to improve the use of residual soil moisture (i.e., post-rainy season soil mositure) for cropping after the main rainy season in Ethiopia. It employs empirical analysis using Kernel Density Estimation (KDE), EOF analysis, and the Penman-Monteith equation to assess the spatial and temporal dynamics of residual soil moisture and crop water demands. This analysis involves examining the levels and variability of residual soil moisture across homogeneous climate regions in Ethiopia from 1981 to 2020 and assessing its potential to support crop water demands. Specifically, the research evaluates the viability of residual soil moisture for five selected legume crops—chickpeas, field peas, common beans, soybeans, and alfalfa.

It should be noted that due to the diverse geography of Ethiopia, the main rainy season (JJAS) is not the same everywhere. Specifically, JJAS is not the main rainy season for the southern part of the country. Hence, the term ‘post-rainy season’ (OND) should be interpreted according to the climatic systems of the specific geographic regions considered.

1.7 Limitations of the study

Scientific study accuracy heavily relies on data availability and quality. In this study, in-situ observation for soil moisture data is scarce, making it difficult to validate satellite and land surface models (LSMs) output across Ethiopia. Limitations also arise since in-situ data sources are incomplete and exhibit inconsistencies, potentially affecting the robustness of satellite and LSMs datasets validation. On the other hand, the spatial and temporal resolution of available datasets for soil moisture and other climate variables are limited to the level of model output. This limitation could constrain the ability to capture fine-scale variations in soil moisture or assess short-term fluctuations with high precision that impacted the depth and granularity of the analyses.

The study on the impacts of climate change and soil acidification employed crop models and climate model simulations. Limitations could arise from inherent assumptions within these models. Predicting future crop suitability under the influence of climate change may also involve uncertainties from climate model projections. Hence, model uncertainties could influence the accuracy of predictions and require careful interpretation of results. While efforts are made to capture diverse geographical regions, the generalization of findings across all possible agroecosystems may be challenging.

1.8 Conceptual framework

This thesis was conducted following a methodological sequence, starting with the validation of soil moisture datasets from reanalysis and satellite sources against in-situ observations. Using the validated soil moisture dataset, the spatiotemporal variability of soil moisture was characterized across Ethiopia (Chapter 2). Second, based on the direct relationship between soil moisture and rainfall inferred from the spatiotemporal variability assessment, rainfall was employed in the crop modeling. Global Climate Models (GCMs) projection from the Shared Socioeconomic Pathway (SSP3) and soil pH data were utilized to conduct crop suitability assessments (Chapter 3). The highly accurate soil moisture dataset from Chapter 2 was also used for residual soil moisture analysis and crop water demand assessment (Chapter 4). The general framework of this dissertation is summarized as follows:

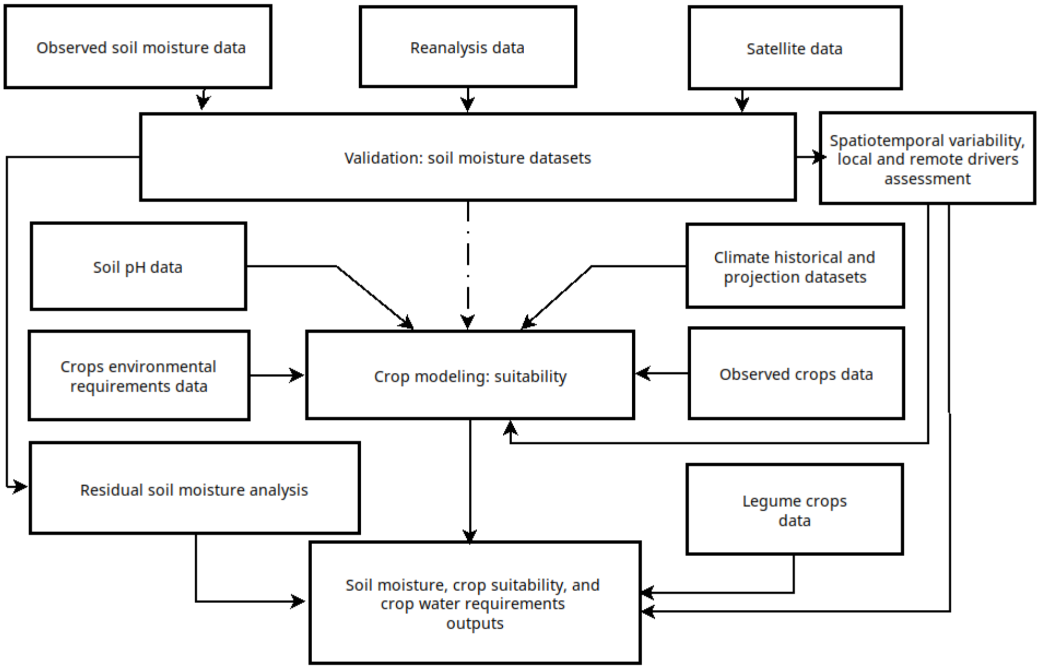

Figure 1.1.: Graphical representation of the workflow for the studies conducted in this dissertation.

1.9 Outline of the thesis

This dissertation comprises four chapters:

- **Chapter One** introduces the overarching objectives of this study, providing a statement of the problem, guiding research questions, scope, limitations, and the significance of the study.

- **Chapter Two** presents the work titled "*Spatiotemporal Variability of Soil Moisture over Ethiopia and its Teleconnections with Remote and Local Drivers*," which examines the spatiotemporal dynamics of soil moisture and its local and remote driving factors over Ethiopia. This work has been published in the Theoretical and Applied Climatology, Springer Nature journal.

- **Chapter Three** delineates the research titled "*Coupled Impact of Climate Change and*

Soil Acidification on Future Crop Suitability in Ethiopia," which explores the intersection between climate change and soil acidification's influence on the future suitability of four key food crops. This work is also published in the MDPI, Sustainability journal.

- **Chapter Four** discusses a detailed exploration of "*Spatiotemporal Dynamics of Residual Soil Moisture and its Role in Legume-based Cropping Systems in Ethiopia*," addressing the availability and potential of residual soil moisture for cropping after the main rainy season. This work is currently under review for publication.
- **Chapter Five** presents summary of findings, conclusions, and recommendations for the entire dissertation.

Chapter 2

Spatiotemporal Variability of Soil Moisture over Ethiopia and its Teleconnections with Remote and Local Drivers

Abstract

Soil moisture is one of the essential climate variables with a significant impact on local climate variability. Despite its importance, studies on soil moisture characteristics in Ethiopia are sparse. This study characterizes the spatiotemporal variability of soil moisture (SM) in Ethiopia and investigates its local and remote influential driving factors. Empirical orthogonal function (EOF) analysis and the KMeans clustering algorithm have been employed to classify the large domain into homogeneous zones. Complex maximum covariance analysis (CMCA) is applied to evaluate the covariability between SM and selected local and remote variables, including rainfall (RF), evapotranspiration (ET), and sea surface temperature (SST). Inter-comparison among SM datasets highlights that the FLDAS dataset better depicts the country's SM spatial and temporal distribution, with a correlation coefficient of r = 0.95 and an RMSD of 0.04 m^3 m^{-3} *compared to observations. Results indicate that regions in northeastern Ethiopia are consistently drier, regardless of the season (JJAS, MAM, and OND) considered. In contrast, the western part of the country consistently shows wetter conditions across all seasons. During summer (JJAS), soil moisture variability is characterized by a strong east-west spatial contrast, with the highest and lowest soil moisture values observed in the central western and eastern parts of the country, respectively. Further analysis indicates that the interannual variability of SM is substantially influenced by RF, although the impact is weaker in some regions. ET likely drives SM in the* *eastern part of Ethiopia due to higher atmospheric moisture demand, which ultimately affects surface humidity and rainfall. Composite analysis based on the five wettest and driest SM years reveals a similar spatial distribution of wet SM with positive RF anomalies across the country and ET anomalies over the southern regions. Remote SSTs also significantly influence SM distribution. Specifically, anomalies in the equatorial central Pacific and western Indian oceans are predominant factors for spatiotemporal SM variations across Ethiopia. Major global oceanic indices such as the Oceanic Nino Index (ONI, r = 0.72), Indian Ocean Dipole (IOD, r = 0.43), Pacific warm pool (PACWARMPOOL, r = 0.48), and Pacific Decadal Oscillations (PDO, r = -0.52) are closely associated with SM anomalies in various parts of the country. The relationship between these remote SST anomalies and local soil moisture operates through large-scale atmospheric circulations linked to regional factors such as precipitation and temperature anomalies. Findings from this study provide a foundation for agricultural water management, enabling farmers and agricultural practitioners to adjust their practices in response to challenges such as moisture scarcity and climate variability.*

Keywords: soil moisture, teleconnections, oceanic indices, EOF, CMCA

2.1 Introduction

Soil moisture, classified as an Essential Climate Variable (ECV) (Dorigo et al. 2017; Wang et al. 2016; Wagner et al. 2012; Seneviratne et al. 2010), plays a crucial role in regulating water and energy exchanges between the land surface and the atmosphere (An et al. 2016; Qiu et al. 2016; Li et al. 2011; Liu et al. 2011) through partitioning the incoming solar radiation into sensible and latent heat fluxes. Its impact extends to influencing the variability of evapotranspiration, runoff, latent and sensible heat fluxes (Dorigo et al. 2017; Seneviratne et al. 2010). Basically, soil moisture is a key factor in modulating spatiotemporal weather variations and precipitation patterns, as it can trigger significant mesoscale atmospheric circulation patterns through anomalous regional soil moisture conditions (Dorigo et al. 2017; Taylor et al. 2012). The slow-varying memory of soil moisture, akin to the ocean, allows it to persist for weeks to months, exerting influence on weather systems through surface energy fluxes and evaporation (Seneviratne et al. 2006; Koster et al. 2004). With its prolonged memory and substantial impact on surface climate variables, soil moisture becomes an attractive source for subseasonal to seasonal predictability. Numerous studies (Thomas et al. 2016; Hirsch et al. 2014; Drewitt et al. 2012; Koster et al. 2011; Koster et al. 2010) have underscored the significance of accurate soil moisture initialization in significantly improving forecast skills, particularly for precipitation and temperature, in specific regions across the globe.

Several studies (Koster et al. 2004; Schär et al. 1999; Zheng and Eltahir 1998) have highlighted the complex relationship between soil moisture and precipitation. Specifically, in mid-latitude regions during the summer season, studies such as Koster et al. (2004) emphasize that the influence of soil moisture on climate surpasses that of the ocean. Additionally, Schär et al. (1999) research underscores the significance of soil moisture states in shaping European summertime precipitation. The impact of soil moisture on precipitation operates through a two-stage process, involving its influence on evapotranspiration (ET) and subsequently, ET's influence on rainfall (RF) (Wei and Dirmeyer 2012; Seneviratne et al. 2010; Guo et al. 2006). While the effects of RF on soil moisture and the reciprocal relationship with ET are comprehensible, understanding how soil moisture directly influences RF remains a complex aspect. Therefore, unraveling the temporal trends, variability, and spatial distributions of soil moisture emerges as a critical prerequisite for elucidating the land's role in shaping the overlying atmosphere (An et al. 2016). Expanding our knowledge in this regard holds significance for advancing our understanding of the complex reciprocity between soil moisture and precipitation dynamics across various scales.

Regardless of the acknowledged significance of soil moisture, the availability of in-situ measurements for soil moisture is generally limited, a challenge particularly pronounced across much of Africa. Consequently, researchers and practitioners resort to indirect methods to estimate soil moisture, relying on sources such as satellite data or outputs from offline Land Surface Models (LSM) driven by atmospheric reanalysis (Dorigo et al. 2017). Recognizing that these indirect estimates have their respective strengths and limitations is essential. For instance, the accuracy of soil moisture estimates derived from land surface models is contingent on the quality of meteorological forcing fields and the model itself (Dorigo et al. 2017; An et al. 2016; Koster et al. 2009). Conversely, satellite estimates encounter challenges in accuracy over vegetated regions and are limited to the top few centimeters of soil (Peng et al. 2017; Feng and Liu 2015; Srivastava et al. 2015). Both reanalysis and satellite methods offer broader spatial coverage and continuous temporal spans with minimal data gaps. However, the extent of agreement or discrepancies among station, reanalysis, and satellite estimates in capturing diverse aspects of soil moisture characteristics in East Africa still needs to be addressed. Despite this, existing literature focuses on soil moisture estimation and validation at the catchment level (Mekonnen 2009). A comprehensive study validating soil moisture across Ethiopia over wider spatial extents and longer time frames still needs to be addressed. Thus, the primary objective of this study is to conduct an inter-comparison of satellite, reanalysis, and in-situ soil moisture datasets to assess the degree of agreement among them and characterize the spatiotemporal variability of soil moisture across Ethiopia.

Studies (Liu et al. 2022b; Feng and Liu 2015; Gaur and Mohanty 2013) contend that precipitation and evapotranspiration, along with factors such as wind, temperature, solar radiation, soil physical properties, topography, and vegetation, play pivotal roles in shaping soil moisture (SM) dynamics. Additionally, findings from (Zhu et al. 2020; Nicolai-Shaw et al. 2016) underscore the significance of oceanic surface temperature in contributing to the persistence and predictability of global soil moisture. However, these investigations exhibit a predominantly global focus, with limited attention given to the specific dynamics within the East Africa region. While there have been some efforts to explore residual soil moisture monitoring (Ayehu et al. 2019) and soil moisture-rainfall (SM-RF) variability (Ayehu et al. 2020) across river basins in Ethiopia, comprehensive studies detailing the spatiotemporal characteristics of soil moisture and its driving factors on a national scale remain scarce. Consequently, there is a need to evaluate both local and remote factors influencing the spatiotemporal variability of soil moisture in Ethiopia. Hence, the second objective of this study is to scrutinize the characteristics of spatiotemporal soil moisture variability and deduce insights into its local and remote drivers.

Generally, this chapter provides a validated dataset on soil moisture, delineates homogeneous climate zones based on soil moisture variability in Ethiopia, and advances our comprehension of the local and remote factors influencing soil moisture dynamics. The findings of this investigation carry implications for weather forecasting, agricultural planning, and hydro-climatological modeling in the country.

2.2 Data sources and location of the study

2.2.1 Location and description of study area

Ethiopia, situated in East Africa between $33^{\circ}E - 48^{\circ}E$ and $3^{\circ}N - 15^{\circ}N$, exhibits a diverse topography, as illustrated in Figure 2.1. The country features a complex terrain, ranging from lowland areas 116 meters below sea level to towering mountains reaching heights of 4600 meters (Fekadu 2015; Zeleke et al. 2013a; Diro et al. 2009a; Diro et al. 2008b). The topography is characterized by a highland plateau in the north, central, partial eastern, and western regions, while the eastern: northeastern and southeastern, and western tips of the country are predominantly lowland areas. Climatically, Ethiopia experiences three main seasons: February to May (Belg), June to September (Kiremt), and October to January (Bega) (Fekadu 2015; Diro et al. 2008b; Gissila et al. 2004; Degefu 1987). Kiremt serves as the main rainy season for the northern and western regions, while Belg is the predominant rainy season for the southern and southeast regions. The Kiremt and Belg seasons play a pivotal role in driving agricultural activities and determining crop growth and productivity across the country. However, the importance of agricultural productivity during the OND season should not be underestimated either.

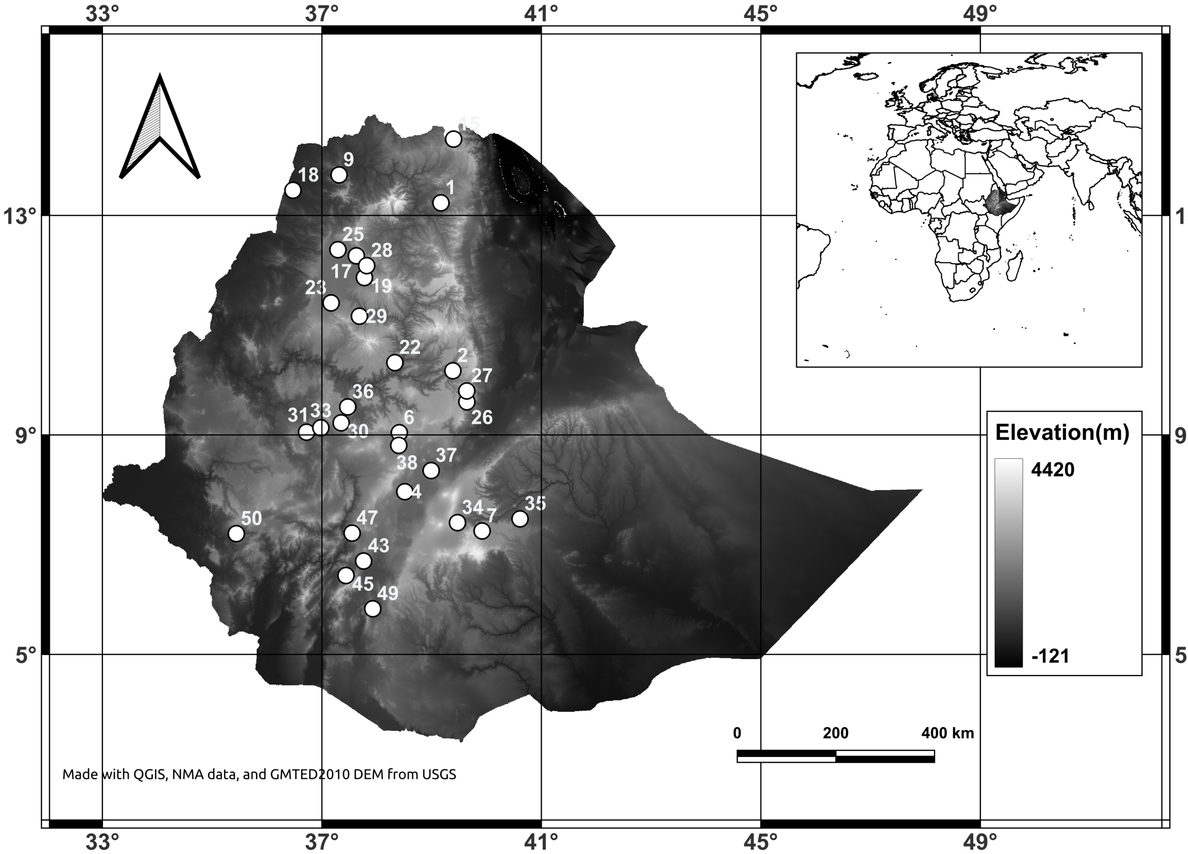

Figure 2.1.: Geographic location, topography (in meters), and distribution of soil moisture stations in Ethiopia. White dots represent in-situ observation stations, with their IDs labeled.

2.2.2 Climate data and oceanic indices

This research incorporates climate data from ground observatory stations, satellite observations, and reanalysis datasets to comprehensively analyze the spatiotemporal variability of soil moisture in Ethiopia. The utilization of these diverse datasets allows for a more thorough investigation into the dynamics and influencing factors of soil moisture across the region. The following section provides a detailed description of each dataset employed in this study.

i. **In-situ dataset**

The observational meteorological station data spanning the period 2018 to 2021, acquired from the Ethiopian Meteorological Institute (EMI) , has been utilized to validate the offline land surface model data and satellite products discussed in the following subsections. For the sake of this validation, only the data for the year 2019 has been employed, given its comprehensive temporal coverage. The geographical distribution of soil moisture recording stations across the country is illustrated in Figure 2.1. These stations record soil moisture in terms of degrees of saturation (%) at 20cm depth from the surface in 15-minute intervals. However, the satellite and reanalysis soil moisture products use volumetric units; therefore, they must be converted to a similar volumetric unit (m^3 m^{-3}). Thus, a conversion from degrees of saturation to volumetric soil moisture has been executed, employing methodologies derived from (An et al. 2016; Dorigo et al. 2011). The conversion process is done as follows:

$$SM_{vol}(m^3 m^{-3}) = \frac{SM(\%)}{100} \times Porosity_{vol}(m^3 m^{-3})$$

Where SM_{vol} is soil moisture in volumetric, $SM(\%)$ is soil moisture degree of saturation, and $Porosity_{vol}$ is soil porosity. The soil porosity data from the ESA CCI version v04.7 applied for soil moisture unit conversions. A thorough quality control has been performed on the station dataset using methods including graphical analysis, Z-score analysis, and autocorrelation. This process was necessary due to the raw data containing a significant number of missing values and unrealistic soil moisture (SM) measurements. As a result, out of 50 stations, only 30 stations were selected for further analysis for the year 2019 (as shown in Figure 2.1).

ii. FEWS NET Land Data Assimilation System (FLDAS)

We utilize a monthly soil moisture dataset derived from the Land Data Assimilation System (FLDAS) developed by the Famine Early Warning Systems Network (FEWS NET) for our analysis. FLDAS incorporates a land surface model simulation, driven by a combination of the Modern-Era Retrospective analysis for Research and Application v2 (MERRA2) reanalysis and precipitation data from the Climate Hazard Group InfraRed Precipitation with Station (CHIRPS). Particularly, FLDAS distinguishes itself by utilizing observation-based precipitation data as a forcing factor for the land surface model. The model provides soil water content at four different layers (10cm, 40cm, 100cm, and 200cm depths) with a spatial resolution of $0.1^\circ \times 0.1^\circ$. For this study, we focus on the soil water content at the 10cm depth. The dataset spans from 1982 to the present, offering an extensive temporal coverage for our analysis (FEWS NET FLDAS, (McNally 2018; McNally et al. 2017)).

iii. Fifth generation ECMWF Atmospheric Reanalysis (ERA5Land)

The ERA5Land soil moisture data (Muñoz Sabater 2019), accessed from the Climate Data Store (CDS) provided by Copernicus Climate Change Services (C3S), is utilized in this study. The dataset exhibits a spatial resolution of $0.1^\circ \times 0.1^\circ$ and a temporal resolution of one hour, spanning from 1981 to the present. The ERA5Land model is derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 climate reanalysis (Hersbach et al. 2019), with an enhanced land surface model resolution compared to ERA5. Regardless of ERA5Land offering information on four soil levels (Layer 1: 0-7cm, Layer 2: 7-28cm, Layer 3: 28-100cm, Layer 4: 100-289cm), our study employed Layer 1 of the model.

iv. Global Land Data Assimilation System (GLDAS2)

Two iterations of the Global Land Data Assimilation System (GLDAS v2.0 and GLDAS v2.1, (Beaudoing and Rodell 2019)) have been utilized in this study. Similar to FLDAS and ERA5, GLDAS is a global offline land surface modeling system, employing the Noah model, which is driven by observed and reanalysis meteorological fields to generate a range of surface and subsurface variables. GLDAS v2.0 employs the Noah land surface model, forced by Princeton meteorological input data, and covers the period from 1948 to 2014. In contrast, GLDAS v2.1 integrates both model and observation data and spans from 2000 to the present. Both GLDAS v2.0 and GLDAS v2.1 datasets offer a soil moisture data at spatial resolution of $0.25^\circ \times 0.25^\circ$ and a monthly temporal resolution (Beaudoing and Rodell 2019). We also employed near-surface air temperature at two meters from this dataset.

v. Satellite dataset

A multi-satellite soil moisture product based on the European Space Agency (ESA) Climate Change Initiative (CCI) satellite observations for soil moisture data (Dorigo et al. 2017) is downloaded from CDS of C3S. It is version 03.3 gridded and combined (i.e., active and passive sensors) multi-satellite observation product (Gruber et al. 2017; Wagner et al. 2012). The merged active and passive products are produced by mixing scatterometer and radiometer soil moisture data, respectively.

The scatterometer is derived from Active Microwave Instrument-Windscat (AMI-WS) and Advanced Scatterometer (ASCAT) (Wagner et al. 2013) sensors while radiometer is derived from Scanning Multichannel Microwave Radiometer (SMMR) (Njoku et al. 1980), Special Sensor Microwave Imager (SSM/I) (Basist et al. 1998), (the Tropical Rainfall Measuring Mission, TRMM) Microwave Imager (TMI)(Cashion et al. 2003), Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E)(Njoku et al. 2003), WindSat Spaceborne Polarimetric Microwave Radiometer (WindSat)(Li et al. 2010), Advanced Microwave Scanning Radiometer 2 (AMSR2)(Imaoka et al. 2012), and Soil Moisture and Ocean Salinity (SMOS)(Kerr et al. 2010) sensors. Moreover, the combined soil moisture data is produced by blending these two merged products. These data are available in daily, dekadal, and monthly temporal resolutions and at $0.25^{\circ} \times 0.25^{\circ}$ spatial resolution with soil water content measurement accuracy of 0.04 $m^3 m^{-3}$ unbiased root-mean-square-error (Dorigo et al. 2017). Thus, a daily soil moisture product is produced from multiple satellite instruments and microwave sensors. Dekadal and monthly means are calculated from these daily data. These products span from 1978 on-wards with global coverage (Wagner et al. 2012).

It must be noted that satellite products have limitations over regions with high vegetation cover, rainfall, water bodies, and organic soils as these surfaces affect the microwave emission (Dorigo et al. 2017; Wang et al. 2016) and result in large uncertainties. Hence, for regions under a dense vegetation canopy, the soil moisture dataset has been masked (C3S SM Product User Guide, 2018). This is more apparent over central-western part of the Ethiopian rain-forest.

vi. **Auxiliary datasets**

To assess the local and remote factors that affect soil moisture variability, blended satellite and station precipitation dataset from CHIRPS (Funk et al. 2015), surface latent heat flux from ERA5Land (Hersbach et al. 2019; Muñoz Sabater 2019), and ERA5 Sea-Surface Temperature (SST) from Copernicus climate data center were employed (Merchant et al. 2019). A global sea surface temperature indices: Oceaic Nino Index (ONI) ($5^{\circ}N - 5^{\circ}S$, $120^{\circ}W - 170^{\circ}W$), Dipole Mode Index (DMI) i.e., an area average of ($10^{\circ}S - 10^{\circ}N$, $50^{\circ}E - 70^{\circ}E$ minus $10^{\circ}S - 0^{\circ}N$, $90^{\circ}E - 110^{\circ}E$), Pacific Warmpool ($60^{\circ}E - 170^{\circ}E$, $15^{\circ}S - 15^{\circ}N$) area averaged, and Pacific Decadal Oscillation (PDO) are downloaded from NOAA Physical Sciences (PSL) Laboratory https://psl.noaa.gov/data/climateindices/list/.

2.3 Methods

2.3.1 Data preprocessessing

For consistent comparisons, all datasets were subjected to a mapping process to the lowest spatial resolution using a first-order conservative remapping method (Hanke et al. 2016; Jones 1999), and were subsequently aggregated to a monthly temporal scale.

2.3.2 Validation procedures

Following the implementation of rigorous data quality control procedures on the soil moisture datasets obtained from stations, the 15-minute observations were transformed through resampling into a monthly temporal scale. Subsequently, monthly data from each Land Surface Model (LSM) and satellite gridded dataset were extracted, involving the calculation of averages from the corresponding grid box located in close proximity to the station's geographical coordinates. This point data extraction from reanalysis and satellite datasets allows us to compare and perform time series analysis with in-situ observations. Assessment of model and satellite dataset performance against the observational data encompassed the evaluation of key metrics, including Spearman correlation skill, Root-Mean-Square-Difference (RMSD), and standard deviation

(Taylor 2001). This multifaceted evaluation aimed to provide a robust analysis of the models and satellite datasets in capturing the essential features of soil moisture dynamics.

2.3.3 EOF and CMCA analysis

The study utilizes EOF analysis to delineate homogeneous zones of soil moisture (SM) in the study area, simplifying the subsequent analysis of other meteorological variables within these zones. This approach helps in the analysis of various meteorological variables within each zone, contributing to a comprehensive understanding of SM characteristics. In addition, to gain a detailed understanding of both local (e.g., rainfall (RF) and evapotranspiration (ET)) and remote factors (e.g., global sea surface temperature (SST)) influencing SM variability, a Complex Rotated Maximum Covariance Analysis (CMCA) has been implemented. Following the methodologies outlined by (Rieger et al. 2021; Dawson 2016; Baldwin et al. 2009; Hannachi et al. 2009), the original input data underwent preparation steps, including the application of the square root of the cosine of latitude area weight. This weight was employed to mitigate the impact of meridian convergence at higher latitudes, which can influence grid size and introduce high sampling variation (North et al. 1982).

$$w_i = \sqrt{\cos(\theta)}$$

Where w_i is weights of data at each grid point, and θ is the latitude of a grid point in radian. To remove seasonal trends and minimize the effect of extreme values, a time-mean of every grid point, x_j, is calculated, and its anomaly is computed.

$$x_j = x_j - \bar{x}$$

$$z_j = \frac{x_j - \bar{x}}{\sigma}$$

Where x_j is the j^{th} observation point, and $\bar{x}$ is the time-mean for that observation. z_j is the standardized anomaly of observation x_j and σ is its standard deviation.

The EOF and CMCA methodologies are implemented on the spatial data represented by anomalies (x_j) and standardized anomalies (z_j), respectively, across a temporal sampling period (t_i), where ($j = 1, ..., r$ and $i = 1, ..., s$). Here, **r** and **s** denote the spatial and temporal dimensions, respectively. The arrangement of this spatiotemporal data in matrix form as **s**×**r** is referred to as S-mode. The S-mode organizes the grouping of time-series patterns in space based on their temporal variability, enabling the identification of teleconnections between these patterns (Jollife and Cadima 2016; Hannachi et al. 2007; Hannachi et al. 2009; Dommenget and Latif 2002). Consequently, employing principal component analysis on the S-mode matrix helps in identifying statistically significant temporal soil moisture variability (Jollife and Cadima 2016; Hannachi et al. 2007; Hannachi et al. 2009).

Consider a *real signal* $X = x(t)$, and its Hilbert transform $H = H[x(t)]$ is obtained through the convolution of X with the function $\frac{1}{\pi t}$:

$$H[x(t)] = H[X] = x(t) * \frac{1}{\pi t}$$

This operation introduces a 90° phase shift to the real signal, and effectively generating a complex-valued signal (i.e., analytical signal) denoted as $\hat{X}$. The inclusion of phase information is crucial for understanding lead-lag relationships among different climate variables. Consequently, the 90° phase shift enables the separation of amplitude and phase, simplifying the evaluation and interpretation of cyclic patterns in the data and the identification of temporal relationships within various components of the climate system (Blaker 2006). This becomes particularly relevant for climate indices associated with modes of variability (e.g., El Niño-Southern Oscillation), which often exhibit entangled relationships involving both amplitude and phase variations (Lanzante 1996; Trenberth 1976). Therefore, the Complex Maximum Covariance Analysis (CMCA) method, which is based on the Hilbert transformation of the input dataset into its real and imaginary components, and the subsequent decomposition of the resulting covariance matrix in complex space, has been employed to discern the co-variability between soil moisture (SM) and other meteorological variables. Mathematically, the Hilbert transformation applied to a real signal to produce the analytical signal can be expressed as follows:

$$\hat{X} = X + iH(X)$$

Where H is the Hilbert transform applied on the *real signal* X and $\hat{X}$ is the resulting *analytical signal*. Where i is the imaginary unit ($i^2 = -1$).

After CMCA analysis, the Promax oblique rotation method ($p = 2$) is applied on the first 100 modes to alleviate the orthogonality constraint imposed by MCA as mentioned in previous studies (Rieger et al. 2021; Richman 1986). Besides, a theta extended model (Fiorucci et al. 2016) with the dominant period of signal 12 (representing the seasonal cycle) has been applied to minimize spectral leakage at the boundary. In accordance with Rieger et al. (2021), a 6-month moving average smoothing technique is applied to all monthly datasets (i.e., soil moisture and sea surface temperature) for the analysis of remote variables teleconnections. Conversely, local variables analysis (i.e., rainfall, evapotranspiration, and soil moisture) undergoes a 12-month smoothing process to align their temporal variability and minimize high-frequency noise.

2.3.4 Data clustering

The process of clustering data into homogeneous, non-overlapping subgroups of similar data points within clusters is accomplished using the KMeans iterative clustering algorithm. KMeans is employed due to its computational efficiency and its ability to scale well with large datasets and numerous features such as its simple iterative approach, enabling it to quickly converge to a solution with fewer iterations than more complex clustering methods. KMeans clustering aims to group data points with smaller variances within clusters, thereby minimizing the sum of squares within the group (Fränti and Sieranoja 2019). Mathematically, this can be expressed as follows:

$$min\left(\sum_{i=1}^{n}\sum_{x_j g_i}(x_j-\bar{x})^2\right)$$

Where $\bar{x}$ and x_j's are the mean and data points within the group g_i. The KMeans algorithm is utilized in conjunction with nondegenerate leading EOFs, incorporating the Elbow method, Silhouette criterion, and expert opinion, to conduct regionalization analysis and partition Ethiopia into five homogeneous soil moisture zones using annual soil moisture data. The initial centroids for KMeans are seeded by the robust, fast, and straightforward kmeans++ algorithm, which has been shown to outperform traditional KMeans in terms of achieving accurate and optimal solutions (Bahmani et al. 2012; Arthur and Vassilvitskii 2006). Studies by Arthur and Vassilvitskii (2006) have demonstrated that kmeans++ achieves superior results on synthetic data compared to KMeans by avoiding random seeding and effectively merging clusters, which are significant drawbacks of the traditional KMeans algorithm. Moreover, the performance of kmeans++ on real-world datasets has also been found to be substantial (Arthur and Vassilvitskii 2006).

2.3.5 Composite analysis

In addition to the methodologies mentioned previously, we have further conducted a wet minus dry composite analysis on soil moisture (SM), rainfall (RF), and evapotranspiration (ET). This analysis involved selecting the extreme five wettest and driest soil moisture years to comprehensively assess the nonlinear relationship among these variables. By examining the contrasting conditions represented by the wettest and driest years, we aimed to gain deeper insights into the complex interactions and dependencies among soil moisture dynamics, precipitation patterns, and evapotranspiration processes. This approach gives more detailed insights of how changes in soil moisture levels influence the interplay between rainfall distribution and evapotranspiration rates, and vice versa. By analyzing extreme conditions, we can uncover potential feedback mechanisms and nonlinear responses that may not be apparent under average or moderate conditions.

2.4 Results and discussion

2.4.1 Spatiotemporal variability of soil moisture datasets

In this subsection, we validate satellite and reanalysis estimates for the year 2019, utilizing available station data over Ethiopia. Figure 2.2 illustrates the annual cycles of soil moisture derived from reanalysis, satellite, and station data for the specified year. Observational data indicates a seasonal trend, with soil moisture levels typically drier (less than $0.3\mathrm{m}^3\mathrm{m}^3$) during the winter period, gradually increasing (above $0.3\mathrm{m}^3\mathrm{m}^3$) until the end of summer, and then declining during autumn months (SON). This observed pattern is in-phase (i.e., all datasets goes in the same direction) and consistently replicated by both reanalysis and satellite estimates.

While acknowledging that soil moisture distribution across Ethiopia may exhibit either a single- or double-peak values, based on the specific region under consideration (as elaborated upon later in this discussion), the single-peak representation of soil moisture presented herein primarily stems from the predominant inclusion of in-situ SM recording stations situated in regions receiving summer rainfall. Notably, all datasets, with the exception of the Combined ESA CCI dataset (hereafter referred to as “Combined”), depict peak soil moisture content in August. Conversely, the Combined satellite data suggests July as the peak month.

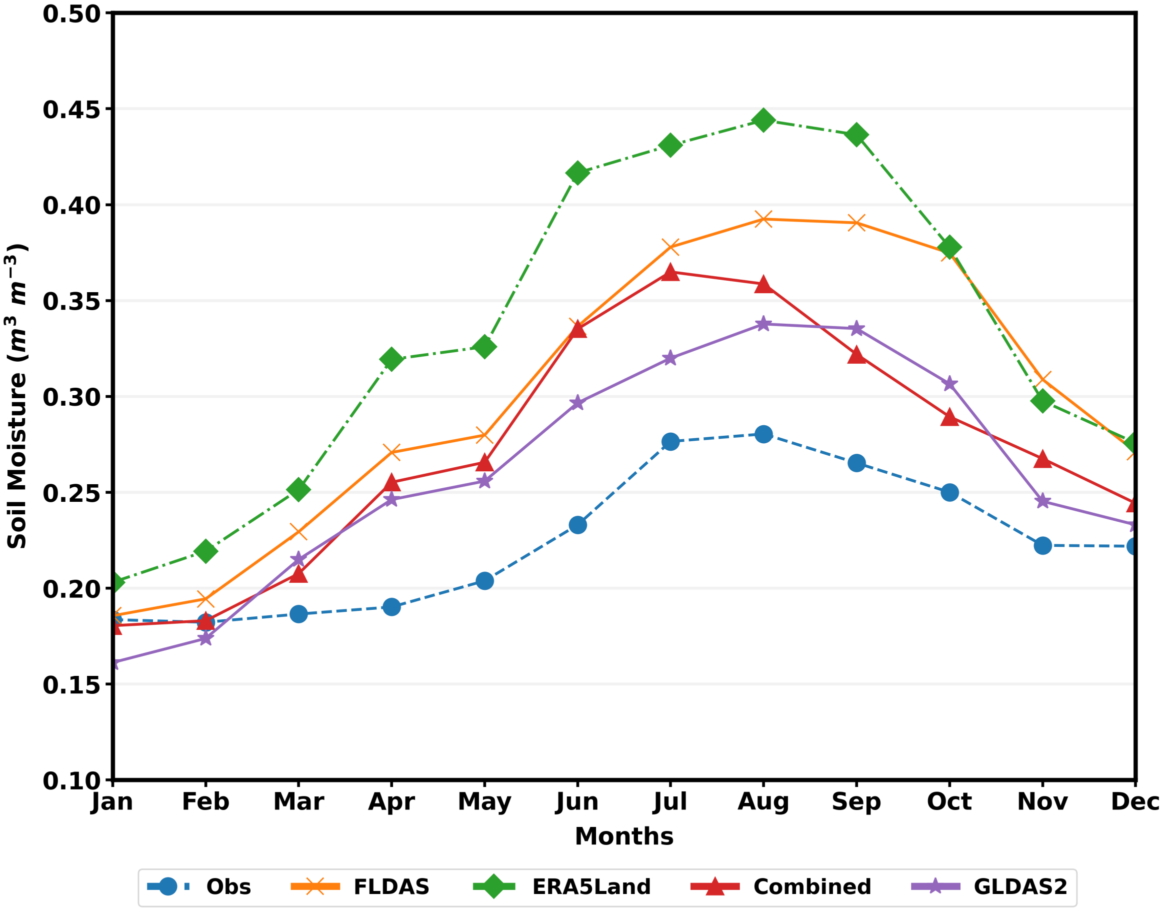

Figure 2.2.: Annual cycle of soil moisture from Observations, and area-averaged FLDAS, ERA5Land, Combined and GLDAS2 for 2019.

Comparative analysis against in-situ station data reveals a tendency for both reanalysis and Combined satellite datasets to generally characterize the annual cycle by high amplitude, with ERA5Land revealing the highest values for most months. Discrepancies between station datasets and indirect satellite/reanalysis estimates may be attributed, in part, to differences in the depth of the top soil layer and consequent variations in porosity at different depths, despite soil moisture values being normalized (Yang et al. 2021b; Gu et al. 2019) . Particularly, station data typically reflect a deeper top soil layer (20cm) compared to the shallower depths represented in reanalysis (7-10cm) and satellite data (5cm).

Figure 2.3 illustrates the spatial distribution of the 2019 annual mean soil moisture, with stations values overlaid, simplifying a comparative analysis of observational, reanalysis, and satellite estimates regarding spatial consistency. Both reanalysis (i.e., Figure 2.3 (a,b,d)) and satellite estimates (i.e., Figure 2.3 (c)) effectively delineate the drier lowlands in the eastern part of the country from the wetter western region. Remarkably, the reanalysis datasets (i.e., Figure 2.3 (a,b,d)), in particular, identifies the southwest as the wettest region. It is apparent that the grid box average of satellite and reanalysis datasets differ proportionately from the corresponding observations by values from 0.05 to 0.1 m^3m^3. This discrepancy likely arises from differences in the representation of top soil layer depth across datasets, impacting absolute soil moisture measurements (Yang et al. 2021b; Gu et al. 2019). It is also likely that variations in soil parameters representations within reanalysis models and the algorithms employed for satellite data analysis contribute to this observed difference (Beck et al. 2021).

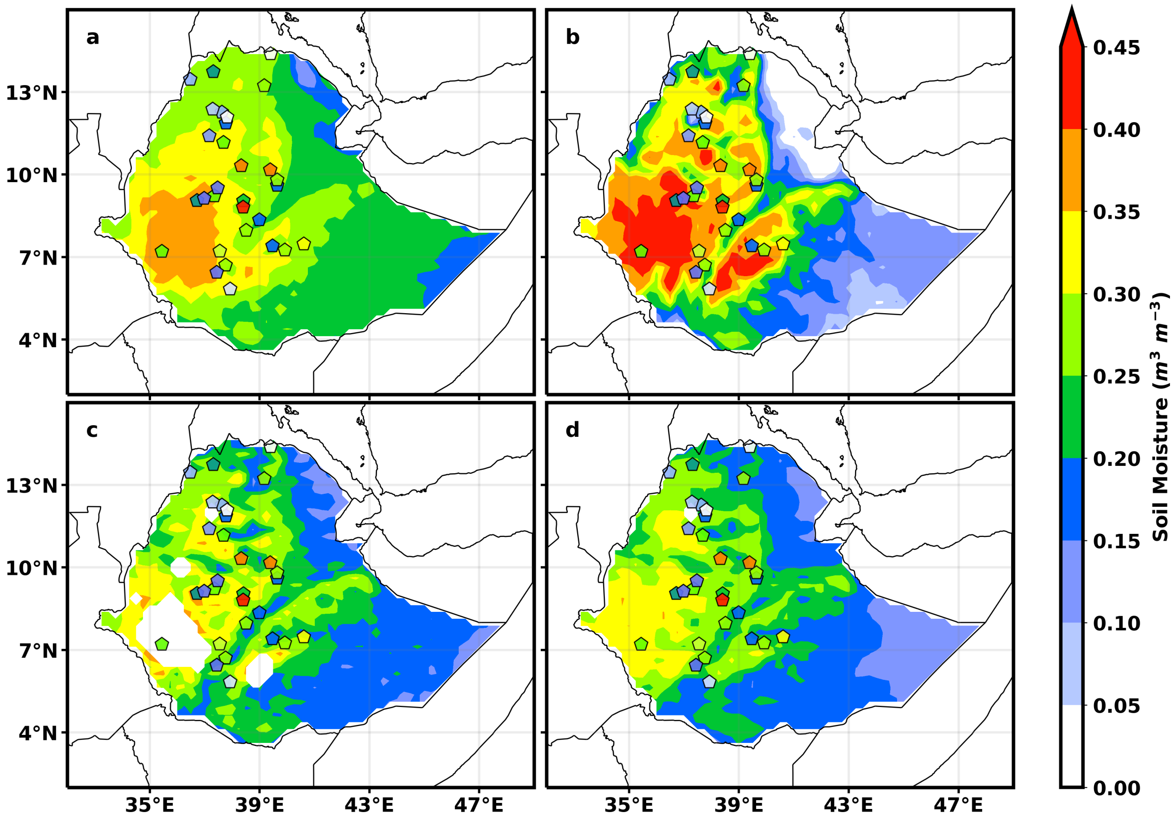

Figure 2.3.: Stations annually averaged grid box data overlayed on each soil moisture dataset climatologies over Ethiopia. (a) FLDAS, (b) ERA5Land, (c) Combined, and (d) GLDAS2 for 2019.

Although ERA5Land values demonstrate comparability with station measurements for the mid-central highlands, the FLDAS dataset consistently captures soil moisture spatial distributions across the country. This assertion is further supported by Taylor diagram analysis (Taylor 2001), which indicates a higher correlation ($r = 0.95$, Table 2.1) and lower root-mean-square difference (0.04 m^3 m^{-3}) for FLDAS against observation. Furthermore, both FLDAS and GLDAS2 soil moisture datasets exhibit significant spatial resemblance and a high correlation ($r = 0.99$). However, GLDAS2 shows slightly lower soil wetness distributions across the country. Consequently, FLDAS has been selected for further analysis, including the identification of homogeneous zones.

Table 2.1.: Correlation coefficients among the soil moisture datasets and their RMSD from observation.

	Obs	**FLDAS**	**ERA5Land**	**Combined**	**GLDAS2**	**RMSD**
Obs	1.00					0.00
FLDAS	0.95	1.00				0.04
ERA5Land	0.90	0.96	1.00			0.05
Combined	0.91	0.93	0.97	1.00		0.03
GLDAS2	0.93	0.99	0.98	0.94	1.00	0.03

2.4.2 Identification of homogeneous soil moisture zones

To delineate regions with similar soil moisture characteristics, we applied both EOF analysis and the KMeans clustering techniques on a regional scale. The EOF analysis conducted on the FLDAS soil moisture dataset provided an eigenvalue spectrum, as shown in Appendix A Figure A.1. This spectrum indicates that the first three EOFs are non-degenerate, meeting the significance criterion outlined by North's rule of thumb (North et al. 1982), and they do not overlap within a 95% confidence interval (Korres et al. 2010). Consequently, we focused on these initial three EOFs to comprehend the total variances in spatial patterns. EOF-1 exhibits a significant spatial pattern, explaining 62.7% of the total variance, while EOF-2 and EOF-3 account for 22% and 6.9% of the total variance, respectively. Collectively, these three EOFs explain 91.6% of the total variance in the data; therefore, the remaining EOFs' explained variances could be negligible and thus discarded as noise.

Given that EOF-1 alone captures more than 50% of the total variance, we primarily relied on the explained variances of the first rank for the classification of homogeneous zones. Based on these EOF results and the application of the KMeans clustering algorithm, we categorized the country into five distinct homogeneous zones. Appendix A Figure A.2 (or the middle panel of Figure 2.4) displays these five non-overlapping homogeneous soil moisture zones in Ethiopia.

Homogeneity within the regions and dissimilarity among the classified regions were assessed using Pearson's product-moment correlation. Table 2.2 presents both the inter- and intra-correlations among the five homogeneous climate regions. Specifically, Reg-I exhibits the highest correlation value within the region ($r = 0.80$), while Reg-III demonstrates the lowest intra-correlation ($r = 0.58$). Moreover, the analysis reveals very low correlations among homogeneous zones, indicating a high degree of classification accuracy.

Table 2.2.: Correlation coefficients among homogeneous zones.

	Reg-I	**Reg-II**	**Reg-III**	**Reg-IV**	**Reg-V**
Reg-I	0.80				
Reg-II	0.30	0.71			
Reg-III	0.31	0.27	0.58		
Reg-IV	0.30	0.27	0.21	0.59	
Reg-V	0.30	0.27	0.21	0.31	0.59

Figure 2.4 illustrates the annual cycles of SM across individual homogeneous regions with the FLDAS, ERA5Land, Combined, and GLDAS2 datasets spanning the 1982-2020 period. In contrast to the nationwide annual cycles depicted in Figure 2.2, the homogeneous regions exhibit one or two peak soil moisture values in a year, depending on the specific region under consideration. The double-peak values nature of the SM pattern is distinctly evident in Reg-III and Reg-V, whereas Reg-I, Reg-II, and Reg-IV exhibit single-peak value. In addition, SM levels over Reg-IV remain consistently wet throughout the year.

Furthermore, Figure 2.4 highlights that the ERA5Land dataset consistently exhibits the highest moisture levels in Reg-I, Reg-II, and Reg-IV, while FLDAS exhibits the highest SM levels in Reg-III and Reg-V. A closer examination of Reg-I and Reg-II reveals that the Combined dataset records maximum moisture levels in July, whereas other datasets exhibit a one-month lag. As depicted in Figure 2.4, annual soil moisture levels in Reg-I, Reg-II, and Reg-IV are notably higher compared to Reg-III, which shows the lowest levels among all regions. Remarkably, these spatial patterns closely align with the topographic features of the country.

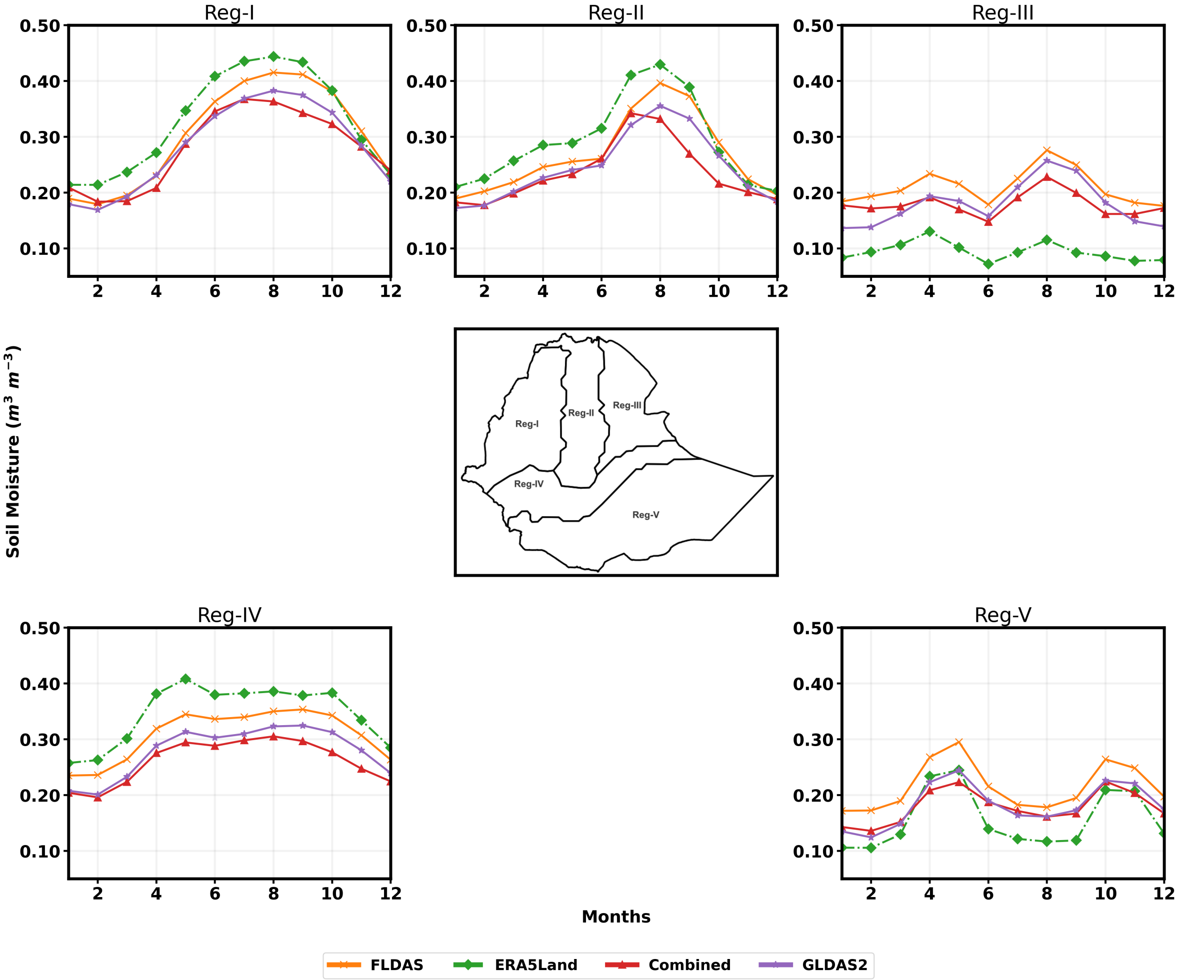

Figure 2.4.: Homogeneous regions annual cycles for FLDAS, ERA5Land, Combined, and GLDAS2 soil moisture datasets (1982-2020). The middle panel shows the five homogeneous regions.

Figure 2.5 illustrates the spatial distribution of annual and seasonal averages of soil moisture (SM) derived from FLDAS data, with overlaid boundaries indicating homogeneous soil moisture zones. It is evident from the figure that the Dallol depression, situated in northeastern Ethiopia (Reg-III), consistently reveals drier conditions regardless of the season under consideration. In contrast, the western part, i.e., Reg-IV, consistently displays higher levels of moisture across all seasons (JJAS, Figure 2.5(b); MAM, Figure 2.5(c); and OND, Figure 2.5(d)) as well as in the annual mean Figure 2.5(a).

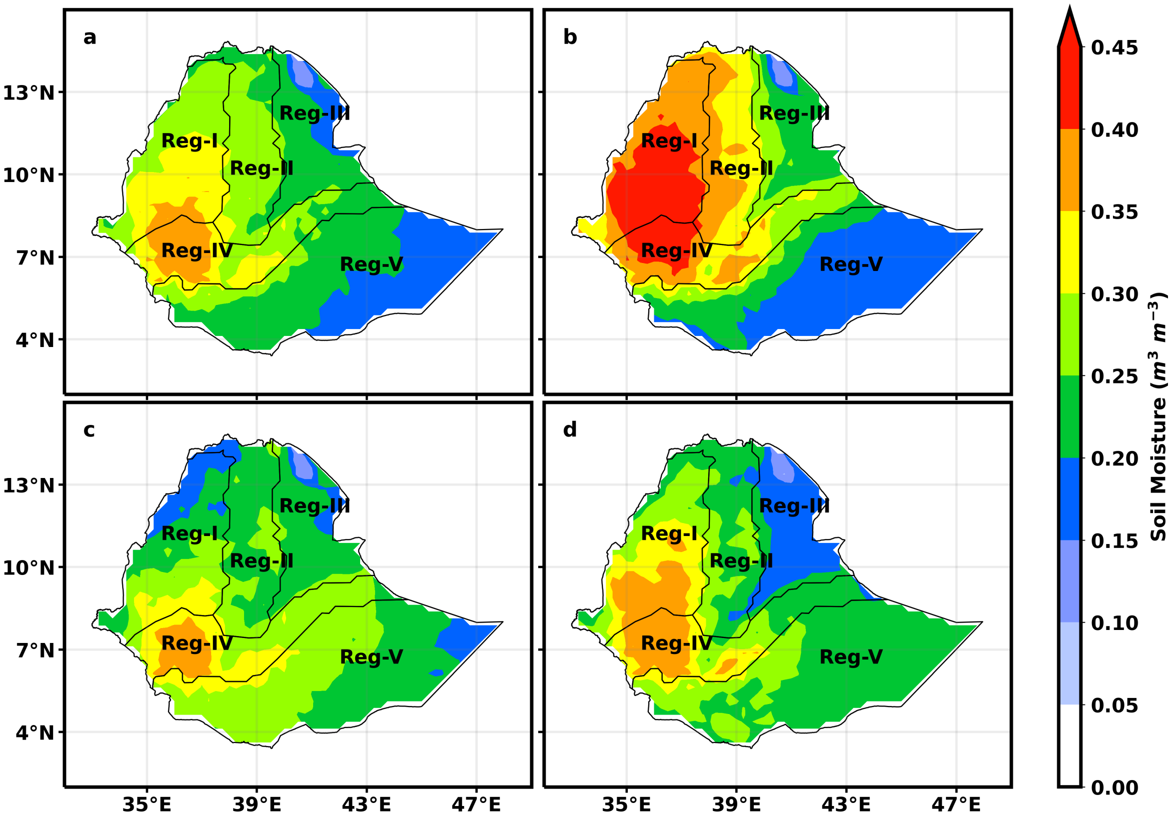

Figure 2.5.: Annual and seasonal averages of soil moisture from FLDAS overlayed on homogeneous zones: (a) Annual, (b) JJAS, (c) MAM, and (d) OND (1982-2020).

During the summer season (JJAS, Figure 2.5(b)), significant spatial variations in SM are observed, characterized by a pronounced east-west contrast. The highest SM values are recorded in Reg-I and Reg-IV, while the lowest levels of moisture are evident in Reg-V and the northeastern border of Reg-III. In contrast, during the Belg season (Figure 2.5(c)), the contrast between wet and dry regions diminishes, with most parts of the country showing SM values exceeding 0.2 m^3 m^{-3}. Despite the Bega season (Figure 2.5(d)) being traditionally dry, the majority of the country, except for low-lying areas in the northeastern region, maintains SM values above 0.2 m^3 m^{-3}, indicating a prolonged soil moisture memory.

2.4.3 Interannual variability of soil moisture datasets in the homogeneous climate zones

Figure 2.6 illustrates the interannual variability of annual mean soil moisture across the FLDAS, ERA5Land, and GLDAS2 datasets for each homogeneous region. Although different regions exhibit varying degrees of wet and dry years, certain years display consistent soil moisture anomalies across all homogeneous zones. Specifically, negative soil moisture anomalies were observed across all zones in 1984 and 2009, whereas 1997 exhibited wetter soil moisture conditions across all zones, with Reg-V experiencing particularly pronounced impacts.

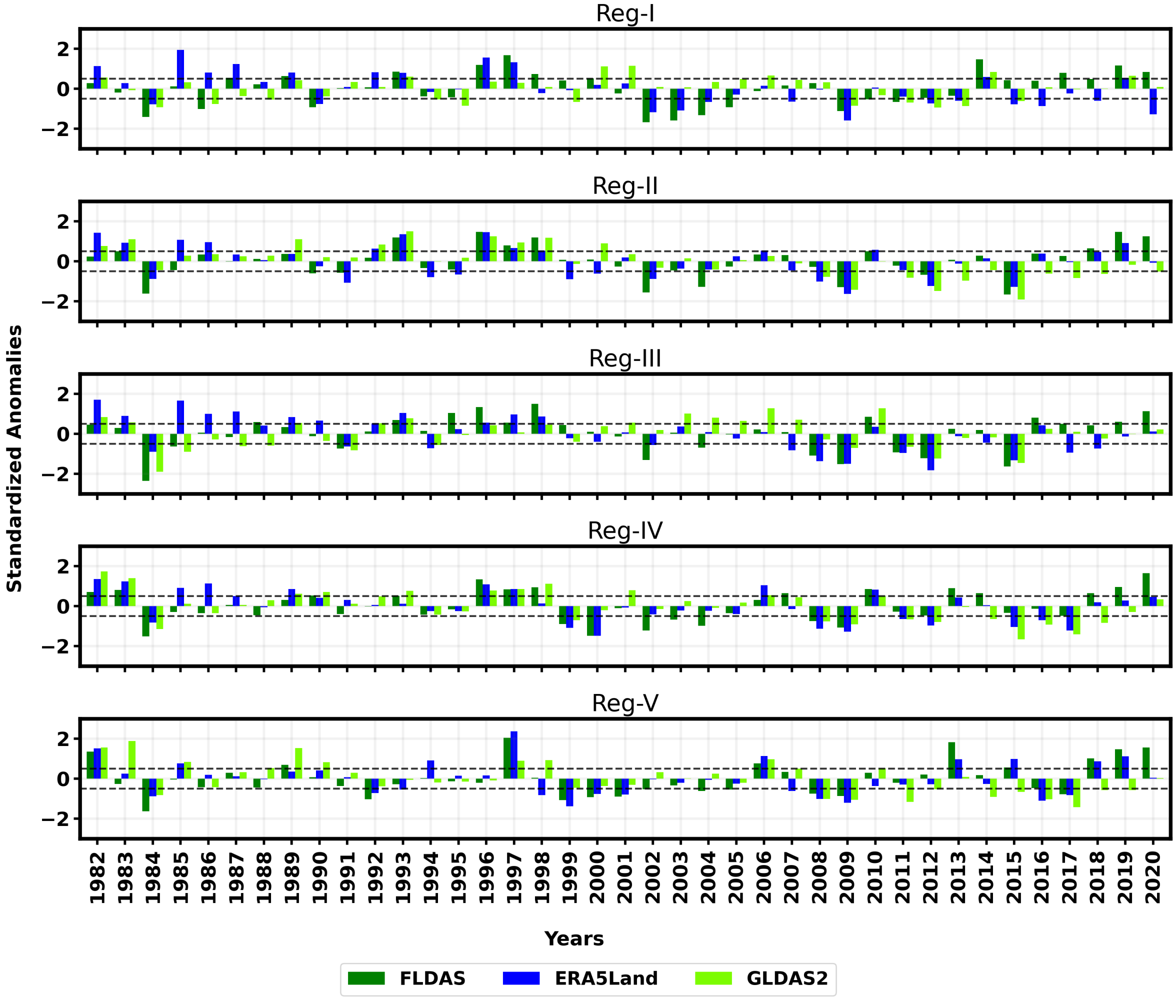

Figure 2.6.: Time series of standardized anomalies of annual mean soil moisture datasets from FLDAS, ERA5Land, and GLDAS2 for each homogeneous zone (i.e., Reg-I, Reg-II, Reg-III, Reg-IV, and Reg-V).

The time series analysis reveals low-frequency variability, characterized by periods of consecutive dry years followed by consecutive wet years. This pattern is evident in the mid-1990s and late 2000s, where most homogeneous zones experience sequences of wet and dry episodes, respectively.

It is noteworthy that not all El Niño years result in similar soil moisture anomalies. For instance, the El Niños of 1997 and, to some extent, 1982, are associated with positive soil moisture anomalies across all zones. In contrast, the El Niño event of 2015 led to severe dry conditions in Reg-II and Reg-III, while Reg-I and Reg-V experienced comparatively low moisture levels. These years are notable El Niño years, remembered for their severe impact on Ethiopia, including some of the worst famines in the country's history. The 1984 El Niño event caused a significant reduction in rainfall during the main growing seasons, exacerbating drought conditions (Viste et al. 2013). This drastic decrease in rainfall severely affected crop yields and water availability, leading to widespread food shortages and famine. The initial phase of the 1997-1998 El Niño also brought severe drought conditions, similar to those of 1984, affecting agricultural production and water resources. However, the latter part of this event saw excessive rainfall, which led to flooding in several regions (Segele and Lamb 2005). During the 2009 El Niño period, Ethiopia experienced below-average rainfall during critical growing seasons, resulting in reduced agricultural output and stress on water resources.

2.4.4 Local and global drivers affecting soil moisture distributions and variations

As demonstrated in previous sections, soil moisture in distinct climatic zones can be influenced by various driving factors. The magnitude of these influences, including local and global soil moisture driving factors, will be further assessed in the following subsections.

i. **Local drivers associated with soil moisture anomalies**

In this subsection, we examined the impacts of rainfall (RF) and evapotranspiration (ET) on soil moisture (SM) variability. Figure 2.7 illustrates the spatial distribution of SM, RF, and ET composites based on the extreme five wettest minus five driest SM years. The SM composites (Figure 2.7(a-d)) indicate wetter anomalies in southwestern Ethiopia and in the eastern highland areas south of the rift valley. These spatial patterns suggest that regions south of the rift valley largely dictate the countrywide SM anomalies across all seasons. Furthermore, the composite analysis reveals a close correspondence between the spatial distribution of wet SM anomalies and positive RF anomalies (Figure 2.7(e)) over most parts of the country. In addition, the results indicate that drier or wetter soil moisture is closely associated with negative or positive ET anomalies (Figure 2.7(i)) in the southern and southeastern regions of the country.

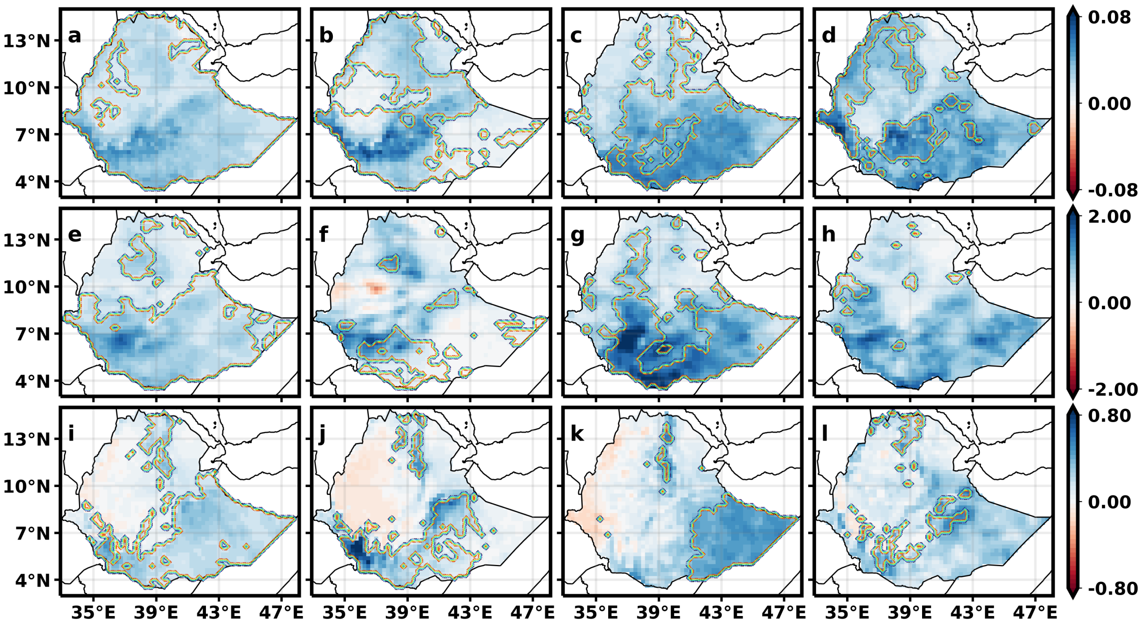

Figure 2.7.: Composites of SM (top row), RF (second row) and ET (third row) for annual (first column), JJAS (second column), MAM (third column) and OND (fourth column) based on extreme five wettest and drier soil moisture years. Contour lines represent regions that are significant at 0.05 level.

In the central and western regions of the country, extremely low and marginally negative insignificant ET anomalies (Figure 2.7(i,j,k)) are observed. During the summer season (JJAS), both rainfall (RF) and evapotranspiration (ET) closely correspond to soil moisture (SM) anomalies in the southwestern and eastern highlands of Ethiopia. Notably, a stronger RF-SM association is evident in the central southern region. These findings suggest that while ET and RF exhibit slightly negative relationships with SM in the western part of the country, a stronger positive relationship exists in the southwestern, central, and eastern regions during the summer season. Moreover, soil moisture anomalies (Figure 2.7(c)) in the central, northeastern, and southeastern parts of the country indicate wetter conditions during the MAM season, following a similar pattern to the corresponding rainfall (RF) distribution (Figure 2.7(g)), except in the northwest. Conversely, the ET anomaly (Figure 2.7(k)) depicts insignificant negative anomalies in the western region, gradually diminishing towards the western borders of the country. These observations suggest an interconnected relationship among SM, RF, and ET in the southeastern part of Ethiopia.

A comparable relationship among soil moisture (SM), rainfall (RF), and evapotranspiration (ET) is evident during the OND season (Figure 2.7(d,h,i)) . This result suggests that the spatial distribution of RF and SM anomalies largely overlap across most regions of the country, whereas the alignment between SM and ET is predominantly concentrated in the eastern part of Ethiopia.

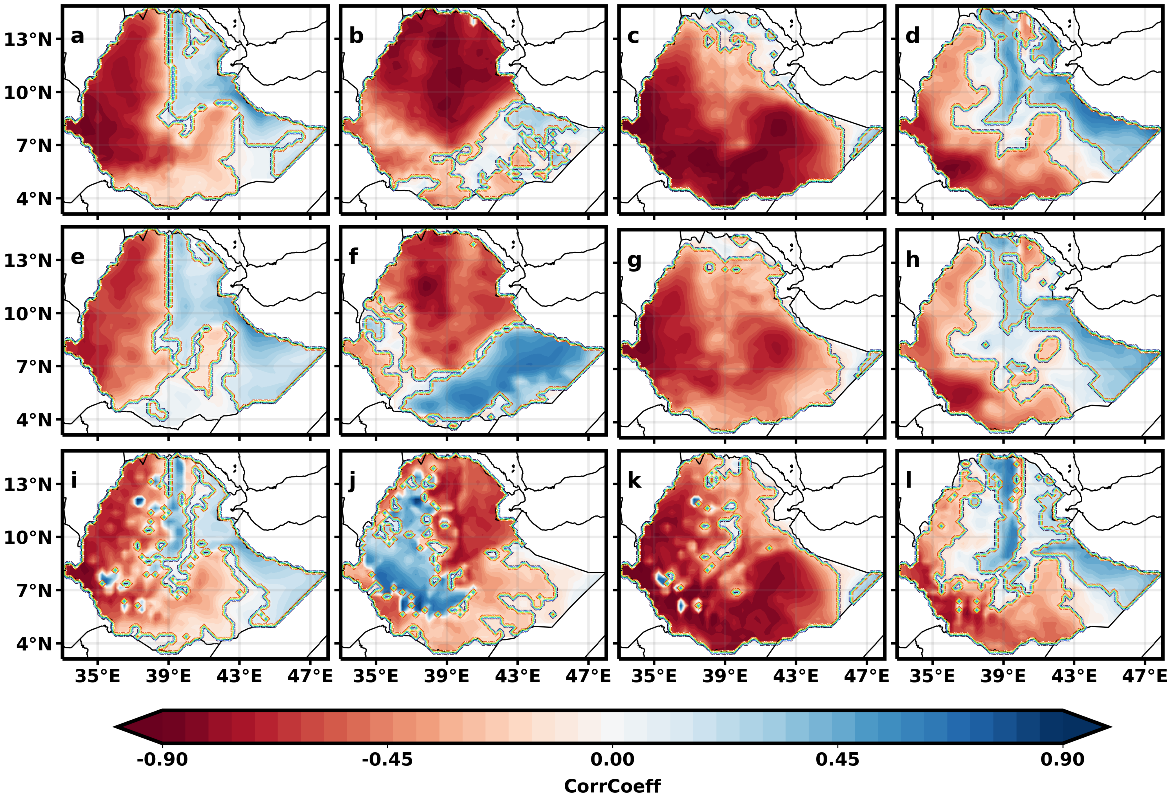

Figure 2.8.: Correlation between near surface air temperature and SM (top row), RF (second row) and ET (third row) for annual (first column), JJAS (second column), MAM (third column) and OND (fourth column). Contour lines represent regions that are significant at 0.05 level.

Figure 2.8 presents the spatial correlation patterns between near-surface air temperature (Tair) and soil moisture (SM), rainfall (RF), and evapotranspiration (ET). It's evident that higher Tair correlates with elevated ET values in the eastern part of the country, while lower values are observed in the western region (Figure 2.8(i)). In the west, the negative correlation implies that the SM plays a role in partitioning more of the net radiation to latent heat flux and lowers the surface temperature via evaporative cooling. This process entails that the land is a driver in the western region. In the east, a positive correlation between Tair and ET signifies that a higher atmospheric demand drives an increase in evapotranspiration. The increase in ET leads to more surface humidity, resulting in an increase in wet-bulb temperature; therefore, it lowers the wet-bulb depression in the planetary boundary layer. Thus, this process leads to an increase in RF (Findell and Eltahir 1999; Eltahir 1998) and enhances the surface moisture. It is, therefore, likely that the ET drives the local SM in the eastern and southeastern region. These annual relationships are predominantly influenced by their winter season associations, whereas correlations during the summer (Figure 2.8(j)) and spring (Figure 2.8(k)) seasons reveal variations across different regions.

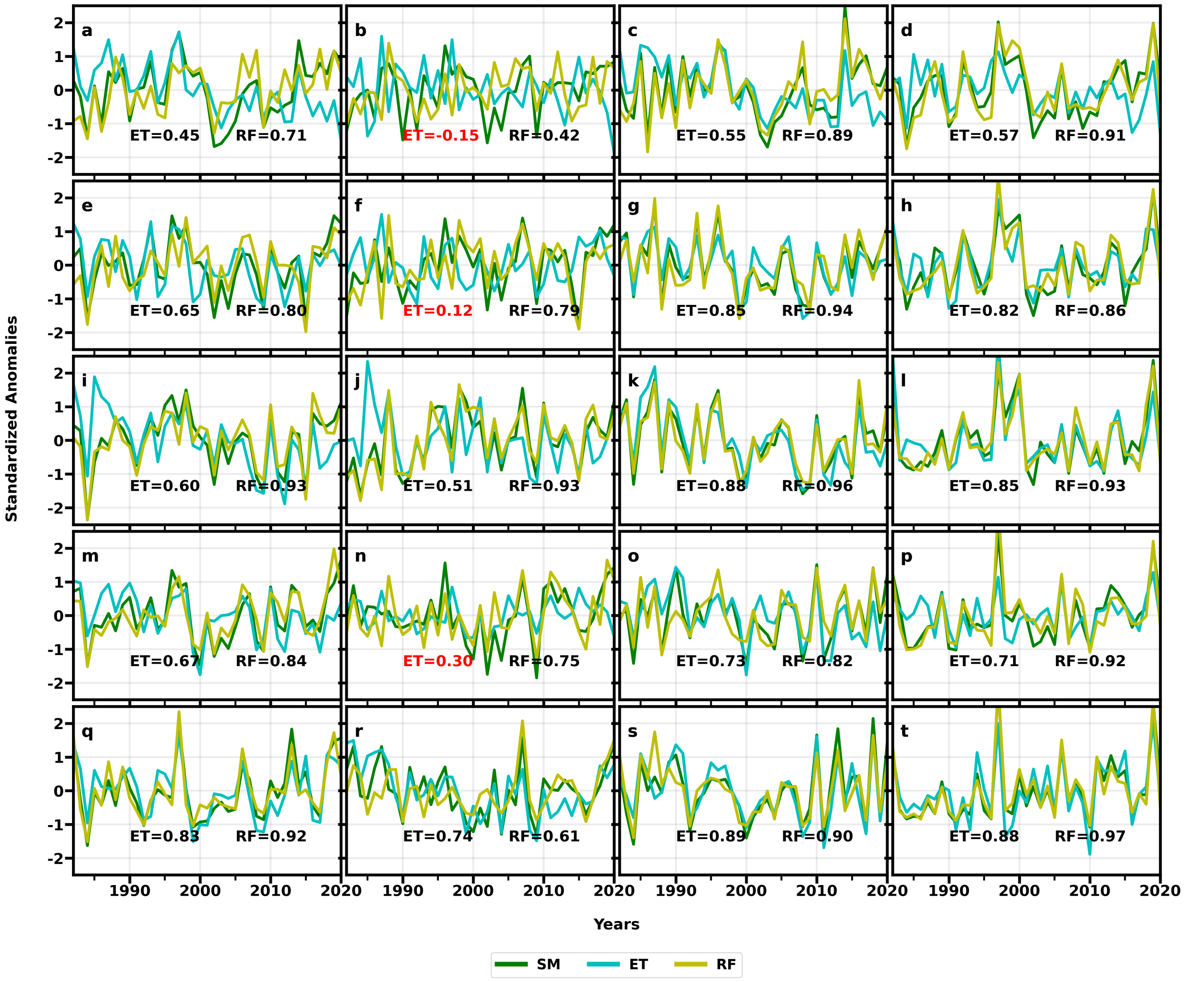

Figure 2.9.: Annual and seasonal time series of SM, ET, and RF for the five homogeneous zones: first column (Annual), second column (JJAS), third column (MAM), and fourth column (OND); first row (Reg-I), second row (Reg-II), third row (Reg-III), fourth row (Reg-IV), and fifth row (Reg-V). Correlation values between SM and RF/ET are overlayed in each panel and insignificant correlations are indicated by red text.

Figure 2.9 shows the annual and seasonal year-to-year variability of SM, RF, and ET. From the data in Figure 2.9, it is apparent that the SM interannual variability goes inline with the RF. This finding is consistent with that of (Seneviratne et al. 2010; Teuling and Troch 2005). Besides, correlations between SM and RF/ET show there are significant relationships in every homogeneous zone except insignificant SM versus ET correlations in Reg-I, Reg-II, and Reg-IV in the summer. RF has significant association with SM in all homogeneous zones and seasons while its magnitude is lower in Reg-I (JJAS). Whereas, ET demonstrated lower associationship with SM during summer in all zones except Reg-III and Reg-V. Overall, correlation magnitudes are high in most seasons and zones whereas ET indicates weak relationships in some zones and seasons.

We have also analyzed the co-variability of SM with RF and ET using CMCA methodology adopted from Rieger et al. (2021). Hence, Figure 2.10 shows the ET-SM phase functions (Figure 2.10(a-j)) and amplitude functions (Figure 2.10(k-t)) of CMCA for the five dominant modes of variabilities. Similarly, Figure 2.11 also presents the RF-SM phase functions (Figure 2.11(a-j)) and amplitude functions (Figure 2.11(k-t)) of the five dominant modes.

Mode-1 contributes 32.8% and 28.5% of the co-variability between ET and SM (Figure 2.10(a,f,k,p)); RF and SM (Figure 2.11(a,f,k,p)), respectively. The amplitude functions (Figure 2.10(k,p) and Figure 2.11(k,p)) show the higher amount of variations over the southern part of the country in both RF-SM and ET-SM co-variability. It is also noted that these modes of variabilities indicated in-phase (Figure 2.10(a,f) and Figure 2.11(a,f)) of RF and ET with SM in this region, hence, it seems possible that increase in RF leads to increase in SM. The in-phase relationship between ET and SM involves a chain of atmospheric processes by which an increase in atmospheric demand for moisture driven by higher temperature leads to increases in ET and RF, and ultimately SM as discussed in the composite analysis.

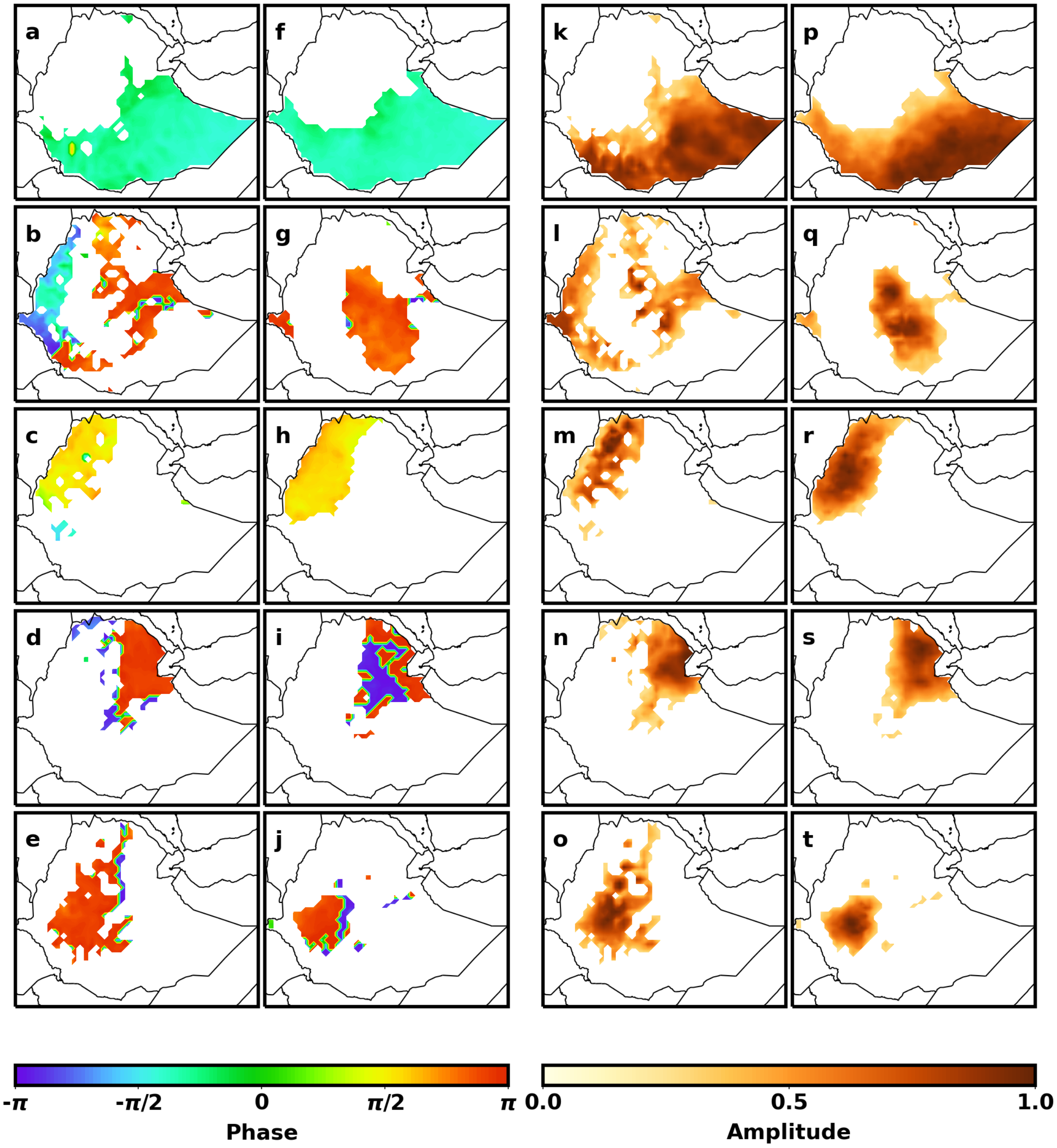

Figure 2.10.: Phase functions for ET (a-e) and SM (f-j) relative phase shifts with respect to their corresponding Principal Components (PCs); and amplitude functions for ET (k-o) and SM (p-t). The maximum normalized scale has been applied and phase values having less than 0.25 amplitude (i.e., insignificant noisy phase values) have been masked out.

Mode-2 contributes 10.4% and 11.7% of co-variations of the ET and SM (Figure 2.10(b,g,l,q));

RF and SM (Figure 2.11(b,g,l,q)), respectively. This ET-SM mode of variabilities represent the central, central-east, and along western tips of the country. The spatial pattern of the second mode of ET-SM co-variability is not collocated since the pattern of SM is over the central highland whereas the signal of ET is at the eastern and western edges of the Ethiopian highland. This result is interesting as the SM over the central highland is associated closely with the remote ET residing over the edges of the highland rather than the ET on the highland itself. This suggests the critical role of regional atmospheric circulation in transporting moist air from lowland to the highland. On the other hand, the second mode of RF and SM (Figure 2.11(b,g,l,q)) covariability explains the central-southern region. This mode of variability shows a complicated phase relationship as it is shifted by $+\pi/2$. Nevertheless, mode-2 of variability also partially overlaps with mode-1, though this outcome is not expected from a rotated EOFs.

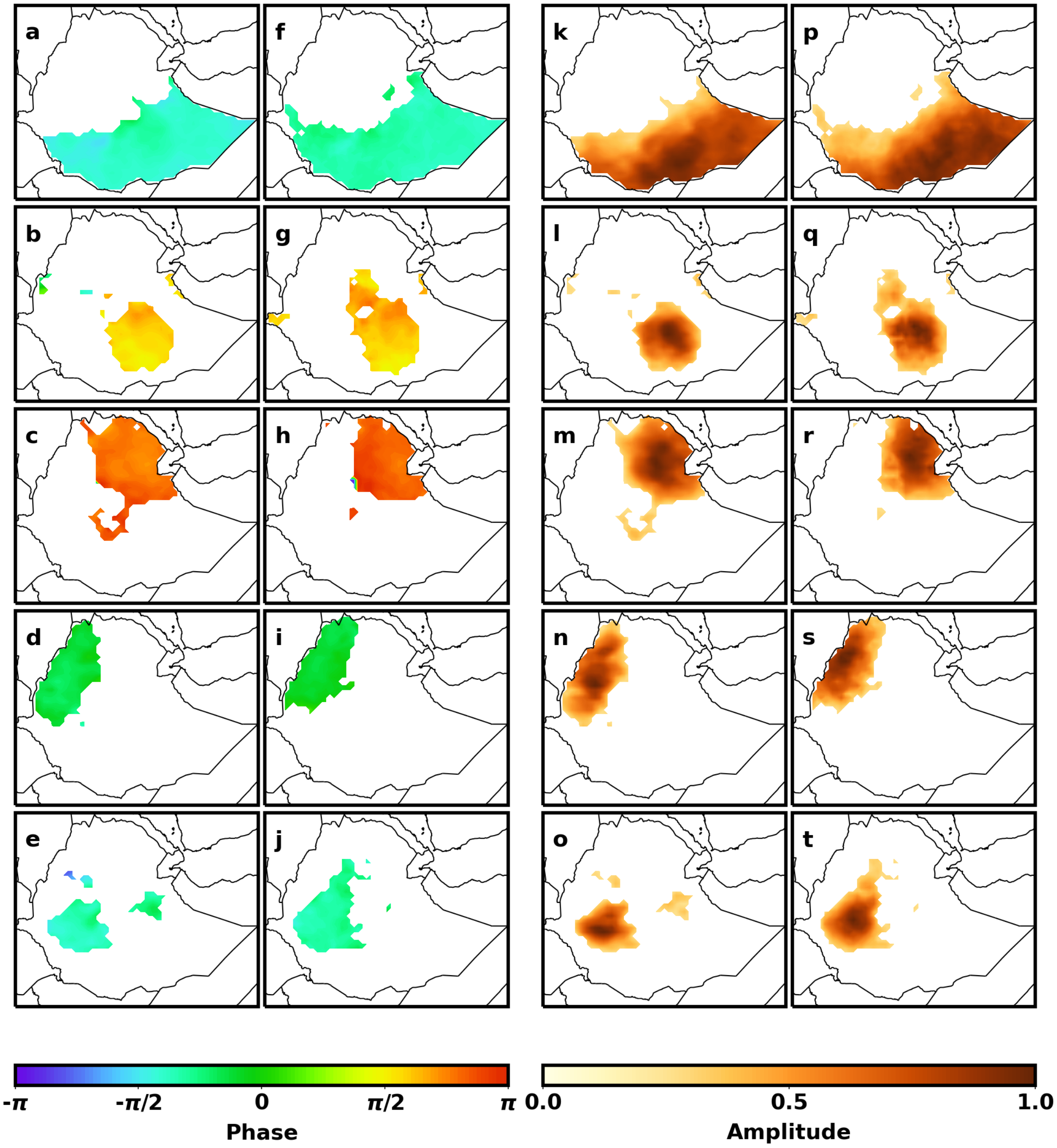

Figure 2.11.: The same as Figure 2.10 but for phase functions of RF (a-e) and SM (f-j); amplitude functions for RF (k-o) and SM (p-t).

Mode-3, on the other hand, represents the northwestern ET-SM (Figure 2.10(c,h,m,r)) and northeastern RF-SM (Figure 2.11(c,h,m,r)) covariability. This mode explains 8.8% (ET) and 10.4% (RF) versus SM covariability. It should be noted that the spatial patterns of mode-3 of ET-SM and mode-4 of RF-SM are interchanged but they represent the same region of the northwest. It has to be noted that mode-4 (RF-SM) showed positive correlation whereas mode-3 (ET-SM) demonstrated a complicated relationship that phase shifted by $+\pi/2$. However, mode-4 of ET-SM (Figure 2.10(d,i,n,s)) and mode-3 of RF-SM (Figure 2.11(c,h,m,r)) represent northeastern regions of the country with 7.6% and 6.9% covariability fractions, respectively. Moreover, mode-3 (RF-SM) and mode-4 (ET-SM) identifies a direct covariability among these variables that likely supports our hypothesis ET drives the local SM in this region via a cascade of atmospheric processes as discussed at the beginning of this section.

Mode-5 (Figure 2.10(e,j,o,t) and Figure 2.11(e,j,o,t)) pointed out a central western spot that outlines the direct relationship between RF and SM and accounts for 5.6% of covariability. The corresponding mode of ET-SM explains 7.5% covariance. This mode highlights a direct relationship between SM with both RF and ET in this region.

ii. Global climatic variables effects on soil moisture

In this subsection the link between global SST and SM variability over Ethiopia has been analyzed using CMCA. Figure 2.12, Figure 2.13, and Figure 2.14 shows the amplitude functions, phase functions, and principal components (PCs), respectively, for the first four leading complex rotated MCA modes of SST and SM. The percentage of covariabilities explained by these modes are 59.7%, 6.3%, 2.1% and 0.9% for mode-1, mode-2, mode-3 and mode-4 respectively.

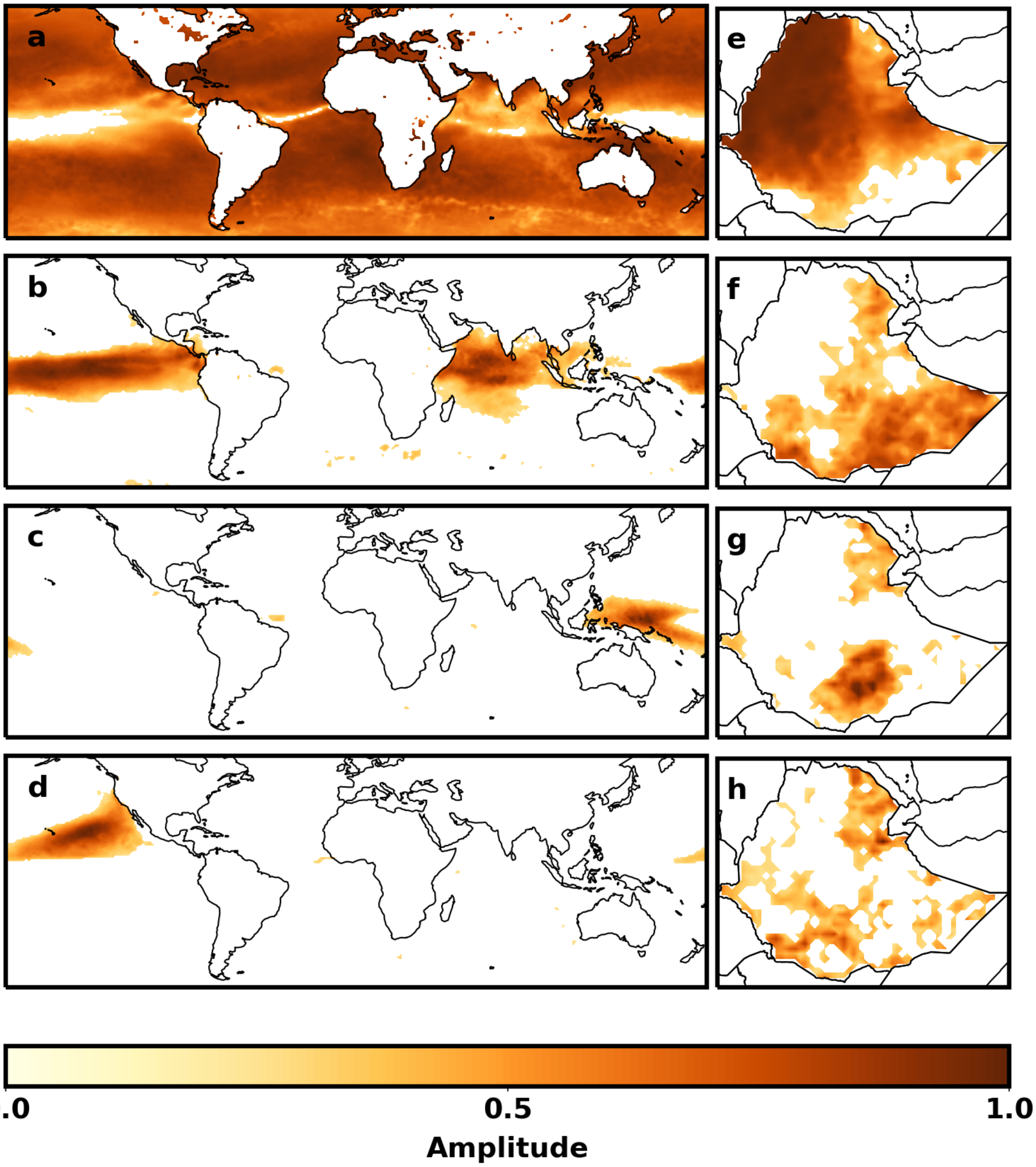

Figure 2.12.: Amplitude functions for global SST (a-d) and soil moisture (e-h).

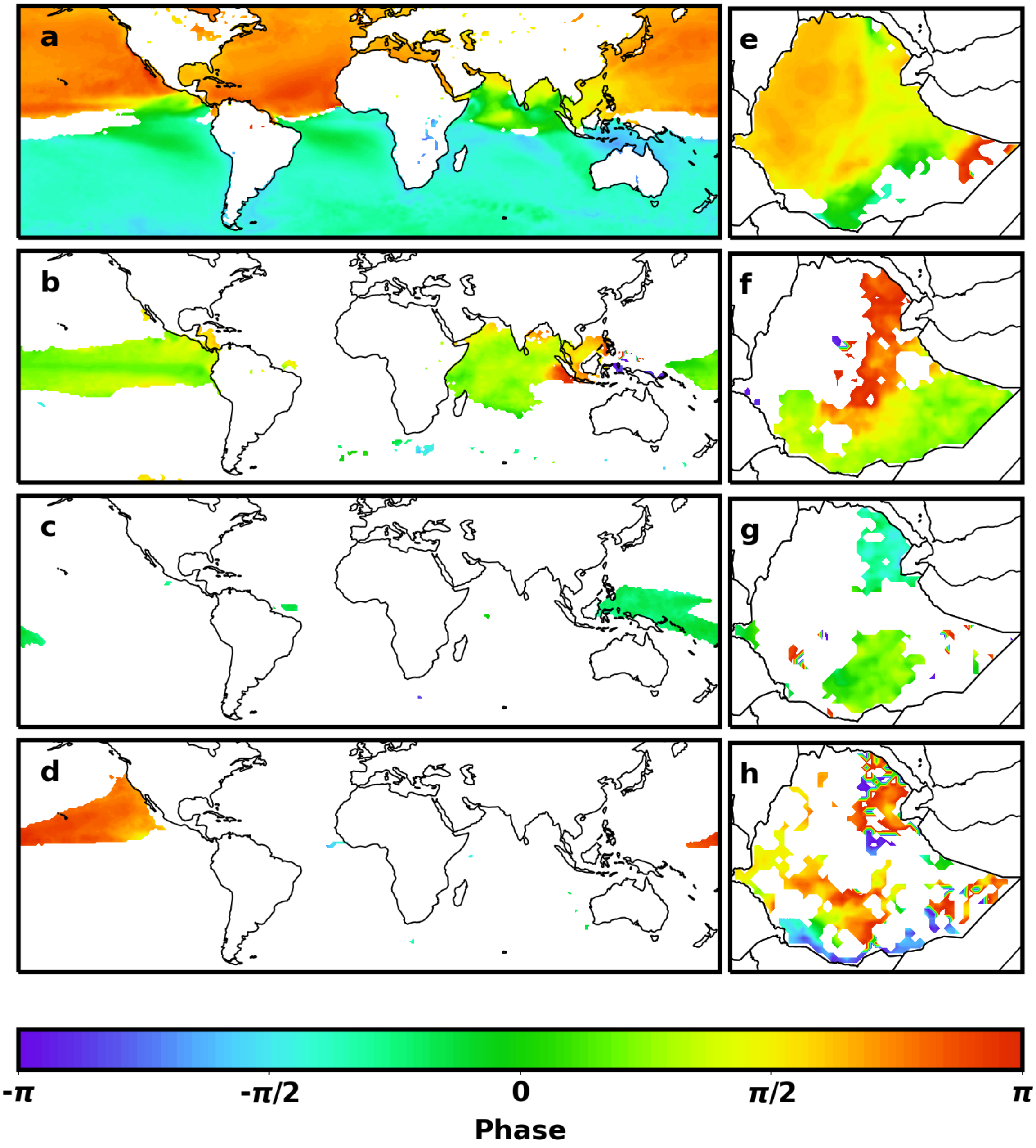

Figure 2.13.: Phase functions for global SST (a-d) and soil moisture (e-h) relative phase shifts with respect to their corresponding SST and SM PC's, respectively.

The first mode (Figure 2.12(a,e), Figure 2.13(a,e), and Figure 2.14(a,e)) shows the annual cycles of the global SST and SM. The spatial amplitude function (Figure 2.12(a)) showed low equatorial SST variability, while the lowest variability is along the equatorial pacific ocean. Studies (Zheng et al. 2016; Mestas-Nuñez and Enfield 2001) have confirmed that this pattern of low variability in sea surface temperatures (SST) is particularly prominent in the eastern equatorial Pacific, which is influenced by ENSO and other climatic factors. Moreover, it is noted that the phase function (Figure 2.13(a)) identified the anti-correlation (negative) between the southern and northern hemisphere SST anomalies that is consistent with findings in Rieger et al. (2021). On the other hand, the annual SM variation (Figure 2.12(e)) is predominantly higher in the northwestern part of the country. Furthermore, the phase function (Figure 2.13(e)) of this mode also showed distinct separate SM regions in the northeast, northwestern, and southern parts of the country. These distributions might be related with summer season (JJAS) rainfall distribution in the country.

The second mode (Figure 2.12(b,f), Figure 2.13(b,f), and Figure 2.14(b,f)) prevails that equatorial pacific and western Indian oceans SST variations predominantly affect SM anomalies over the southern and northeastern part of the country. The anti-correlations between the northeastern SM and equatorial pacific and western Indian oceans SST anomalies are well identified by the phase functions shown in Figure 2.13(b,f). Whereas, the southern part of the country's SM is directly correlated with these oceanic regions. Moreover, the second mode temporal variation is highly associated ($r = 0.72$) with the Oceanic Nino Index (ONI) as shown in Figure 2.14(b). An ENSO (El-Nino Southern Oscillation) phenomena that a higher than normal SST anomalies in the eastern and lower than normal SST anomalies in the western equatorial pacific ocean (El-Nino) or the vice versa (La-Nina) are associated with lower and higher SM anomalies in the northeastern part of the country. Whereas, the El-Nino condition is directly linked with the southern part of the country. The physical mechanism that links the negative association between the central pacific ocean SST anomalies and the SM in the northeastern part of the country as studies (Gleixner et al. 2017a; Diro et al. 2011; Segele et al. 2009a; Korecha and Barnston 2007; Camberlin 1997) indicated is due to weakening of Tropical Easterly Jets (TEJ) and weak upper level divergence. This weakening of TEJ and the upper level divergence leads to a reduction in rainfall and this inturn reduces soil moisture in the region or vice versa. It is also interesting to mention the second mode and the Dipole Mode Index (DMI), an area average of ($10^{\circ}S - 10^{\circ}N$, $50^{\circ}E - 70^{\circ}E$ minus $10^{\circ}S - 0^{\circ}N$, $90^{\circ}E - 110^{\circ}E$) Indian Ocean SST anomalies, significant level of relationship is $r = 0.43$ with p-value < 0.0001. It is a well established phenomenon that the Indian Ocean Dipole (IOD) is directly associated with OND rainfall in the south and southeastern part of the country (Lüdecke et al. 2021; Bahaga et al. 2015; Liebmann et al. 2014; Behera et al. 2005; Black 2005; Saji et al. 1999) that possibly reflected on the local SM.

The third mode (Figure 2.12(c,g), Figure 2.13(c,g), and Figure 2.14(c,g)) shows SST anomalies over Oceania that directly affect the SM in northeastern and central southern part of the country. This mode is clearly associated with Pacific Warm Pool (PACWARMPOOL) and the correlation between PACWARMPOOL index and SST anomalies time series ($r = 0.48$) over Oceania are presented in Figure 2.14(c). The pacific warm pool SST anomalies directly vary with the northeastern and central southern regions with slight negative and positive phase shift in these regions, respectively. It is also apparent that the warm pool has a positive link with the western tip of the country (Gambella region). However, unlike studies (Lyon and DeWitt 2012; Peterson et al. 2012; Williams et al. 2012; Funk et al. 2008) indicated the negative associationship between the south-central Indian and west Pacific Ocean SST anomalies and East African rainfall, the southern central and northeastern local SM has positive links with Pacific warm pool.

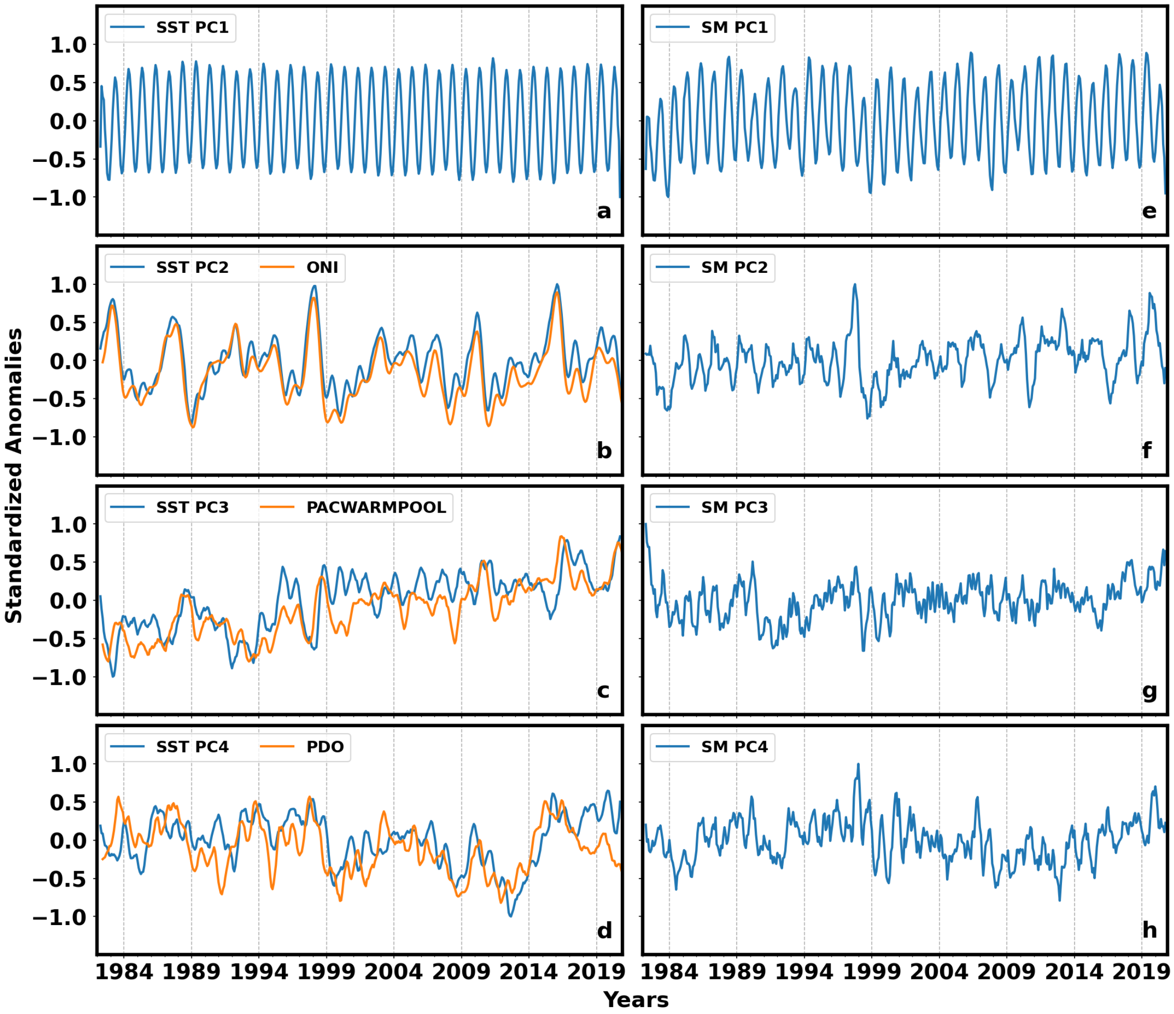

Figure 2.14.: Principal components (PC1, PC2, PC3, PC4) of SST (left) and soil moisture (right) with global oceanic indices overlayed on SST PCs. The correlations between SST PCs and the global oceanic indices are: Oceanic Nino Index (ONI) $r = 0.72$, Pacific Warm Pool (PACWARMPOOL) $r = 0.48$, and Pacific Decadal Oscillation (PDO) $r = -0.52$ for p-value < 0.0001. For readability and smoothly overlay the PDO index over SST PC4, we invented PC4 of SST and the corresponding SM PC4.

The fourth mode (Figure 2.12(d,h), Figure 2.13(d,h), and Figure 2.14(d,h)) illustrated a widespread effect of the Pacific Decadal Oscillation (PDO) manifestation across the country-wide SM anomalies that were dominated by negative correlations (Figure 2.13(h)) all over the country. Though the physical mechanisms that drive this relationship are complex and not well understood, studies (Lüdecke et al. 2021; Taye and Willems 2012) also found that PDO has negatively correlated with Ethiopian rainfall. However, this mode also presented a direct correlation in the northeastern, some patches of central and southeastern regions, and along the narrow band in the southern tips of the country. Figure 2.14(d) shows correlation between the PDO index and northeastern Pacific SST anomalies (SST PC4). The dominant influence of PDO in the southern region rainfall is discussed by (Jury 2016, 2010a), and it might also be the case that it reflect on the local SM via their direct relationship.

2.5 Summary and conclusions

Soil moisture is crucial in shaping land-atmosphere interactions, affecting both energy exchange and the water balance. This study addresses the scarcity of a reliable in-situ soil moisture observational network, emphasizing the importance of a comprehensive evaluation of the spatiotemporal characteristics of soil moisture in Ethiopia. The research aims to examine the agreement among station, reanalysis, and satellite estimates and explores the spatiotemporal variability of soil moisture in relation to local and remote drivers.

To identify the most representative soil moisture dataset, correlation and Root-Mean-Square-Error (RMSE) analyses were employed. Additional analyses, such as Empirical Orthogonal Functions (EOFs) and KMeans clustering, categorized Ethiopia into homogeneous soil moisture zones. Complex Maximum Covariance Analysis (CMCA) and composite analysis were applied to investigate the relationship between soil moisture variability and local (evapotranspiration and rainfall) and remote (sea surface temperature - SST) drivers.

The comprehensive inter-comparison of diverse datasets conducted in this study provided valuable insights into the spatiotemporal variability of soil moisture across Ethiopia. Despite the observed consistency in the general patterns, variations in absolute magnitudes and peak timings were evident among the datasets. Notably, the Combined satellite datasets displayed an earlier peak in soil moisture within the seasonal cycles. Additionally, ERA5Land exhibited a tendency to overestimate soil moisture in wet regions while underestimating it in drier areas. However, amidst these variations, the study identified FLDAS as a highly skilled dataset ($r = 0.95$), successfully capturing the spatiotemporal characteristics of soil moisture across the diverse landscape of Ethiopia. This finding underscores the significance of dataset selection in accurately representing soil moisture dynamics, emphasizing the relevance of FLDAS for reliable assessments in the region.

The EOF and KMeans analysis delineated five distinct non-overlapping climate zones with high intra-zone and low inter-zone correlations. The annual cycle of soil moisture exhibited a single-peak value in the western part (Reg-I) and a double-peak values in the eastern and southern parts (Reg-III and Reg-V). The study noted the northeastern tip (Dallol depression) as drier, while the central southwestern region remained wetter throughout the year. These patterns aligned with the seasonal rainfall cycle in Ethiopia (Fekadu 2015; Diro et al. 2008b; Gissila et al. 2004; Degefu 1987).

Further investigation revealed a strong correlation between soil moisture and the variation in rainfall and evapotranspiration in the southern region. Higher soil moisture values consistently correlated with increased levels of both rainfall and evapotranspiration, highlighting a robust coupling between these meteorological variables. The analysis also clarified that, in the southeastern region, atmospheric factors—particularly temperature—played a pivotal role in land-atmosphere interaction, influencing the positive correlation between evapotranspiration and soil moisture. This influence is evident in the composite analysis and the leading modes of Complex Maximum Covariance Analysis (CMCA), indicating that the positive correlation between evapotranspiration (ET) and soil moisture (SM) stems from heightened moisture demand due to increased temperature. This, in turn, activates a sequence of atmospheric processes, where elevated temperatures lead to intensified evaporation and enhanced convection, resulting in an augmentation of soil moisture. Furthermore, an examination of the impact of global Sea Surface Temperature (SST) anomalies on local soil moisture underscored significant relationships, emphasizing the influence of oceanic variability. This comprehensive analysis of the effects of global SST anomalies on local soil moisture demonstrated noteworthy correlations with various oceanic indices: ONI ($r = 0.72$), IOD ($r = 0.43$), PACWARMPOOL ($r = 0.48$), and PDO ($r = -0.52$). These correlations signify substantial relationships between local soil moisture and oceanic indices, mediated by large-scale circulations and influencing other climatic variables such as rainfall and surface temperature.

This study has significantly contributed to our understanding of soil moisture variability in the Horn of Africa, offering valuable insights into the spatiotemporal dynamics of soil moisture over Ethiopia. Through the identification of the most representative reanalysis dataset, the research contributes essential knowledge for better land-atmosphere interaction models and climate adaptation strategies in the region. This research serves as a foundation for effective soil moisture management, promoting soil water conservation and improving water use efficiency in agriculture. Furthermore, soil moisture data is instrumental in guiding water resource allocation and informing policy development at regional and national levels. Policymakers can utilize this information to formulate efficient water management strategies, allocate irrigation quotas, and address water-related challenges. In addition, understanding soil moisture patterns enables farmers and policymakers to anticipate and prepare for droughts, floods, and other extreme events, allowing for the implementation of measures to minimize losses and enhance resilience in agricultural systems.

However, despite these achievements, it is crucial to acknowledge a limitation associated with the relatively short length of records in the station soil moisture dataset. To further enhance the reliability and depth of our analyses, future research endeavors should prioritize the incorporation of longer observational soil moisture data records. This expansion in temporal coverage will undoubtedly contribute to a more comprehensive understanding of soil moisture patterns, enabling more accurate assessments and facilitating the development of effective climate adaptation and agricultural strategies for Ethiopia.

Chapter 3

Coupled Impacts of Climate Change and Soil Acidification on Future Crop Suitability in Ethiopia.

Abstract

Agricultural sustainability is increasingly challenged by the dynamic climate conditions, particularly affecting rainfed agricultural systems, such as those prevalent in Ethiopia. This study undertakes an in-depth examination of the compounded effects of climate change and soil acidity on the future potential of crops suitability, with Ethiopia serving as a pertinent case study. Leveraging the EcoCrop crop suitability model, we parameterized and executed simulations for four key food crops crucial to Ethiopia's agricultural landscape: teff (Eragrostis tef), maize (Zea mays L.), barley (Hordeum vulgare L.), and common wheat (Triticum aestivum L.). Our analysis encompasses both present-day conditions and mid-century climate projections. To measure the influence of soil acidification on crop suitability, we conducted a series of simulation experiments. By systematically reducing soil pH values by 0.5, 1.0 and 1.5, and re-ran the suitability model to observe the resultant changes in the areas deemed suitable for each crop. Evaluation of the performance of the model involved comparing the modeled suitable areas against reference data, revealing a satisfactory alignment for all four crops. Our findings, based on the utilization of default soil pH values, suggest minimal alterations in the suitability of maize (0.08%), barley (1.8%), and wheat (0.4%) by mid-century, attributable in part to anticipated increases in rainfall across the country. Conversely, teff (5.1%) demonstrates a projected increase in suitability, following the projected rise in precipitation. However, our investigation into the effects *of soil acidification unveils a direct correlation between decreasing soil pH and the contraction of suitable areas for all crops, with teff (-26.7%), barley (-30.9%), and wheat (-34.3%) being particularly susceptible. We conclude that our study underscores the profound ramifications of soil acidification on crop suitability in Ethiopia under the backdrop of climate change. Hence, we recommend for the integration of precautionary measures aimed at mitigating soil acidification within broader climate change adaptation strategies. Such proactive steps are imperative to safeguarding the long-term agricultural viability of the rainfed cropping systems in Ethiopia.*

Keywords: crop suitability, soil pH, agriculture, climate adaptation, soil quality, EcoCrop, sustainability.

3.1 Introduction

In recent years, the world has faced the harsh reality of climate change (IPCC 2014). Climate change is causing changes to both atmospheric and biophysical conditions, with significant impacts on crop growth and productivity (Chemura et al. 2020; Srinivasan et al. 2019; Asseng et al. 2015; Rosenzweig et al. 2014; Asseng et al. 2011; Rowhani et al. 2011). There is a mounting need for climate adaptation measures to ensure crop yields are maintained at levels sufficient to sustainability provide food and other products to society. However, there is also potential for maladaptation, where some adaptation measures could contribute to other environmental degradation challenges. For instance, while optimal application of crop nutrition (fertilizer) is critical for optimal crop growth in nutrient-deficient soils, inappropriate or excessive use of fertilizers can cause significant changes to soil properties, leading to decrease in soil pH levels (e.g., Ammonium and urea-based fertilizers undergo a nitrification process, which releases hydrogen ions (H^+) into the soil, increasing soil acidity) (Elias 2017; Chimdi et al. 2012b; Fageria et al. 2010). In Ethiopia, as is typical across sub-Saharan Africa, fertilizer application is generally expected to be significantly lower than the global average. However, there have been instances where excessive fertilizer applications have led to environmental degradation (Alemu et al. 2022; Abate et al. 2015; Fageria et al. 2010; Stumpe and Vlek 1991).

Soil acidification can affect crop growth and performance. A rise in soil acidity can affect the availability of plant nutrients and increase the uptake of toxic elements (e.g., Aluminum, Manganese, and Hydrogen) and leaching of essential plant nutrients (e.g., Calcium, Magnesium, Sodium, and Potassium) below the root zone (Chimdi et al. 2012b; The et al. 2006; Ramankutty et al. 2002). For instance, as soil pH decreases (becomes more acidic), aluminum becomes more soluble, and aluminum ions are released from soil minerals, increasing in concentration in the soil solution (e.g., $Al_2O_3 + 6H^+ \rightarrow 2Al_3{}^+ + 3H_2O$). On the other hand, as soil pH decreases, calcium becomes less available and is more likely to leach away due to the dissolution of calcium carbonate ($CaCO_3$) and displacement by hydrogen ions (e.g., $CaCO_3 + 2H^+ \rightarrow Ca_2{}^+ + CO_2 + H_2O$). In addition to lowering crop yields, soil acidification reduces crop quality and predisposes plants to other biotic and abiotic stress factors. It damages root tips and hinders root elongation, reducing the plant's ability to absorb water and nutrients and making them more susceptible to pathogens and diseases. Acidic conditions can also negatively affect nitrogen-fixing bacteria, leading to lower nitrogen availability for crops (Sainju et al. 2019; Sadeghpour et al. 2017). Soil acidification unevenly affects various crop species and varieties, and can lead to a vicious cycle where farmers either increase the use of fertilizers to gain lost yields or invest in expensive corrective measures such as liming. However, evaluating the impact of soil acidity changes on distinct crops is essential to understand the impact of agricultural activities such as intensification measures on specific crops for planning and implementing transformational agricultural interventions for a changing climate.

Soil acidification is a critical bottleneck for crop production in high rainfall regions of Ethiopia as it is expanding in area and magnitude, and severely limiting crop productivity (Desta et al. 2021; Trunhe and Yli-Halla 2016). The central western Ethiopian regions are already showing signs of higher soil acidification that is close to the lower limits for most crops. Several studies (Alemu et al. 2022; Desta et al. 2021; Abate et al. 2017) indicate that there has been a significant rise in soil acidity throughout the high rainfall regions, which is posing a challenge to sustainable crop production. This region is known for its extensive agricultural activities and widespread crop production due to its favorable biophysical and biochemical conditions. Thus, intensified farming using inorganic fertilizers to enhance crop production in the region is widely practiced. According to Abate et al. (2015) the use of mineral fertilizers such as Di-Ammonium-Phosphate (DAP) and Urea to improve maize production increased by 12% from 2004 to 2013 in Ethiopia. Excessive use of DAP and Urea can lead to an imbalance in soil nutrients by providing high levels of nitrogen and phosphorus while potentially neglecting other essential nutrients such as potassium, calcium, and magnesium (Fu et al. 2024; Masso et al. 2017). Additionally, high levels of chemical fertilizers can disrupt soil microbial communities, which are essential for nutrient cycling and organic matter decomposition (Weil 2017). This disruption can result in reduced microbial activity, leading to decreased soil fertility and poor soil structure (Liu et al. 2022a).

Continuous and increased use of fertilizers and other intensification methods to increase crop yields can lead to undesirable outcomes. Such outcomes can include decreased yields (as nutrients become unavailable), soil degradation, nutrient leaching and eutrophication that result in environmental damage, increased costs of production and increased greenhouse gas emissions (especially N_2O) from farming (Yadav et al. 2020; Sainju et al. 2019; Kunhikrishnan et al. 2016; Fujii et al. 2012; Peters et al. 2011). In particular, one of the downsides of long-term inappropriate use of nitrogen fertilizers is soil acidification (Schroder et al. 2011; Kariuki et al. 2007; Garvin and Carver 2003). This is due to the fact that nitrogen fertilizers usually contain ammonium ($NH4^+$) or nitrate ($NO3^-$) ions, which are nitrogen forms easily absorbed by plants. However, fertilization with ammoniacal-nitrogen sources significantly increases both active and potential soil acidity, impacting nutrient availability and plant growth in the soil-plant system (Gidda et al. 2015). Different nitrogen fertilizers have varying effects on soil pH, such as decreasing soil pH when applied as ammonium sulfate and increasing soil pH when applied as sodium nitrate (as sodium nitrate fertilizers can lead to an increase in soil pH if the soil is in a highly acidic state) (Johnston et al. 1986). These soil acidity challenges can be mitigated to some extent by using liming agents. Liming helps decrease soil acidity by applying calcium carbonate ($CaCO_3$) and optimizes soil properties by neutralizing hydrogen ions in the soil solution, leading to an increase in soil pH (Gasanova et al. 2020).

Climate change is the other component of the equation, exerting a significant impact on crop suitability and production. Studies (Zeleke et al. 2017; Araya and Stroosnijder 2011; Segele and Lamb 2005) indicated that seasonal and interannual rainfall variability are a leading cause of crop failure and drought in most parts of Ethiopia. Rainfall variability, as result of climate change, has direct implications for agricultural productivity and food security. In regions dependent on rainfed agriculture, inconsistent rainfall can lead to crop failures and reduced yields (Araya and Stroosnijder 2011). This is particularly evident in arid and semi-arid regions where variability in precipitation can exacerbate drought conditions, leading to prolonged periods of water scarcity and reduced agricultural output (Narimisa & Narimisa, 2018). As the impacts of climate change become more apparent, some regions in Ethiopia that were previously unsuitable for certain crops are now becoming more suitable, while other regions that were once ideal for those same crops are now becoming less ideal (Evangelista et al. 2013). Several studies have assessed suitability changes at the watershed (Girmay et al. 2018; Yohannes and Soromessa 2018; G.Selassie et al. 2014) and country (Evangelista et al. 2013) scales, while other studies have investigated the dynamics of soil acidity in Ethiopia, considering the causes, extent of the problem, effects on crop production and potential methods for amelioration (Gurmessa 2021; Golla 2019; Takala 2019; Abate et al. 2017). These studies stress the significance of climate factors and of soil quality in determining crop yields and production potential in Ethiopia. To our knowledge no studies have assessed the intersection between these two important factors under current or projected climatic conditions as they have to date been considered separately.

There is a need to juxtapose the projected changes in climatic conditions and soil acidity changes on agricultural potential to ensure that agricultural development in Ethiopia is sustainable, productive, profitable and remains within planetary boundaries. The aim of this study is to assess the impact of increases in soil acidity on crop suitability in a changing climate in Ethiopia. Specifically, the objectives are to (i) determine the suitability extent of four key food crops in Ethiopia, (ii) model the impacts of climate change on these food crops (iii) assess the effects of soil acidification on changes in crop suitability for each food crop under climate change. Our findings provide an improved understanding of the interaction between climate change and acidification impacts, with a focus on soil pH. Such information is required by policy makers, extension systems and farmers to design and implement more robust resilience pathways that enhance crop yields and quality without degrading soil resources. Our study also provides information on potential climate change adaptation challenges, to avoid potential for maladaptation.

3.2 Data sources and location of the study

3.2.1 Study area and topography

Located in East Africa, Ethiopia has a diverse topography that spans from 116 meters below sea level to towering mountains reaching 4600 meters high (Jimma et al. 2023; Zeleke et al. 2013b; Diro et al. 2009b), as shown in Figure 3.1. The country's northern, central, part of eastern, and western regions are classified as highland plateaus, while the eastern, southern, and western areas are predominantly lowlands (Jimma et al. 2023). The annual rainfall amounts vary significantly across the country, ranging from 2400 mm in the southwest to 500 mm in the northeast. The mean temperature fluctuates from 5°C in the highlands to about 40°C in the lowlands (Gebrechorkos et al. 2023). Agriculture, especially crop production, is crucial in Ethiopia as it provides food for the population and contributes approximately 40% of the gross domestic product (GDP). Moreover, an estimated 75% of the country's workforce is employed in the agricultural sector (Yigezu Wendimu 2021).

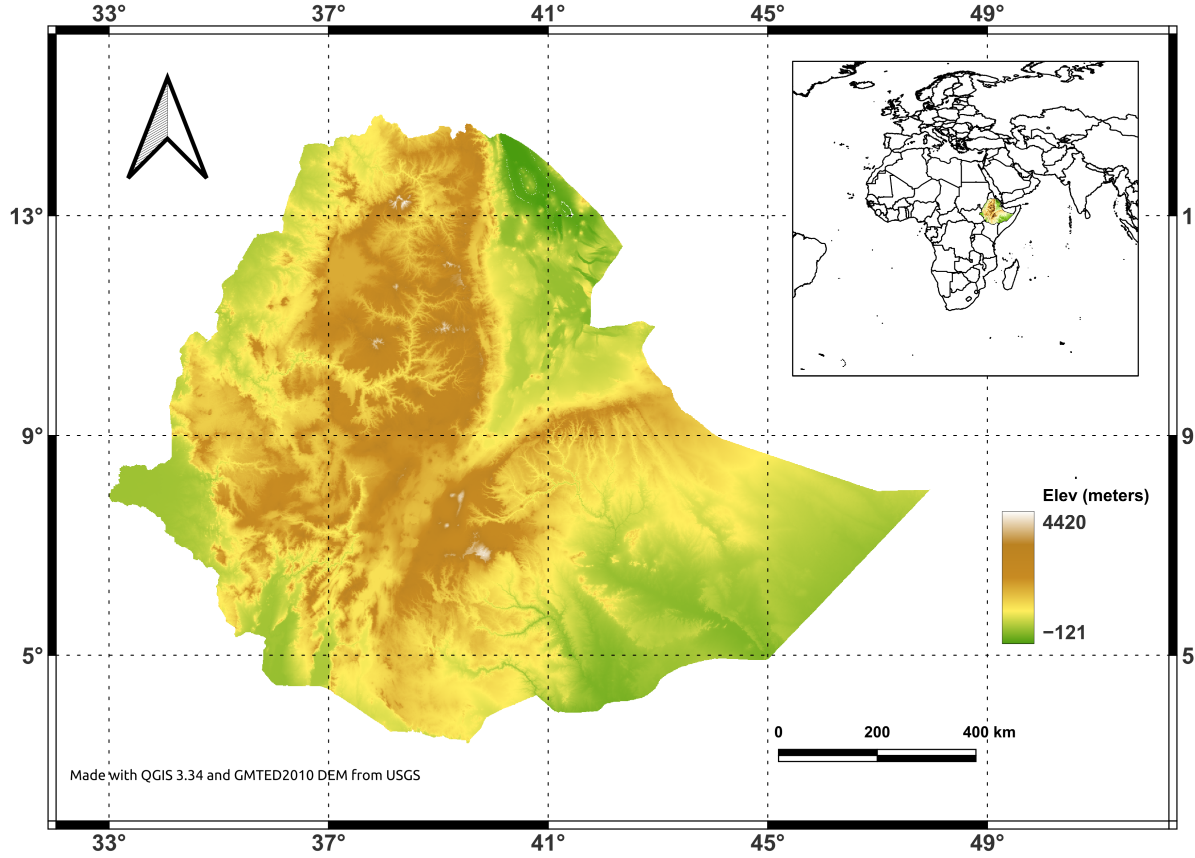

Figure 3.1.: Location of the study area and topographic features of the country.

3.2.2 Climate datasets

The study used climatic variables of rainfall and temperature from the WorldClim database (WordlClim 2023). This database provides historical and future (based on CMIP6 Shared Socioeconomic Pathways (SSPs) projections) monthly data of rainfall, temperature, and other variables at high spatial resolutions (30 seconds, 2.5 minutes, 5 minutes, and 10 minutes). The dataset was calibrated, assuming high spatial autocorrelation, and was generated by computing the absolute or relative difference between global climate model (GCM) outputs for baseline periods (1960-1990) and target years (e.g., 2041-2060), with global cross-validation correlations of 0.99 for temperature and 0.86 for rainfall (Fick and Hijmans 2017). Thus, we specifically employed the WorldClim version 2.1 dataset at a spatial resolution of 2.5 minutes. We opted to use the 2.5 minutes spatial because of the large scale nature of the study that covers the whole country. The model was set up for historical (1970-2000) and mid-century (2041-2060) periods under the SSP370 scenarios. The mid-century was selected to align the results with the Nationally Determined Contributions of the Paris Agreement that set 2050 as the target year for climate outcomes. We selected the SSP370 as it is now the most realistic pathway considering current greenhouse gases (GHG) emission trends and policy directions. It represents a “Rocky Road” with regional rivalry and high challenges to mitigation and adaptation as countries focus on achieving energy and food security goals within their own regions at the expense of broader-based development. This scenario estimates that global warming will reach 2.1°C by the 2050s (Brief 2018). We selected seven general circulation models under the scenario (Table 3.1) for this analysis based on their known performances in East Africa. These models are CMCC-ESM2, GFDL-ESM4, INM-CM5-0, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL.

Table 3.1.: Climate models outputs employed for future climate analysis.

Climate models	**Model descriptions**	**Refs.**
GFDL-ESM4	Geophysical-Fluid-Dynamics-Laboratory-Earth-System-Model	John et al. (2018)
MPI-ESM1-2-HR	Max Planck Institute for Meteorology, Earth System Model	Schupfner et al. (2019)
MRI-ESM2-0	Meteorological Research Institute (MRI) of Japan, Earth System Model	Yukimoto et al. (2019)
UKESM1-0-LL	UK Earth System Model	Good et al. (2019)
INM-CM5-0	Institute for Numerical Mathematics, Climate Model	Volodin et al. (2019)

Climate models	Model descriptions	Refs.
CMCC-ESM2	Centro Euro-Mediterraneo sui Cambiamenti Climatici, Earth System Model	Lovato et al. (2021)
IPSL-CM6A-LR	Institut Pierre-Simon Laplace, Climate Model	Boucher et al. (2019)

3.2.3 Soil data

The topsoil pH data for Ethiopia was obtained from the ISRIC-World Soil Information databases, recognized for providing an extensive and consistent large-scale soil information resource derived from observed soil profiles (Hengl et al. 2015). The operational framework of ISRIC encourages inclusive and collaborative efforts for assembling, collating, and generating global soil information applicable across diverse fields, with a specific emphasis on crop modeling in agriculture (Lagacherie et al. 2022; Clark et al. 2020; Folberth et al. 2019). This dataset spans the African continent with a spatial resolution of 250m, encompassing measurements at six standard soil depths: 0-5cm, 5-15cm, 15-30cm, 30-60cm, 60-100cm, and 100-200cm. In this study, we employed the topsoil layer (0-5cm) pH level.

3.2.4 Crop observation datasets

The Global Biodiversity Information Facility (GBIF) database serves as an expansive taxonomic repository and information system, dedicated to documenting all known species and facilitating global access to vital biological data. Supported by governmental funding worldwide, GBIF operates as an international network and data infrastructure, striving to provide open access to comprehensive life on Earth data for individuals worldwide (GBIF 2023). Offering detailed information on utilized protocols and species abundance across the planet, GBIF stands as a well-established database within the scientific community. The dataset provides geographic information regarding the general locality of multiple individuals of the same species. In this study, we leverage GBIF as an observational dataset to validate occurrences of four pivotal food crops—teff (*Eragrostis tef*), maize (*Zea mays L.*), barley (*Hordeum vulgare L.*), and common wheat (*Triticum aestivum L.*)—within Ethiopia.

3.2.5 Crop environmental requirements data

In this study, we utilized the Food and Agriculture Organization of the United Nations (FAO) Ecological Crop Screening System (ECOCROP) database to gather information on the environmental requirements of key food crops in Ethiopia, including minimum and maximum values for temperature, annual precipitation, and soil pH. Developed by the FAO's Land and Water Division in the 1990s, ECOCROP serves as a valuable tool for identifying plant species suitable for specific environments and purposes, contributing to the concept of Land Use Planning (LUP). This database contains comprehensive data on the characteristics of over 2000 plant species and their environmental requirements, enabling the determination of crop suitability for designated environments (FAO 2023). Specifically, we retrieved the environmental requirements for teff (*Eragrostis tef*), maize (*Zea mays L.*), barley (*Hordeum vulgare L.*), and common wheat (*Triticum aestivum L.*), and assessed their suitability for cultivation in Ethiopia.

3.3 Methods

3.3.1 Crop suitability modeling

We used the EcoCrop model for assessing current and projected crop suitability in Ethiopia. This model was selected because the EcoCrop crop suitability model is effective for evaluating the suitability of diverse crops, considering the prevailing climatic conditions and soil pH levels. EcoCrop is a simplified tool that assesses the crop-specific cropland suitability of various crops by analyzing their ideal ranges of rainfall and temperature during the growing season. It uses the Sprengel-Liebig Law of the minimum to evaluate the most limiting factor for environmental variable responses (Ploeg et al. 1999). EcoCrop is a rule-based model that estimates absolute environmental suitability for each crop type from a combination of dynamic weather variables and static soil predictors. For all variables, default parameters indicate the extreme minimum and maximum value beyond which the crop cannot grow (suitability is zero) and a minimum and maximum optimal value within which suitability is one (Manners et al. 2021; Ramirez-Villegas et al. 2013). In the midst of extreme and optimal values, suitability is determined with linear interpolation between zero and one. It therefore shows where a species can be grown without major environmental constraints. EcoCrop model requires few crop-specific parameters to run, can be setup for many crops, including those where less detailed ecophysiological information is available to run process-based modelling (Vermeulen et al. 2013). It also provides map outputs for spatialized impact and targeting and accommodates scenario-based simulation iterations to visualize how agricultural system work and identify important drivers of change. The model also requires relatively fewer input data to produce reliable results that match with those models with more sophisticated inputs. In addition, EcoCrop considers the important genotypic variation related to crop growth duration, and thermal and water-related tolerance limits without providing the detailed variety-level information (Rippke et al. 2016). Table 3.2 shows the crop types, species, area harvested and yield of four key food crops commonly grown in Ethiopia that we have conducted a suitability analysis.

Table 3.2.: Key food crop types and species considered in this study.

Crops	Scientific name	Area harvested (000 ha)	Yield (t/ha)
Teff	Eragrostis tef (Zucc.) Trot	3,017	1.71
Maize	Zea mays L. s. mays	2,530	4.24
Barley	Hordeum vulgare L.	960	2.45
Wheat	Triticum aestivum L.	1950	2.67

Source: Central Statistics Agency, 2029.

3.3.2 Model calibration and validation

We evaluated the model for accuracy by comparing the suitability with reference data. We developed and implemented a comprehensive evaluation of the produced suitability maps as this is important for building confidence in the produced crop suitability maps for climate change and agriculture policy applications. The reference data used for the evaluation was the Global Biodiversity Information Facility (GBIF) data (GBIF 2023). To evaluate our model, we extracted the reported 'occurrence' of each crop from 2000 to align with the baseline period, then compared it to the modeled suitable area for that crop. We computed the detection accuracy by evaluating the ratio of GBIF points located within the suitable area to the total number of GBIF points. Subsequently, we converted the absolute suitability values into binary classifications through a suitability analysis based on the model's performance. To determine the threshold values, we considered geographic locations with observations of a particular crop species exceeding 70% (i.e, model accuracy greater than 0.7) are suitable for that crop.

3.3.3 Assessing impacts of soil acidification on crop suitability under climate change

For EcoCrop input, we used climatological data for the dynamic environmental variables (i.e., rainfall and temperature) for twelve time steps corresponding to the 12 months of a year and static soil pH levels to determine a suitability index ranging from zero to one. To emulate the impacts of acidification on crop suitability we run the suitability model with current soil pH values (baseline, bl) and then we acidified the soil by reducing the soil pH by 0.5 (bl-0.5), 1.0 (bl-1.0) and 1.5 (bl-1.5) while the climatic data remained the same. These values were selected because they represent the observed ranges of soil acidification over the past decades from natural processes and intensive inorganic fertilizers usage (Yadav et al. 2020; Golla 2019; Sainju et al. 2019). By combining the rainfall and temperature data with each soil acidity level, we conducted a crop suitability analysis for future climate scenarios (i.e., 2050). It should be noted that the effects of climate change and soil acidity on crop suitability have been considered independently, without examining how one variable affects the other (e.g., the impact of climate change on soil acidity).

3.4 Results

3.4.1 Climate, soil pH, and crop suitability in Ethiopia under current climate

Figure 3.2 presents an overview of the baseline (1970-2000) rainfall and temperature climatology, and soil pH distribution across Ethiopia. There is a clear contrast that rainfall amount is high in the western mountainous parts, whereas it is low in the lowland eastern regions (Figure 3.2(a)). The temperature is also lower in the central highlands; conversely, it is higher in the country's eastern areas and along the western boundaries (Figure 3.2(b)). There are distinct soil pH levels in the country's western ($pH<6$), central ($6<pH<7.5$), and eastern ($pH>7.5$) regions (Figure 3.2(c)).

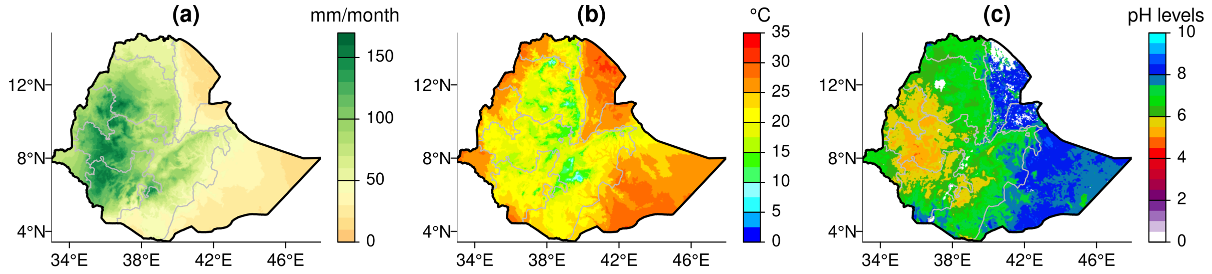

Figure 3.2.: Baseline (a) Rainfall and (b) Temperature climatology (1970-2000), and (c) Current soil pH distribution across Ethiopia.

Table 3.3 presents the environmental and soil pH requirements based on FAO's crop ecological requirements database, ranging from minimum to upper optimum values for the four crops considered in this study (FAO 2023).

Table 3.3.: Environmental and soil pH requirements for the four crops (i.e., teff, maize, barley, and wheat) considered in this study.

Crops	Temperature range (°C)	Precipitation range (mm/month)	pH ranges
Teff	2-28	65-389	5.0-6.5
Maize	10-23	49-180	4.5-7.0
Barley	2-20	31-200	6.0-7.5
Wheat	5-23	45-174	5.5-7.0

Source: FAO's ecocrop database, 2023.

Using EcoCrop we determined the suitability values of each crop in Ethiopia. Figure 3.3 shows the current suitability of teff, maize, barley, and wheat based on the environmental and soil pH level requirements specified in Table 3.3. The degree of crop suitability has been delineated by the range of values between zero and one. Our results indicate that teff, maize, barley, and wheat are all suitable crops for specific regions of the country. Teff, in particular, thrives in areas with high rainfall amounts (90-170 mm/month), moderate temperatures (12.5-22.5°C), and a soil pH level between 5.0 and 7.0. Similarly, barley and wheat are grown in high rainfall and modest temperature regions, although they tend to prefer neutral pH levels along the central and eastern highlands. Maize is a bit more flexible regarding soil acidity levels and is commonly grown in the southwestern parts of the country and along the East African rift valley ridges where soil pH levels are between 4.5 and 7.0.

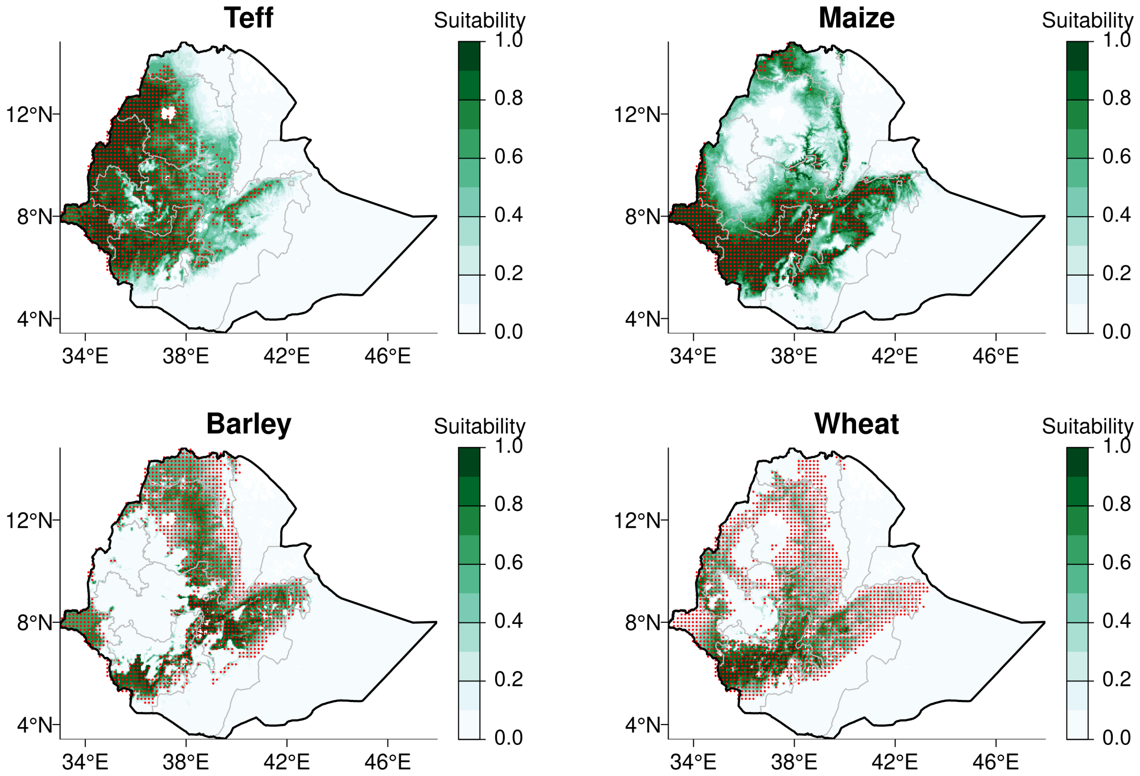

Figure 3.3.: Current crop suitability maps for teff, maize, barley, and wheat across Ethiopia. Red hatch's indicated GBIF observed data points.

3.4.2 Projected climate and crop suitability in Ethiopia

The future climate change expected by the 2050s is projected lead to a rise in rainfall of up to 18 mm/month in the central north and eastern highlands of Ethiopia (Figure 3.4). However, no significant rainfall changes are projected for the south-eastern and north-eastern parts of the country, which are known dry areas (Figure 3.4(a)). The temperature is also projected to increase throughout the country with higher warming rates up to 2.1°C in the northern, south-central, and western regions by 2050 (Figure 3.4(b)).

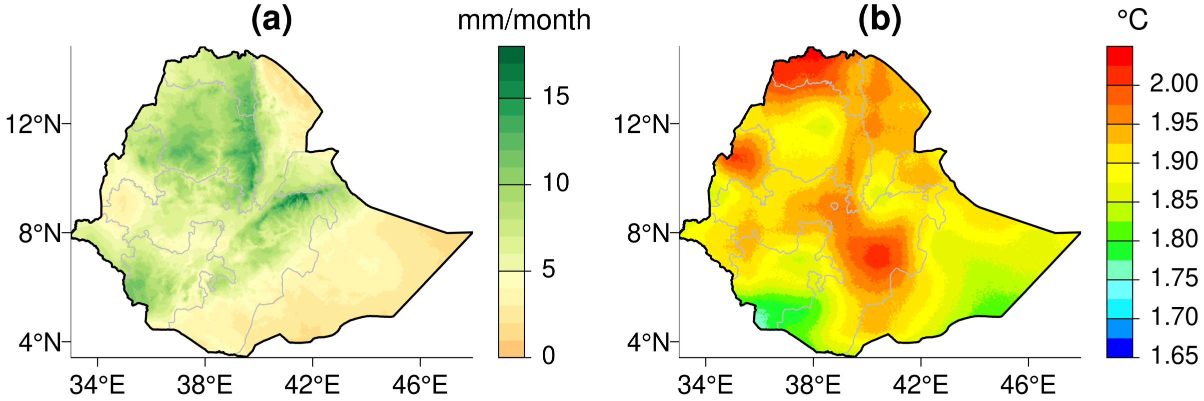

Figure 3.4.: Rainfall (a) and temperature (b) change by the middle of the 21st century (2041-2060) in Ethiopia with respect to the historical period (1970-2000).

Figure 3.5 shows the suitability difference between future (2050) and current crop suitable land areas for the four different crops in Ethiopia, keeping the soil pH levels the same as the current distribution. Based on the projected 2050 climate data, the results indicate that teff, barley, and wheat will be viable in land areas along the rift valley ridges as these regions will become more favorable due to enhanced rainfall and a moderate rise in temperature in the region. However, maize will likely no longer be a suitable crop in the northern and central highlands.

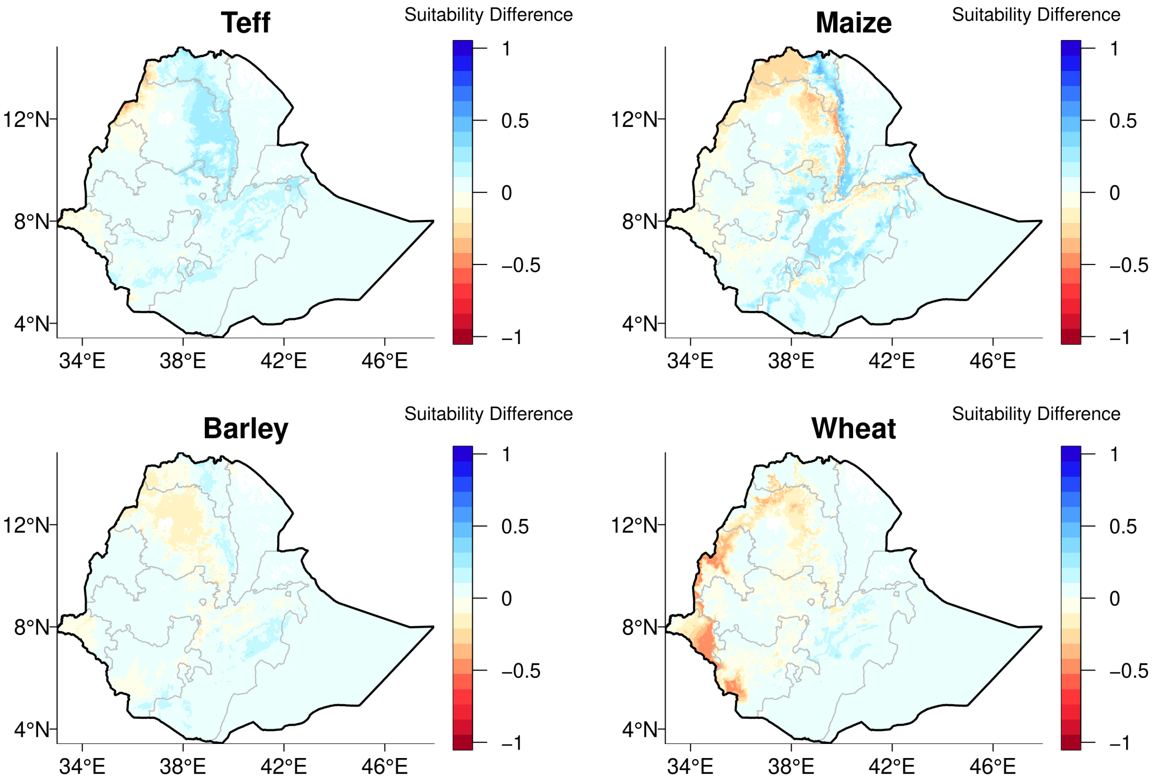

Figure 3.5.: Change in future crop suitability by 2050s with respect to the current suitability using ssp370 future climate scenario for rainfall and temperature while the soil pH levels are the same as the current distribution.

Additionally, the changes in the suitability due to climate change is shown by the area density plots in Figure 3.6. Highly suitable areas (>0.8) for teff will increase compared to the current climatic conditions but these will decrease for barley and wheat, with no changes for maize. Our results show that no major shifts are projected in already marginal areas where suitability is below 0.25 between the current and the future climatic conditions, but shifts will happen in areas that have moderate (between 0.5 and 0.75) suitability. The density distribution for maize is quite distinct with most regions being either highly suitable or unsuitable. Both the highly suitable areas (>0.75) as well as the moderately and marginally suitable areas (>0.5) will likely increase for maize under future climate change (Figure 3.6).

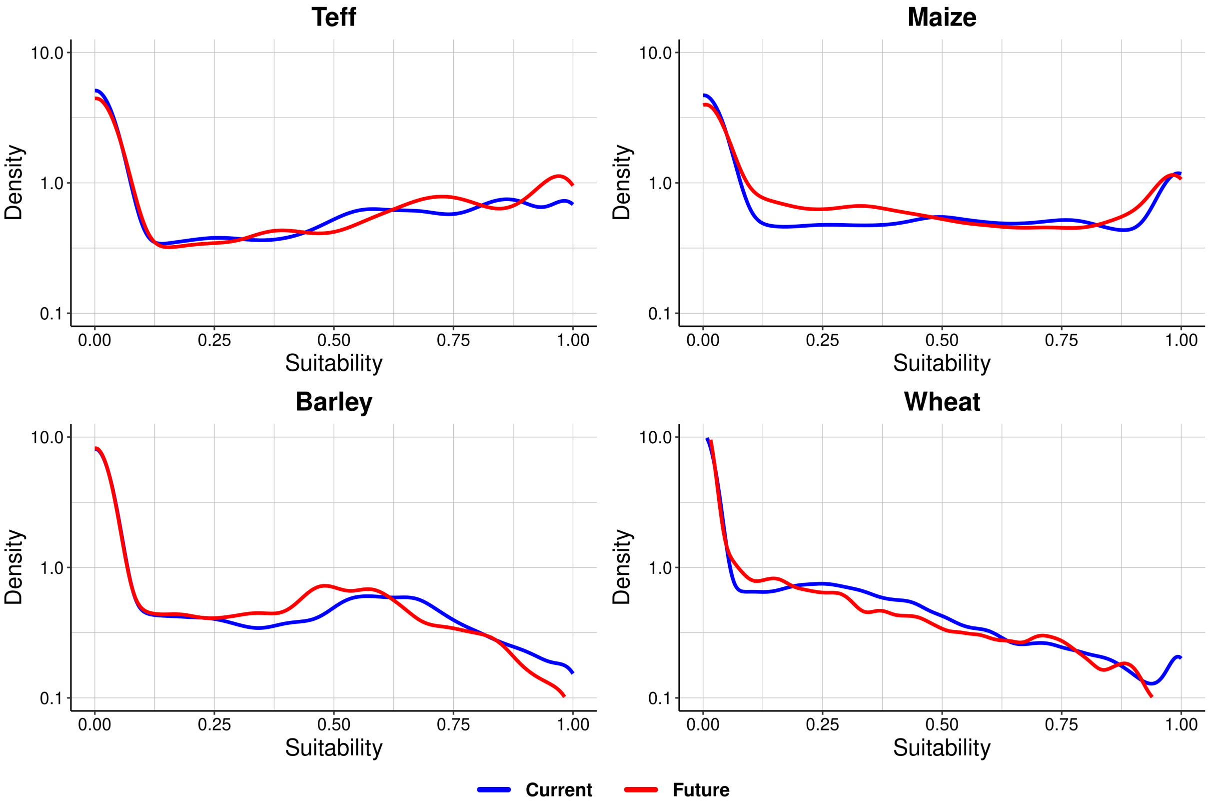

Figure 3.6.: Density plots showing the changes in the distribution of the suitability values for teff, maize, barley and wheat in Ethiopia between the current and projected climate. When the blue line is above the red line it shows that the area with that suitability is higher under current conditions and vice versa.

3.4.3 Effect of different levels of soil acidification on changes in crop suitability under climate change

As future soil acidity levels are expected to increase due to natural processes and aggressive inorganic fertilizer usage throughout the country (Alemu et al. 2022), we simulate the potential impacts on crop suitability. According to Figure 3.7, by the 2050s, there will be changes in crop suitability as the soil pH level decreases by 0.5 from its current levels. Teff is expected to lose a significant size of suitable land in the western-central regions. Similarly, barley and wheat will become less viable in most areas in the west. On the other hand, maize has gained more favorable land areas along the central-eastern highlands and southwestern tips (Figure 3.7). The unsuitability for teff, barely, and wheat is because the soil acidity level has dropped below the lower limit of these crops in most parts of the western regions (Figure 3.7). However, maize's suitability in the country's western areas will not be much affected due to its lower pH limit, which can be as low as 4.5. Besides, maize is gaining more territories over the central-eastern region due to the decrease in pH level that renders the soil pH level within the requirements for maize growth.

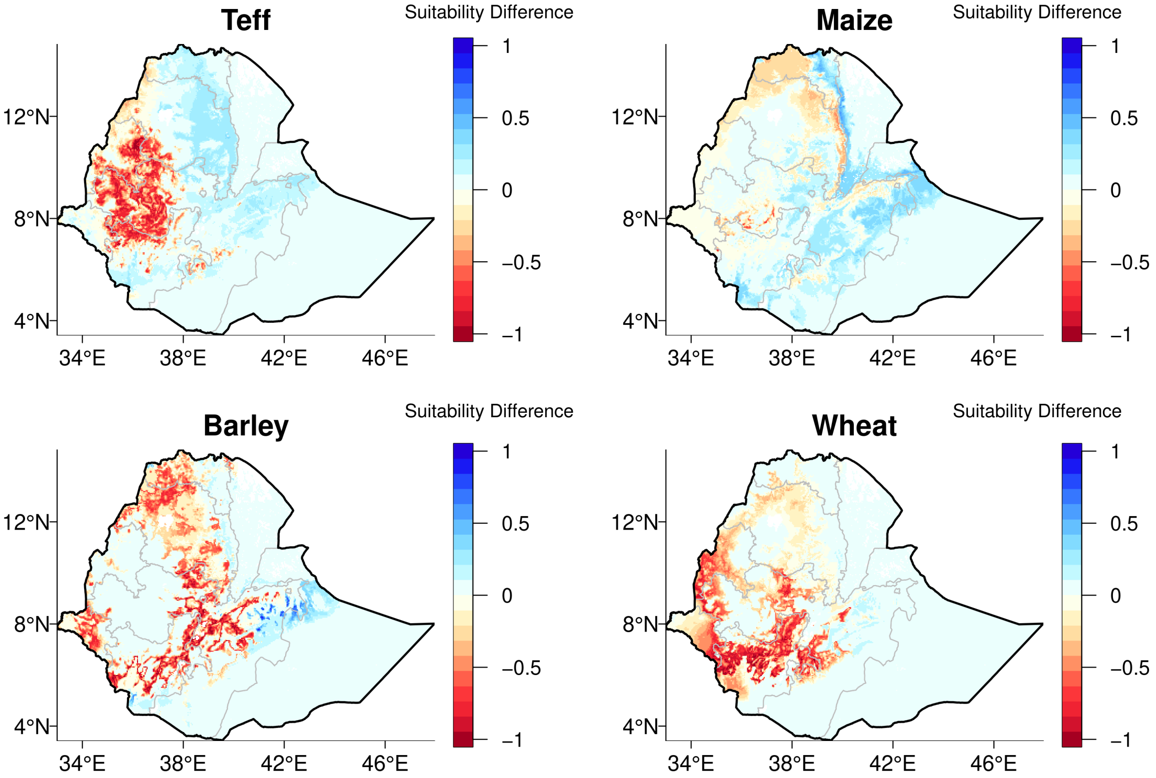

Figure 3.7.: Change in future crop suitability by 2050s with respect to the current suitability using ssp370 future climate scenario for rainfall and temperature if the soil pH levels decrease by 0.5 from the current distribution.

As shown in Figure 3.8 (soil pH levels decrease by 1.0) and Figure 3.9 (soil pH levels decrease by 1.5), it is evident that further increase in soil acidity has a more negative impact on crops. The decrease in soil pH leaves most parts of the western region of Ethiopia acidic and unsuitable for all crops. Thus, there is a trend of crop suitability migrating towards the eastern highlands due to the decrease in soil pH level and a change in soil properties from basic pH to neutral pH levels. It has also been noted that soil pH levels in the northeastern and southeastern regions decline to neutral pH levels. However, the environmental variables (i.e., rainfall and temperature) required for these crop's growth do not meet the minimum requirements as indicated in Table 3.3. Therefore, there is little or no enhancement in crop suitability in these regions.

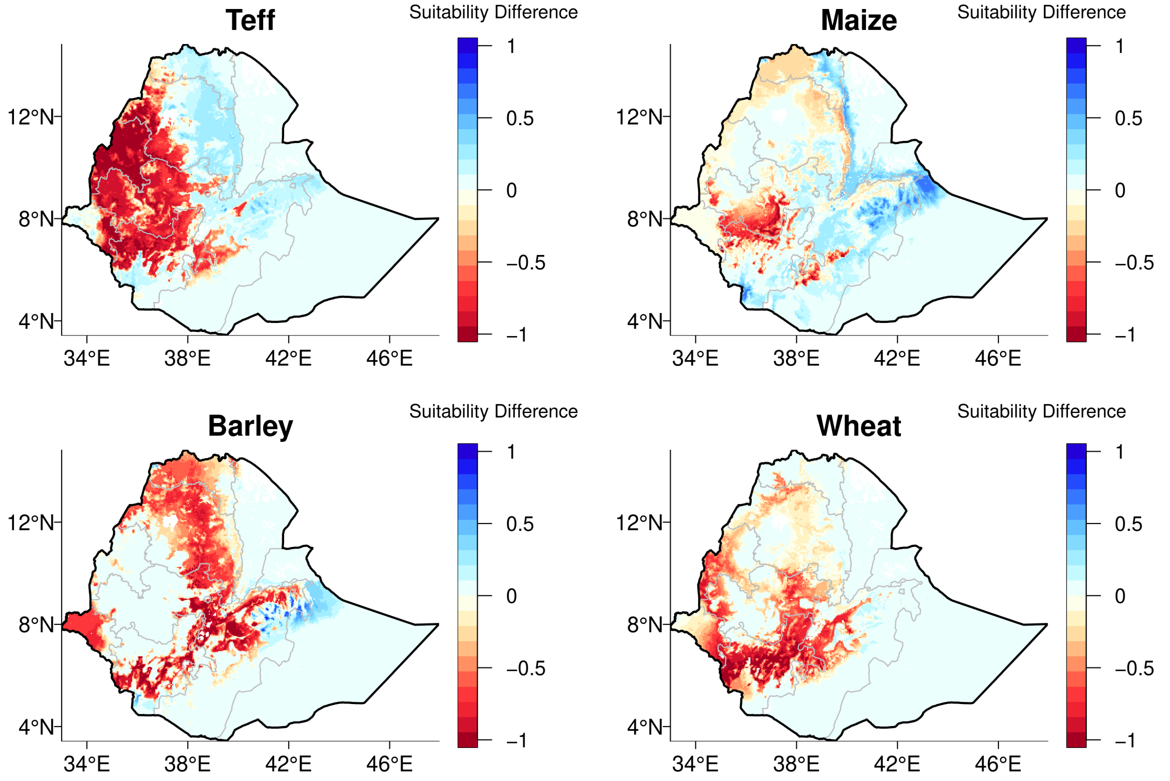

Figure 3.8.: The same as Figure 3.7 but the soil pH levels decrease by 1.0 from the current distribution.

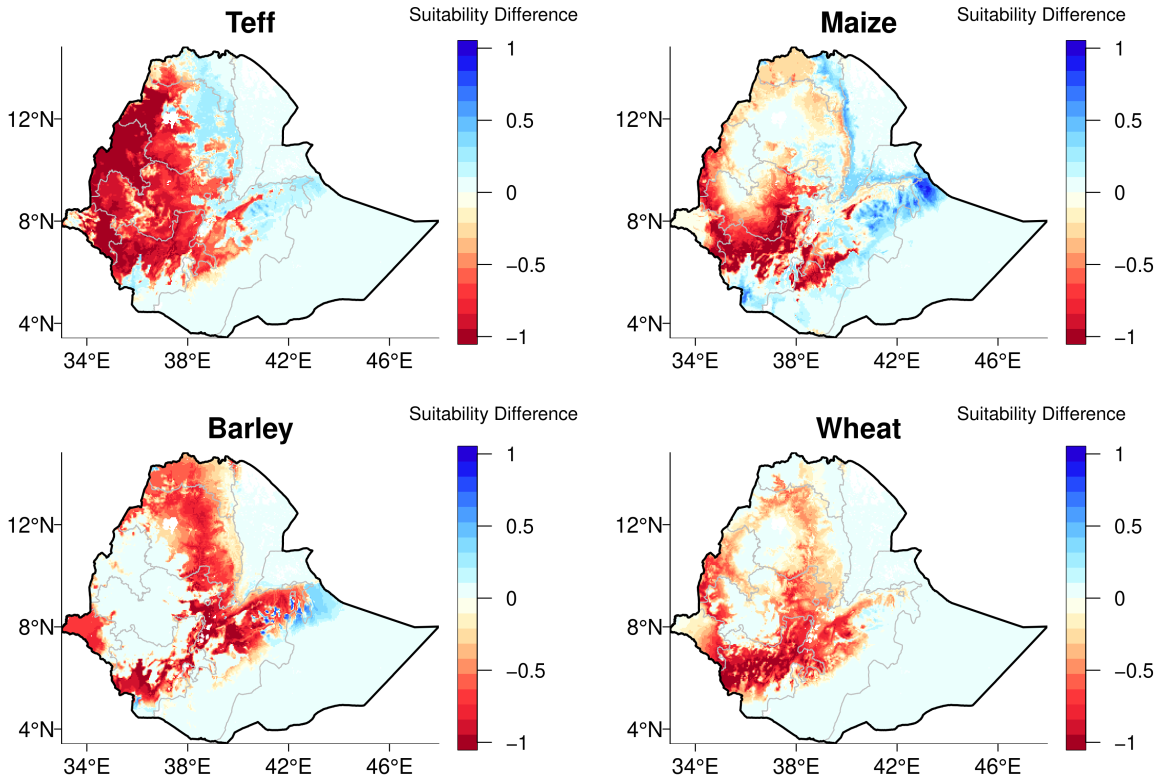

Figure 3.9.: The same as Figure 3.7 but the soil pH levels decrease by 1.5 from the current distribution.

Compared to the historical (1970-2000) period, due to a changing climate, we project increases by 5.1%, 0.08%, 1.8%, and 0.4% for teff, maize, barley, and wheat, respectively, in suitability by 2050 (Figure 3.10, dark blue bar). While soil pH distribution is the same as the current state, climate change creates more favorable areas for all crops along the central and eastern highlands. The increase in suitable land arises because of an increase in rainfall and temperature over the highlands which meets the basic environmental requirements of the crops. However, a slight increase in soil acidity by 0.5 (Figure 3.10, light blue bar) leads to suitable areas for teff, barley, and wheat dropping by -3.1%, -9.0%, and -11.7%, respectively. In contrast, suitable land for maize increases by 2.03% is due to soil pH level changes from basic to neutral pH levels in the central-eastern highlands and gain of new favorable land areas. Comparatively, maize suitability remains the same in the western regions due to its soil acidity tolerance up to 4.5 pH level. Furthermore, teff, maize, barley, and wheat lose -17.8%, -1.6%, -24.1%, and -22.6% of suitable area, respectively, by decreases in soil pH level by 1.0 (i.e., light red bar in Figure 3.10).

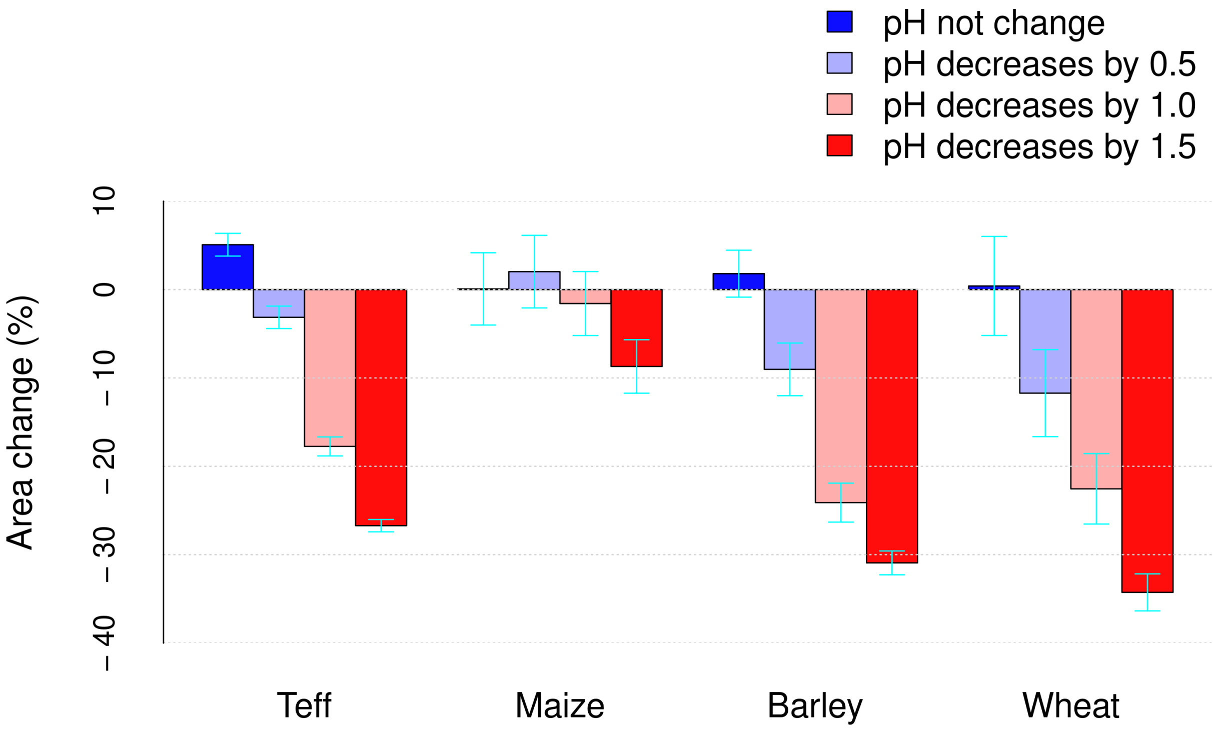

Figure 3.10.: Change in crop suitable area across the country under the future climate (2050) and soil pH level changes.

The worst-case scenario of declining soil pH level by 1.5 (i.e., red color bar in Figure 3.10): decreases teff, maize, barley, and wheat suitable land areas by -26.7%, -8.7%, -30.9%, and -34.3%, respectively. Therefore, the increase in soil acidity is likely to leave the western and most regions of the country unsuitable for all crops once the soil pH level crosses the lower threshold limit of all crops.

3.5 Discussion

In this study, we investigated the combined effect of soil acidification and future climate change on crop suitability in Ethiopia. Our approach utilized a crop suitability model to assess the impacts of climate change on four key food crops (with and without adjusted soil pH parameters) under current and projected 2050 climatic conditions for Ethiopia. We selected Ethiopia as a case study because soil acidification is recognized as a prevailing issue in the country's most cultivable lands (Alemu et al. 2022; Desta et al. 2021; Abate et al. 2017; Elias 2017; Abate et al. 2015; Chimdi et al. 2012b). Our study (i) provides a spatially explicit assessment of climate change impacts on four key food crops in Ethiopia; (ii) identifies where and for which crops soil acidification have impacts on crop suitability, and; (iii) provides an integrated study of the impacts of soil acidification and climate change impacts on cropping systems.

The climate of Ethiopia is spatially variable as shown by the rainfall and temperature climatologies, with significant influence on crop potential in the country. Considerable areas in the country are dry with rainfall of less than 100 mm per month. These areas correspond with warm areas where temperatures are above 22.5°C. This interaction between temperature and rainfall is important as it influences potential evapotranspiration which affects the climatic water balance that in turn determines the length of the growing period, crop water requirements, and crop types to be grown (Dile et al. 2020; Asmamaw 2017; Merasha 1999). In a country where less than 5% of the total cultivated land is irrigated (Moges and Bhat 2020), any spatial and temporal changes to this balance between temperature and rainfall is likely to have significant impacts on agricultural production. In this study we confirm the link between rainfall and soil pH in Ethiopia where soils in the high rainfall areas are acidic, while those in the low rainfall areas tend to be alkaline (Desta et al. 2021; Golla 2019). The highly acidic soils are the Nitisols, Alisols, and Fluvisols, which encompass some of the most intensive crop production areas in Ethiopia (Agegnehu et al. 2019).

We also report a differential response to soil pH among the four crops in terms of their suitability in Ethiopia. Teff is distributed across highly acidic areas, while maize, barley, and wheat are less commonly found in acidic soils. The finding that maize is not suitable in acidic areas is not surprising; as a crop it is known to prefer soils with a near-neutral pH. Indeed, grain yield reductions of between 3 and 71% have been attributed to acidic soils in maize field trials (Tandzi et al. 2015; Hayati et al. 2014). The variation in yield reduction under low soil pH is explained by the level of acidity in the soil, the agro-climatic conditions of the environment, and the genotypes of maize varieties. It was expected that common wheat would be similarly or more acidic soil sensitive than maize (Page et al. 2021). More studies on the genotype × environment interactions in relation to soil acidity responses of both maize and common wheat genotypes in Ethiopia need to be performed.

Our assessment of changes in climate variables shows an increase in both temperature and rainfall by 2050 in line with many reported projections. While the increases in temperature are apparent due to emissions driven global warming, the increase in rainfall for Ethiopia and the whole East African region is surprising, especially when it is not aligned to observed trends (the East Africa Paradox). Similar increases in precipitation have been reported in other studies (Moges and Bhat 2020; Abera et al. 2018; Fentaw et al. 2018). An evaluation by Gleixner et al. (2020) of ERA5 data shows positive changes over East Africa in rainfall and concludes that representation of the cycle of precipitation is substantially improved in most recent general circulation model. It is in this context of increasing rainfall and temperature where crop suitability models are required to investigate if, where, and by how much, suitability thresholds for crop growth and performance are crossed under climate change.

Our findings suggest no major changes in crop suitability for maize, barley, and wheat in Ethiopia by mid-century using current soil pH values, while climate change will benefit teff suitability. Positive crop production outcomes under climate change have previously been reported for Ethiopia, influenced by the projected increases in rainfall (Chemura et al. 2021; Thomas et al. 2019; Alemayehu and Bewket 2016; Araya et al. 2015). The findings from this study are noteworthy in two ways. Firstly, the country can position itself to become a regional food basket, leveraging the increasingly favorable climatic conditions for major crop production. This is possible through building capacity of farmers in the remaining and newly suitable areas through supporting agricultural inputs and extension services, while establishing value chains and markets to harness the outputs. This is an important finding because much of current research on climate change reports negative impacts, without recommendations on how to deal with projected positive climate change impacts such as those reported in our study. Secondly, while the overall results show a positive or no impact of climate change on crop suitability of the four crops, spatially explicit models such as used in this study show some areas as having negative impacts. Therefore, "broad brush" adaptation planning should not be used as a blunt instrument based on national trends, but should be targeted towards where adaptation interventions are most needed at the local level. Thus, locations with projected negative impacts on crop suitability (especially for maize and teff) are revealed in our results where adaptation planning should focus to strengthen resilience. Targeting of adaptation interventions based on scientific evidence is important for generating expected outcomes, avoids maladaptation and ensures the best investment of scarce resources to address the climate change. For example, we suggest agricultural systems transformation where farmers begin to grow the most suitable crops in their areas to meet their food requirements and/or for markets, with possible transport and storage systems enabling exchange and trade in agricultural commodities between regions made possible or easier or less costly. Development and distribution of crop varieties that are more tolerant to the climatic and soil conditions will also help in ensuring sustaining agricultural production.

Our most significant finding is that neglecting to address soil pH will lead to more pronounced climate change impacts on all crops in Ethiopia, potentially transforming projected positive impacts into negative ones, especially for teff, barley, and wheat. Certainly, this impact increases with the severity of the soil acidification and there is a need to design and implementing intervention measures to avoid this outcome. Indeed, it has been demonstrated that it is not possible to supply food, feed, fiber, and fuel to support a growing world population in a changing climate without taking care of soil health (Weyers and Gramig 2017). In support of this view, Lehmann et al. (2020) indicated that it is important for agricultural intensification and land management efforts to focus on soil health management to realize multiple benefits at multiple scales for crop production, ranging from water use and quality, human health, animal health, climate, and biodiversity. Our study demonstrates a crucial interactive link between climate and soil pH, influencing crop potential in tropical regions. Hence, it is imperative to include soil health into the ongoing discourse on the impacts of climate change on crops. Soil health management strategies such as the use of organic amendments, conservation farming methods and others should be considered as integral aspects in agricultural resilience building.

We applied a crop suitability model to investigate the impact of soil acidity on crop suitability under climate change in Ethiopia. While our results are robust based on the data and model used, users of such results should consider some caveats associated with our presented approach. Our future projections of crop suitability are produced by combining a mechanistic understanding of crop requirements with climate and soil data. However, other factors such as agronomic practices (e.g. precision agriculture, alternative N sources e.g., legumes) are not explicitly captured, and yet they may be important at localized levels of farms and fields. In our study, we provide wide-scale results for agricultural planning purposes, which would need to be further downscaled for each localized area in each grid pixel. Our modeling also assumes that the established equilibrium between current climate and soil data with crop requirements remains the same under future climate. Yet this may change due to genetic improvement of crops for new environments and biophysical conditions over time. Lastly, since our study is a national-scale study, the area suitability calculations also include other land that may not be available for agricultural production because of the resolution and this should be factored in when using the results for decisions.

3.6 Conclusion

We investigated the combined effect of soil acidity and climate factors in determining the potential of four key food crops (teff, maize, barley, and common wheat) in Ethiopia under changing climate conditions. Our study is important for agricultural resilience building as integrated studies that consider both soil health and climate are rare. We conclude that by 2050, the climate in Ethiopia is projected to undergo shifts characterized by increases in both rainfall and temperatures. The interaction between these climatic changes and shifting soil pH is anticipated to impact crop suitability. Using default soil pH values, we project that there are no significant changes in the suitability of maize, barley and wheat, while an increase in the suitability of teff by 2050 will occur due to projected increases in rainfall in the country. However, and perhaps most importantly, the no change and positive changes in suitability under climate change is eroded if the soil acidifies, with the severity of the change corresponding to the magnitude of the change. It is therefore recommended that due consideration be given to soil acidity in planning agricultural adaptation strategies. Intensification measures that lead to increased soil acidity could potentially reverse expected benefits. Future research should consider understanding the relative weights of climate versus soil factors in determining crop suitability to identify what to focus more on in terms of designing and implementing adaptation investments. It will also be important to understand the mechanisms of impact of soil pH on crop suitability by using process-based models that explain the limiting pathways of the variables on crops (as this is not shown with our models). It would also be worthwhile to upscale our study to regional, continental, and global scales to further understand how the interaction between the soil and the climate factors will play out in influencing crop suitability under climate change at larger supra-national scales.

Chapter 4

Spatiotemporal Dynamics of Residual Soil Moisture and its Role in Legume-based Cropping Systems in Ethiopia

Abstract

There is a need to increase agricultural productivity to meet growing food demand in a changing and variable climate without expanding currently planted area. One approach to increase productivity is through double cropping where farmers grow and harvest two crops in a calendar year, instead of one. However, there is limited information on the likelihood of success of double cropping approaches across Ethiopia that can inform planning regarding double cropping systems to enhance food security. This study investigates the spatiotemporal variability of soil moisture during the OND (October-November-December) season in Ethiopia and its implications for crop productivity. Employing advanced statistical techniques, we analyze the spatial and temporal distribution of soil moisture across Ethiopia from 1981 to 2020, focusing on selected crops including legumes such as chickpea (Cicer arietinum), field peas (Pisum sativum), common bean (Phaseolus vulgaris), soybean (Glycine max), and alfalfa (Medicago sativa), to assess the potential of residual moisture to support post-rainy season cropping. Our analysis indicates pronounced gradients in soil moisture levels during the OND season, with eastern regions of Ethiopia exhibiting lower moisture levels (< 60 kg.m^{-2}) compared to western regions (> 150 kg.m^{-2}). The central highlands, which are pivotal for agricultural activities, demonstrate significant variability in soil moisture (standard deviations > 25 kg.m^{-2}), with implications on agricultural sustainability. The northern and southeastern tips of the country are particularly *vulnerable to prolonged drought, where climate change and frequent dry spells exacerbate moisture deficits, consequently impacting crop productivity. Despite these challenges, promising opportunities for future crop production emerge in the southeastern region, which is characterized by increasing moisture levels over time (decadal trend magnitude,* $\tau = 0.59$*). Our results further indicate that residual soil moisture adequately meets and supports crop water requirements in the western, central, and southwestern regions of Ethiopia during the OND. In these regions, residual moisture supports more than 90% of the cropland water requirements of the various crops during the initial and late-season growth stages. However, the crop water requirement coverage drops to less than 20% during the mid-season development stage. Hence we demonstrate the significance of residual soil moisture potential in sustaining crop productivity in Ethiopia, especially in regions with higher moisture levels. By leveraging residual soil moisture as a water resource, combined with implementing supplemental irrigation where necessary, Ethiopian farmers can meet crop water requirements for double cropping, while increasing their resilience to climate variability.*

Keywords: post-rainy season, climate change, agricultural sustainability, soil water, residual moisture, post-harvest cropping, legumes

4.1 Introduction

Understanding the dynamics of soil water availability is central to implementing sustainable agricultural practices, especially in regions prone to seasonal variations in precipitation. Soil water availability refers to the amount of water present in the soil that is accessible to crops for their growth and development (Bhattacharya 2021; Cassel and Nielsen 1986). It is influenced by a range of factors that include soil type, soil texture, soil structure, and organic matter content. Adequate soil water availability is crucial for crop growth, as water is essential for key physiological processes, including nutrient uptake, photosynthesis, and transpiration (Waraich et al. 2011; Vaadia et al. 1961).

Soil moisture (which is correlated with soil water availability) is a fundamental variable crucial for crop productivity worldwide (Gaona et al. 2023). Regardless of the hydrological regime of a particular area, soil moisture is a pivotal component determining crop productivity. However, the process of climate change poses significant challenges to soil moisture regimes, with potential for knock-on effects on crop productivity (Demem 2023; Kotir 2011; Gornall et al. 2010). Agricultural water management technologies and practices are crucial for boosting agricultural output, increasing crop yields, and reducing reliance on unpredictable rainfall systems (Nguru et al. 2023; Srivastav et al. 2021). The dynamics and availability of soil moisture not only influence what crop to grow, but also dictate the timing of cropping patterns, ultimately shaping agricultural strategies and productivity outcomes. Understanding the relationship between climate change and soil moisture dynamics is imperative for devising effective adaptation measures in agriculture (Hatfield et al. 2011). Without comprehensive spatially explicit studies on soil moisture regimes and trends, agricultural transformation efforts such as introduction of a second or third crop in a calendar year remain very limited or constrained by anecdotal evidence.

Across many countries in Africa, including Ethiopia, farmers utilize post-rainy moisture (also known as residual moisture) to cultivate additional crops following the main growing season, thereby increasing agricultural productivity per unit area (Mwila et al. 2021; Minta et al. 2014; Goff et al. 2010). Even in areas characterized by a monomodal climate regime, farmers can harness any residual moisture from the main season to cultivate short-period crops (Kar and Kumar 2009). For example, in Ethiopia, it is common practice to cultivate legumes such as, chickpea during the OND season (Korbu et al. 2022; Kebede 2020; Getachew 2019; Loon et al. 2018). Many legume crops have low water requirements and short growing periods, making them well-suited for cultivation with residual moisture. Beyond their role in crop production, leguminous crops can contribute to soil fertility (Mwila et al. 2021; Bationo et al. 2011; Mapfumo 2011). Nitrogen-fixing legume species introduced during the post-rainy season can enhance soil nitrogen availability, consequently improving productivity for the subsequent main seasons.

Although post-rainy season agricultural practices such as growing second and third crops are crucial for ensuring food security (Mapfumo 2011; Howden et al. 2007), enhancing soil fertility (Mwila et al. 2021; Debaeke and Aboudrare 2004), and providing fodder for livestock (Brychkova et al. 2022; Minta et al. 2014), their adoption is declining and not universally applicable for several reasons (Kar and Kumar 2009). This decline in adoption of such practices may arise due to (a) a lack of knowledge regarding suitable crops for residual moisture utilization, (b) uncertainty regarding whether post-rainy moisture levels are adequate to support crop growth, and (c) insufficient awareness among farmers about the efficacy of such practices.

Climate change can be characterized by heightened variability in precipitation patterns and an increase in the intensity and frequency of extreme weather events (Cattani et al. 2018; Brown et al. 2017; Field et al. 2014). As a climate change adaptation approach, post-rainy season cropping could provide a climate resilient option to boost agricultural yields. Given the high variability of post-rainy season residual soil moisture availability, improved water management practices are essential (Danga et al. 2009). Efficient water management practices, informed by analysis of soil moisture content and crop water demand, are essential for optimizing post-rainy season legume-based cropping systems.

In Ethiopia, optimizing post-rainy season cropping practices is critical, due to the country's distinct climate and variable rainfall patterns. In this study empirical analysis conducted in Ethiopia is leveraged to investigate the optimization of post-rainy season cropping through detailed residual soil moisture analysis. To date, few studies have attempted to investigate post-rainy season moisture availability for the second cropping. For instance, Korbu et al. (2022), have demonstrated a response of chickpea cultivars to varying moisture-stress, while Chimdessa et al. (2019) have detected yield improvements for maize through soil moisture conservation during the cropping season from August to December at Bale Zone in Southeastern Ethiopia. In addition, Yang et al. (2021a) have illustrated improved cereal crop yields associated with soil moisture conditions in the Upper Blue Nile Basin (UBNB) by integrating a process-based crop and hydrologic models. These studies have been conducted at both the field level and on a basin-wide scale.

There remains a need to conduct a residual soil water availability assessment for cropping after the main rainy season on a country-wide scale to optimize the utilization of arable lands for double cropping. This study places a specific emphasis on post-rainy season residual soil moisture analysis for informed decision-making. The study has two objectives: i) to investigate residual soil moisture levels, along with their temporal and spatial fluctuations, following the main rainy season, spanning from October to December (OND) across Ethiopia; ii) to investigate the viability of cultivating selected legume crops during the post-rainy season, while accounting for the presence of residual soil moisture within identified climatic zones.

4.2 Data sources and location of the study

4.2.1 Study area and agroecologies

The study was conducted for Ethiopia, which is positioned in the eastern part of the African continent, and characterized by an extensive complex of mountain ranges and deep valleys, covering much of the central and northern regions (Abera et al. 2019). The country's climate reveals substantial variations due to altitude differences and its proximity to the equator (Fazzini et al. 2015; Jury 2010b). Ethiopia experiences distinct wet and dry seasons, with the main rainy season, locally known as kiremt, typically occurring from June to September (JJAS), and a shorter rainy season, called belg, from March to May (MAM) (Segele and Lamb 2005). Figure 4.1 depicts the study area map and the agroecologies of Ethiopia as defined by the Ethiopian Ministry of Agriculture (MoA).

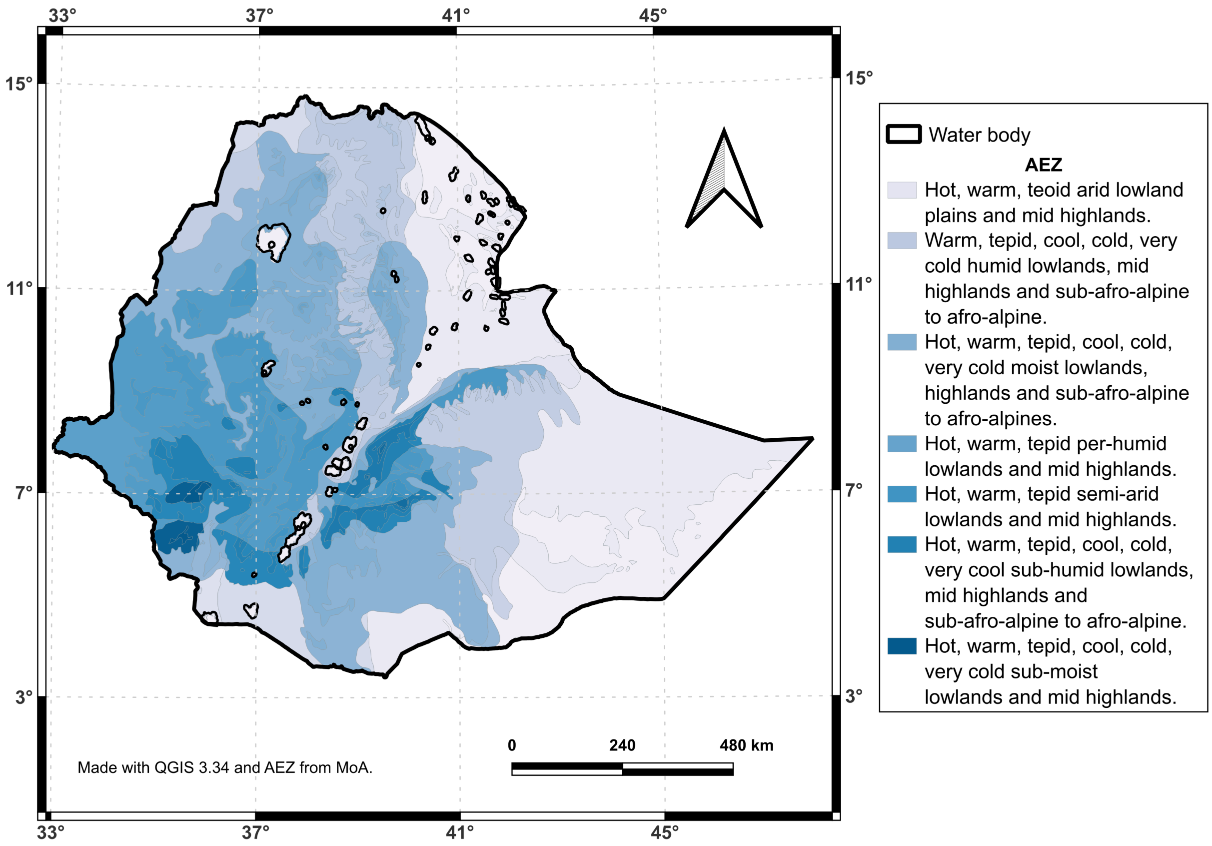

Figure 4.1.: Study area map showing the distribution of agroecologies in Ethiopia.

Agriculture has vast significance for Ethiopia, providing livelihoods for a large portion of the population and making a substantial contribution to the national economy (Yigezu Wendimu 2021; Evangelista et al. 2013). Ethiopia's agroecologies cover a wide spectrum of agricultural systems, from highland cropping to pastoralism in lowland areas (Demem 2023; Asefa et al. 2020). Highland agriculture includes the cultivation of crops such as teff, wheat, barley, maize, and pulses. Lowland areas, particularly in the eastern and southeastern parts of the country, have arid to semi-arid climates (Abera et al. 2019). Pastoralism is prevalent in these regions, with communities raising livestock such as cattle, goats, sheep, and camels (Alemayehu et al. 2020). Agro-pastoralism, combining crop cultivation with livestock rearing, is practiced in some lowland areas with access to water sources.

4.2.2 Climate and elevation datasets

This study employs the Global Land Data Assimilation System (GLDAS) dataset, a comprehensive global offline land surface modeling system utilizing the Noah Land surface model, focusing on around 36 land surface fields. The model is driven by observed and reanalysis meteorological fields, facilitating the generation of a diverse array of surface and subsurface soil moisture data across varying depths: the top 10cm, 10-40cm, 40-100cm, and 100-200cm layers. GLDAS provides multiple versions of the soil moisture dataset, containing v2.0, v2.1, and v2.2 (Beaudoing and Rodell 2019; Rodell et al. 2004). For this study, we specifically utilize v2.0 and v2.1. In v2.0, the Noah land surface model is simulated through enforcing of Princeton meteorological input data for the period spanning 1948 to 2014. On the other hand, v2.1 is generated by combining both model and observational data, covering the time frame from 2000 to the present. The datasets selected for this study have a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ and are temporally resolved on a daily basis. Considering cultivation of crops with shallow root depth during the post-rainy season, we utilized soil moisture data from the top 40cm for this study.

The GLDAS Elevation dataset, derived from GTOPO30 (EROS 2017; Gesch et al. 1999), a global digital elevation model with a horizontal grid spacing of 30 arc seconds, has been sourced from the GLDAS data repository (https://ldas.gsfc.nasa.gov/gldas/elevation). This dataset is utilized in the Penman-Monteith reference evapotranspiration (ET_o) equation to calculate crop water requirements.

Agroclimatology datasets sourced from the National Aeronautics and Space Administration (NASA) via the Prediction Of Worldwide Energy Resources (POWER) platform (https://power.larc.nasa.gov/) and AgERA5 through Copernicus Data Store (CDS) (Boogaard et al. 2020), have been utilized for point location and spatial analysis, respectively. These resources offer a comprehensive range of solar and meteorological datasets, including temperature, wind speed, humidity, and solar radiation, to support research in renewable energy and agricultural applications. Specifically, our study has incorporated temperature variables (minimum, maximum, and mean), rainfall data, relative humidity, solar radiation, wind speed, and dew point temperature from these datasets at $0.25^{\circ} \times 0.25^{\circ}$ spatial resolution.

4.2.3 Crop coefficients and masks

This study utilizes the crop information database resource (developed by the Food and Agriculture Organization (FAO) of the United Nations) to access crop coefficients ($\mathrm{K_c}$) that employed to calculate the crop water requirements ($\mathrm{ET_c}$) of individual crop species (FAO 2023). The FAO database offers extensive information on crop water needs, irrigation techniques, and water management practices for a wide range of crops cultivated globally. It encompasses detailed data on crop-specific parameters, including evapotranspiration rates, irrigation scheduling recommendations, and water use efficiency metrics. In addition, we employed cropland masks version v03 sourced from the Anomaly Hotspots of Agricultural Production (ASAP) data catalog (https://data.jrc.ec.europa.eu/) to quantify cropland fractions across the country (Pérez-Hoyos et al. 2017).

4.3 Methods

4.3.1 Spatiotemporal analysis of OND residual soil moisture

To assess the spatiotemporal variability of residual soil moisture during the October to December (OND) season, we used robust statistical methodologies, ranging from the sample mean to advanced techniques such as Empirical Orthogonal Functions (EOFs) and the K-means clustering algorithm (Dawson 2016; Li and Wu 2012). The long-term averages, variabilities, and monotonic shifts in residual soil moisture, were calculated using sample mean, standard deviations, and Kendall-Tau trend statistics, respectively.

To identify and categorize the overall distribution of moisture levels across nationwide, we have set threshold values denoting dry, normal, and wet conditions. The thresholds for moisture values used to differentiate between wet, normal, and dry days were determined by averaging the respective 10th and 90th percentiles (Heino et al. 2023; Knapp et al. 2015; Haensler et al. 2013) of moisture levels in each homogeneous climate region over time (Huijgevoort et al. 2012). Considering the extremum soil moisture values below the 10th percentile (86.69 kg.m^{-2}) are insufficient to meet the water demands of most crops, and values above the 90th percentile (116.24 kg.m^{-2}) represent surplus, we utilized these threshold values to categorize moisture levels into dry (< 86.69 kg.m^{-2}), normal (86.69 kg.m^{-2} – 116.24 kg.m^{-2}), and wet (> 116.24 kg.m^{-2}) conditions. In addition, we defined a dry spell as ten or more consecutive dry days with less than 86.69 kg.m^{-2} (below the 10th percentile) of soil moisture value and assessed the occurrences of dry spells during the season.

The non-parametric Kernel Density Estimation (KDE) technique is employed both temporally and spatially to estimate the probability density distribution of residual soil moisture values. KDE is utilized to identify clusters or areas of heightened density within the dataset, enabling the exploration of its underlying structure (Gramacki 2018; Gray and Moore 2003). This method provides a smoothed approximation of the probability density function (PDF), facilitating a visual representation of the data distribution. To reduce noise in the data, Scott's Rule of Thumb bandwidth selection criterion (Bashtannyk and Hyndman 2001) is applied, and threshold values of 1.5 for spatial and 1.0 for temporal density distributions analysis are established.

4.3.2 Homogeneous climate regions classification

To decompose the covariance structure of spatial soil moisture data into dominant modes of variability, EOF analysis has been applied to identify major patterns of moisture variability within the dataset. Thus, unsupervised K-means clustering algorithm is utilized to partition the soil moisture dataset into clusters, minimizing the sum of squared distances between data points and their corresponding cluster centroids (Fränti and Sieranoja 2019). To address drawbacks associated with the traditional K-means algorithm, such as sensitivity to initial centroids and slow convergence issues, we have adopted the efficient K-means++ initializer and executed the algorithm multiple times with different initializations (Bahmani et al. 2012; Arthur and Vassilvitskii

2006).

To standardize the data and remove seasonal patterns, a time-mean was calculated at each grid point, and anomalies were then derived. To address changes in grid size particularly at higher latitudes, an area-weighting technique based on the square root of the cosine of latitude was applied (Jimma et al. 2023; Rieger et al. 2021; Dawson 2016; Baldwin et al. 2009; Hannachi et al. 2009).

Empirical Orthogonal Functions (EOF) analysis was performed on the anomaly data for the OND season, spanning a 40-year period (1981-2020). This analysis identified four dominant modes explaining the highest variability during this season (these EOF modes are provided in Appendix B Figure B.1). Subsequently, KMeans clustering was applied to these EOF modes, resulting in the identification of five centroids representing clusters.

The determination of the number of centroids follows to the Elbow criterion (Nainggolan et al. 2019) and was substantiated by domain experts judgment. This approach effectively classified the country into five distinct and non-overlapping homogeneous climate regions. The classification was based on the close association of each data point with the minimum squared distances within its respective region relative to data points in other regions.

4.3.3 Crop selection and crop water requirements analysis

To enhance agricultural productivity and climate adaptation among smallholder farmers, we explore the potential of integrating available soil moisture levels with selected drought tolerant crops water requirements. One approach involves assessing the water needs of different crop species based on their physiological traits, growth stages, and prevailing environmental conditions. Drawing on both scientific knowledge and traditional farming practices observed across Ethiopia, particularly the cultivation of second crops after the primary season (JJAS), we have chosen potential key legume food and feed crops such as chickpea (*Cicer arietinum*), field peas (*Pisum sativum*), common bean (*Phaseolus vulgaris*), soybean (*Glycine max*) and alfalfa

(*Medicago sativa*) for evaluation in leveraging residual soil moisture to support double cropping (Minta et al. 2014; Assefa et al. 2011).

Crop water requirements are analyzed by employing the Penman-Monteith method, which is a widely used approach for estimating reference evapotranspiration ($\mathrm{ET_o}$). Reference evapotranspiration represents the rate of evapotranspiration from a well-watered reference surface under standard weather conditions (Nguru et al. 2023; Abraham and Muluneh 2022; Allen 1998). To determine crop water requirements, $\mathrm{ET_o}$ is multiplied by the crop coefficients ($\mathrm{K_c}$). The formula for calculating $\mathrm{ET_o}$ using the Penman-Monteith method is as follows:

$$ET_o = \frac{0.408 \times \Delta \left(R_n - G\right) + \gamma \times \frac{900}{T+273} \times u \times \left(e_s - e_a\right)}{\Delta + \gamma \times \left(1 + 0.34 \times u\right)}$$

Where:

- ET_o = Reference evapotranspiration (mm/day)
- R_n = Net radiation at the crop surface (MJ/m^2/day)
- G = Soil heat flux density (MJ/m^2/day)
- T = Mean daily air temperature at 2 meters height (°C)
- u = Wind speed at 2 meters height (m/s)
- e_s = Saturation vapor pressure (kPa)
- e_a = Actual vapor pressure (kPa)
- Δ = Slope of the saturation vapor pressure curve (kPa/°C)
- γ = Psychrometric constant (kPa/°C)

The psychrometric constant (γ) is a parameter used to quantify the relationship between air temperature and the vapor pressure gradient in the atmosphere, and it is defined as the ratio of the specific heat of moist air at constant pressure to the latent heat of vaporization of water. The formula to calculate the psychrometric constant is:

$$\gamma = \frac{c_p \cdot P}{\varepsilon \cdot \lambda}$$

Where:

- γ = Psychrometric constant (kPa/°C)
- c_p = Specific heat of moist air at constant pressure (kJ/kg/°C)
- P = Atmospheric pressure (kPa)
- ε = Ratio of the molecular weight of water vapor to the gas constant for dry air (dimensionless)
- λ = Latent heat of vaporization of water (kJ/kg)

To calculate the psychrometric constant, several parameters are typically employed, including the specific heat of moist air, atmospheric pressure, the ratio of molecular weights between water vapor and dry air, and the latent heat of vaporization of water (Alexandris and Kerkides 2003; Buck 1981). The following typical values for these parameters are utilized in the calculation process.

- $c_p \approx 1.013$ kJ/kg/°C
- $P \approx$ Standard atmospheric pressure (calculated based on altitude)
- $\varepsilon \approx 0.622$
- $\lambda \approx 2.45$ kJ/kg at 0°C (this value varies slightly with temperature)

The individual components of the Penman-Monteith equation represent different factors influencing evapotranspiration, including radiation, temperature, wind speed, humidity, and soil properties. These components are combined to estimate the overall rate of evapotranspiration from the reference surface.

To determine crop water requirements (ET_c), ET_o is multiplied by the crop coefficients (K_c). Thus, the crop water requirement is calculated using:

$$ET_c = ET_o \times K_c$$

Where:

- K_c is the crop coefficient

By integrating the selected crops and assuming a uniform planting date of October first for all crops, coupled with careful assessments of their water requirements utilizing the FAO-recommended Penman-Monteith method (Allen et al. 2005; Smith et al. 1998), we present our research findings based on homogeneous climate regions for the OND season.

To better quantify the extent by which post-rainy residual soil moisture supports each crop's water requirements, we used pixel-based spatial analysis. We selected specific pixel locations representing normal (i.e., average), driest (i.e., < 10th percentile), and wettest (i.e., > 90th percentile) conditions and conducted pixel-based assessments of crop water requirements. Furthermore, to refine the analysis solely on croplands, we utilized a cropland mask and excluded non-cropland areas.

The spatial analysis for total cropland areas and the coverage of individual crops within these croplands at various growth stages was conducted as follows: First, we calculated the percentage of cropland fractions in Ethiopia by dividing the number of pixels within the cropland area masks by the total number of pixels covering the entire country. Second, we determined the size of the selected crop coverage within the cropland area by dividing the total number of pixels supporting crop water requirements by the total number of cropland pixels. Thus, the results are presented as percentages.

4.4 Results

4.4.1 Seasonal and monthly soil moisture variability

Figure 4.2 illustrates the long-term soil moisture average, standard deviations, and trends in Ethiopia (1981-2020). The wet regions are predominantly located in the central and western parts of the country, with soil moisture exceeding 150 kg.m^{-2} across central-western Ethiopia. A discernible gradient is evident moving towards the east, reaching as low as 60 kg.m^{-2} in the southeastern tips of the country (Figure 4.2(a)). Soil moisture exhibits high variability along the central and western highlands, particularly extending from the central highlands to the northwestern tips of the country (standard deviations > 25 kg.m^{-2}). In contrast, the eastern low land regions demonstrate relatively low variability, with the northeastern region exhibiting the lowest (standard deviations < 7.5 kg.m^{-2}) (Figure 4.2(b)). The northeastern and northwestern regions exhibit strong increasing moisture trends, while the southeastern region also displays a moderate increase in trends. Overall, there is a decreasing soil moisture trend along the central south-north direction and increasing trends in the northwest and eastern regions (Figure 4.2(c)).

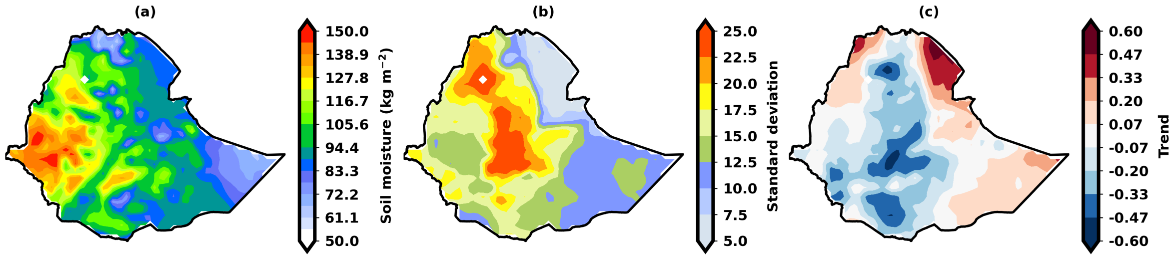

Figure 4.2.: Seasonal soil moisture (a) Average, (b) Standard deviation, (c) Trend in the OND season (1981-2020).

Figure 4.3 displays the progresses of moisture, variability, and trends during the months of the OND season. The highest moisture levels are observed in October, followed by a decrease in November and December Figure 4.3(a-c). Moisture variability follows a similar pattern, as depicted in Figure 4.2(b), and this variability also declines from October to December Figure 4.3(d-f). This decrease in variability may be linked to a reduction in moisture during these months of the season. In contrast, the moisture trends are relatively consistent across all months of the season, with slight variations in the magnitude of the trend observed at the central and northeastern tips of the country Figure 4.3(g-i).

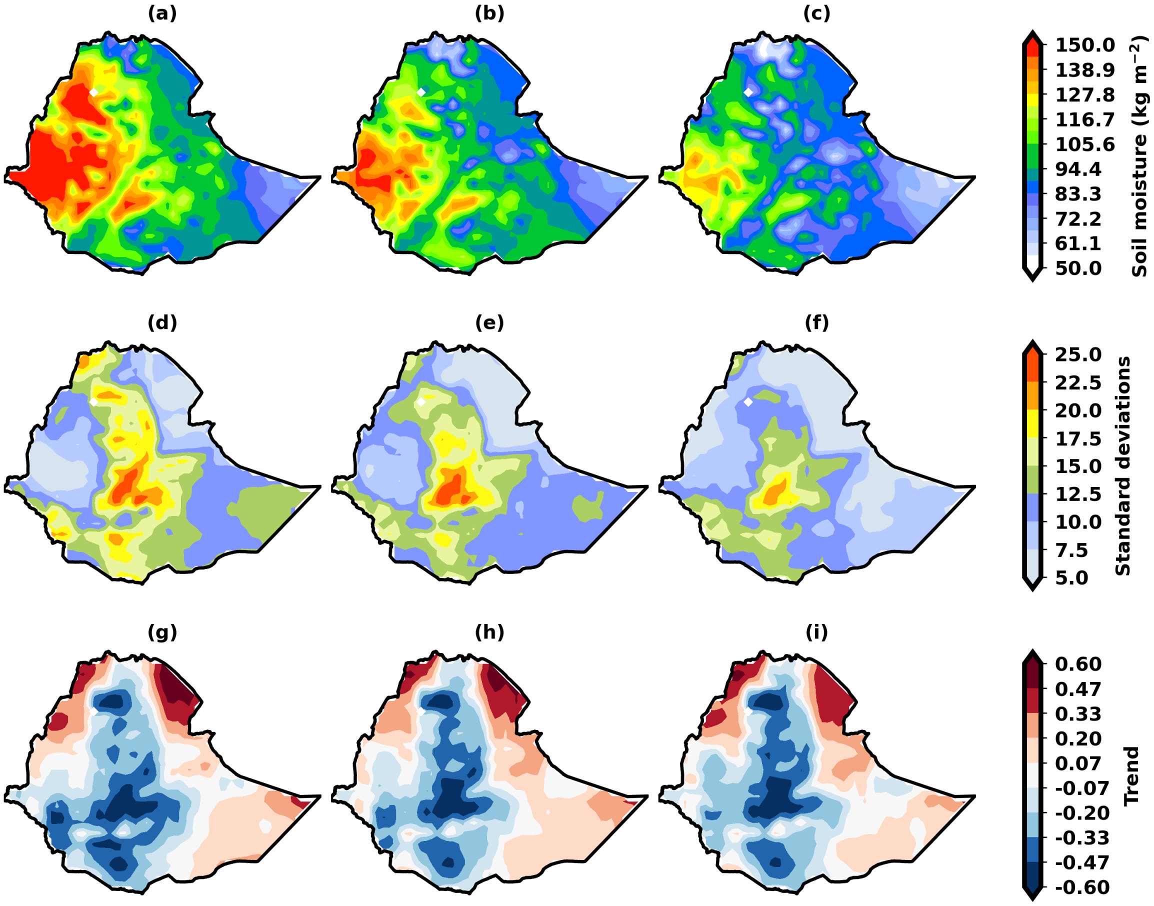

Figure 4.3.: Soil moisture Average (first row), Standard deviations (second row), and Trends (third row) are presented for October (first column), November (second column), and December (third column) over the period 1981-2020.

4.4.2 Long term residual moisture characteristics across Ethiopia

Considering the threshold values established (dry days < 86.69 kg.m^{-2} and wet days > 116.24 kg.m^{-2}) based on the 10th and 90th percentiles of moisture level values, Figure 4.4 illustrates the percentages of wet, normal, and dry days during the season. The majority of wet days are concentrated in the western region (Figure 4.4(a)), while normal days are distributed throughout the country, excluding the western and easternmost tips (Figure 4.4(b)). A high percentage of dry days is observed primarily at the northern and southeastern tips of the country (Figure 4.4(c)).

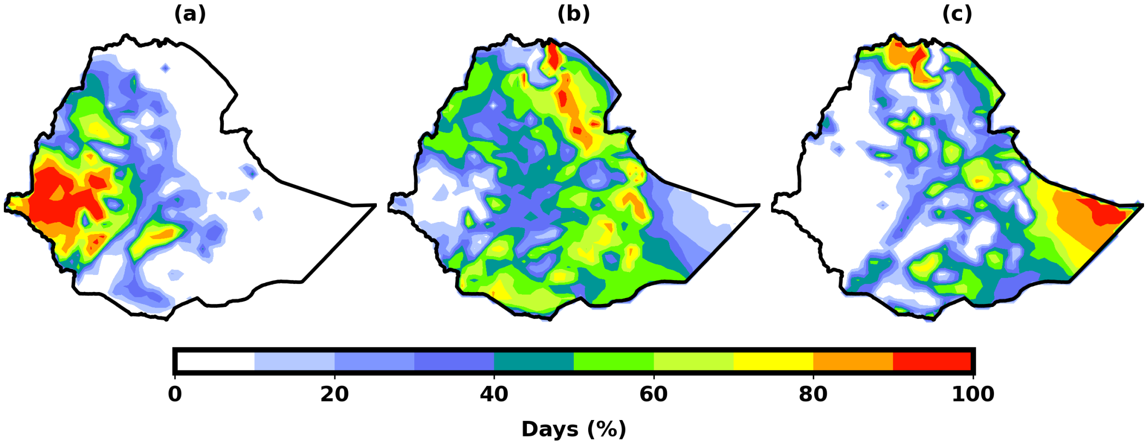

Figure 4.4.: Seasonal percentages of (a) wet days, (b) normal days, and (c) dry days during the OND season for the period 1981-2020.

Figure 4.5 depicts the number of dry spells, count of dry days within those spells, and frequency of dry spell occurrences across the country. The figure illustrates a substantial number of dry spells occurring in the eastern parts of the country, particularly most areas of southeastern, certain pocket areas in the southwestern tips, and northern regions (Figure 4.5(a)). In these areas, the number of dry spells is notably high, with the count of dry days in these spells exceeding 150 days in the northern and southeastern tips of the country (Figure 4.5(b)). This suggests the possibility of these regions staying dry (below the minimum threshold) for consecutive seasons. Additionally, a significant number of dry days in dry spells is observed in most parts of the eastern regions, particularly in the central-eastern and northern regions. Moreover, the frequency of dry spell occurrences ranges from 1 to 55, with the highest frequencies observed between 30 and 45 (Figure 4.5(c)). These areas are dispersed throughout the eastern part of the country, with the southeastern and northern regions revealing a high frequency of dry spells.

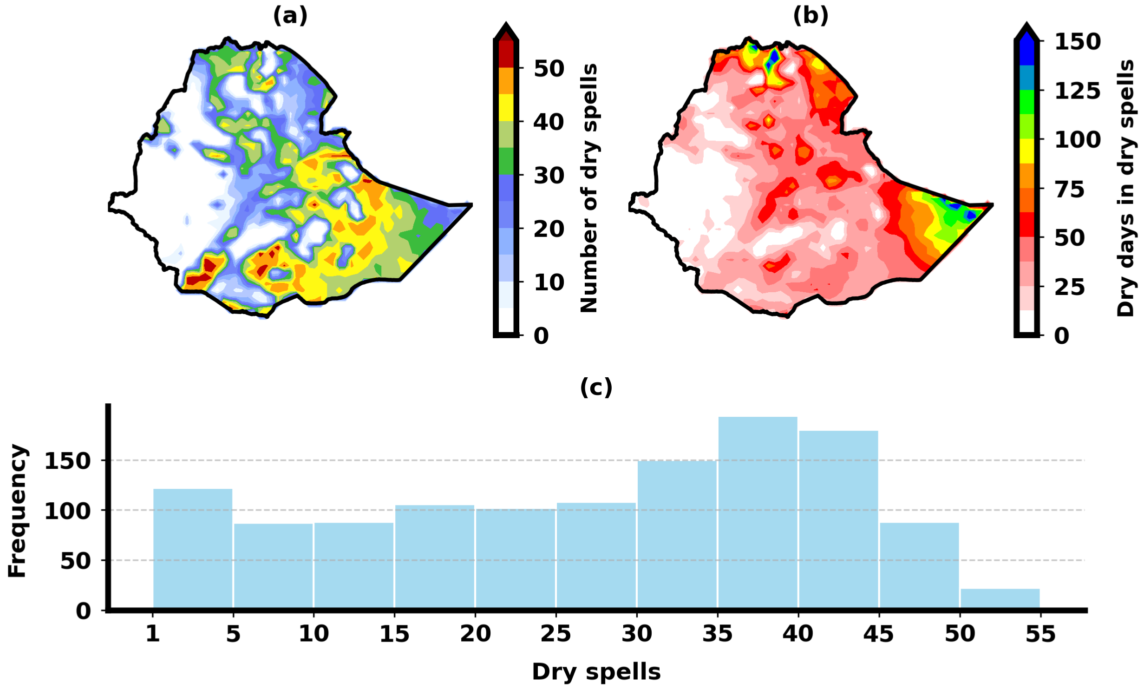

Figure 4.5.: Seasonal number of (a) dry spells and (b) dry days within dry spells, along with (c) the frequency of dry spells across Ethiopia for the period 1981-2020.

4.4.3 Homogeneous regions and their attributes of residual soil moisture

The regionalization process (see Section 4.3.2) clustered the country into five homogeneous climate regions: northwest, central, northeast, southwestern-central, and southeast. Figure 4.6 illustrates the five homogeneous climate regions in Ethiopia, determined by post-rainy season (OND) soil moisture levels.

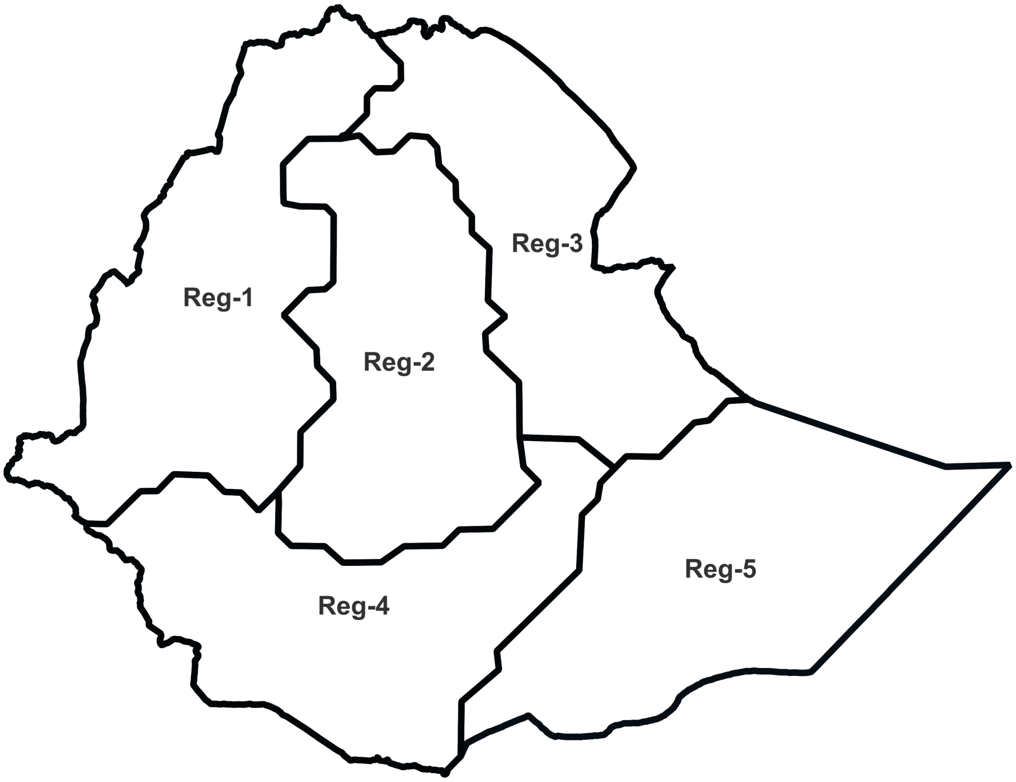

Figure 4.6.: The five homogeneous soil moisture regions in Ethiopia: Northwest (Reg-1), Central (Reg-2), Northeast (Reg-3), Southwestern-central (Reg-4), and Southeast (Reg-5).

The seasonal cycles of the five homogeneous soil moisture climate regions are depicted in Figure 4.7. As observed in the figure, the moisture levels in Reg-1, Reg-2, and Reg-3 indicate a gradual decline throughout the months of the season. In contrast, the soil moisture in Reg-4 and Reg-5 increases until the end of October and then starts declining towards the end of the season. Moreover, the initial moisture level of Reg-1 at the start of the season is higher than that of all other regions, and its lowest value at the end of the season is higher than the seasonal maximum moisture of some regions (e.g., Reg-3 and Reg-5). Generally, the amplitude of moisture levels significantly differs among the homogeneous regions throughout the season Figure 4.7.

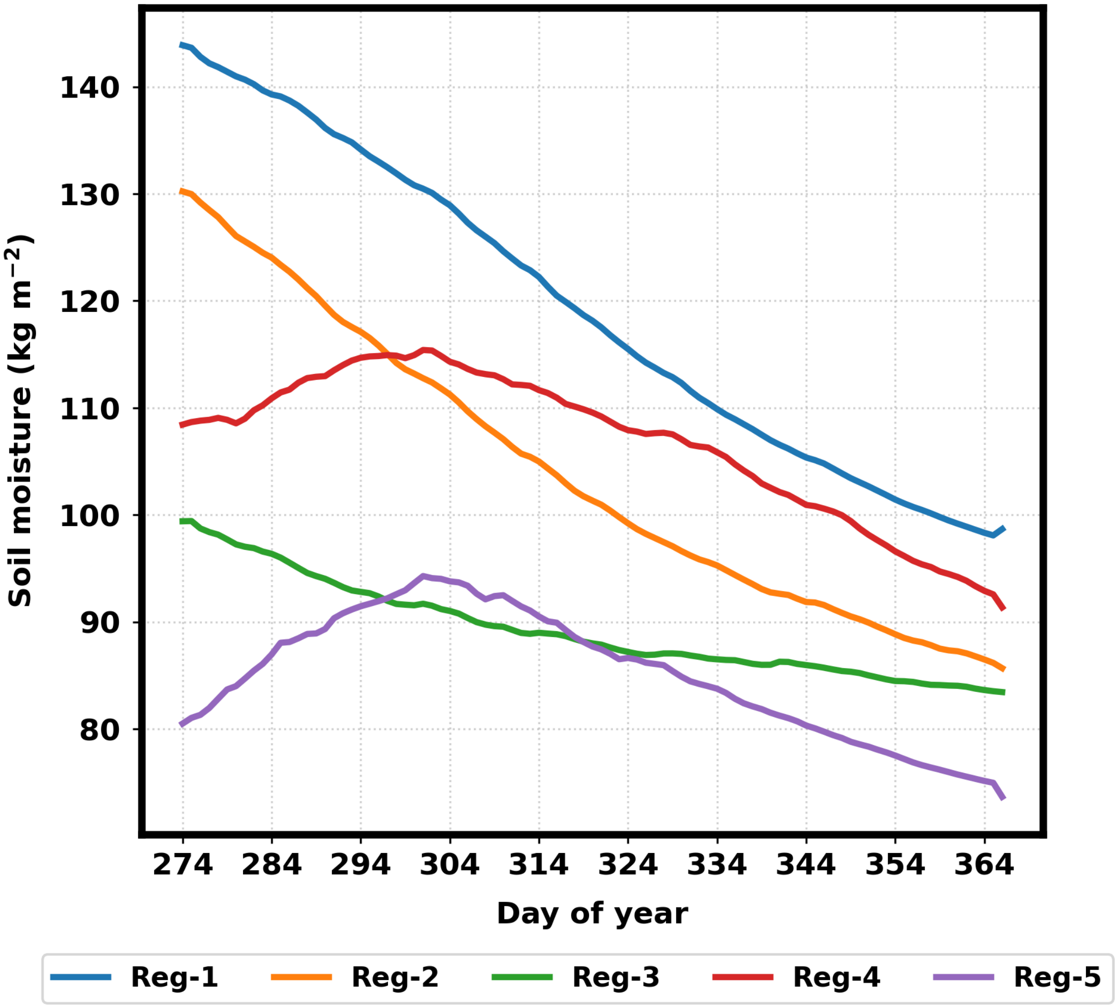

Figure 4.7.: Seasonal cycles of average soil moisture in homogeneous regions (1981-2020).

The interannual variabilities of homogeneous moisture regions significantly differ from one another, as demonstrated by the varying amplitudes of moisture anomalies shown in Figure 4.8. Notably, there are significant consecutive dry years, i.e., below the long-term average, across homogeneous regions. Examples include the periods of consecutive dry years such as 2007-2012 in Reg-1, 1983-1988 in Reg-3, 2012-2018 in Reg-4, and 1991-1996 in Reg-5. The longest consecutive dry period is observed in Reg-2, spanning from 2001 to 2020, with the exception of two normal years (i.e., 2006 and 2013). In Reg-2, it is also interesting to note that the moisture level remains above the long-term mean from 1981-2000, except for small negative amplitude anomalies in 1984 and 1987. This region exhibits notable moisture variability and a pronounced decreasing trend in moisture levels, as depicted in Figure 4.2(b,c). Moreover, significant wet years, such as 1997-2000, have been observed in all regions except Reg-5.

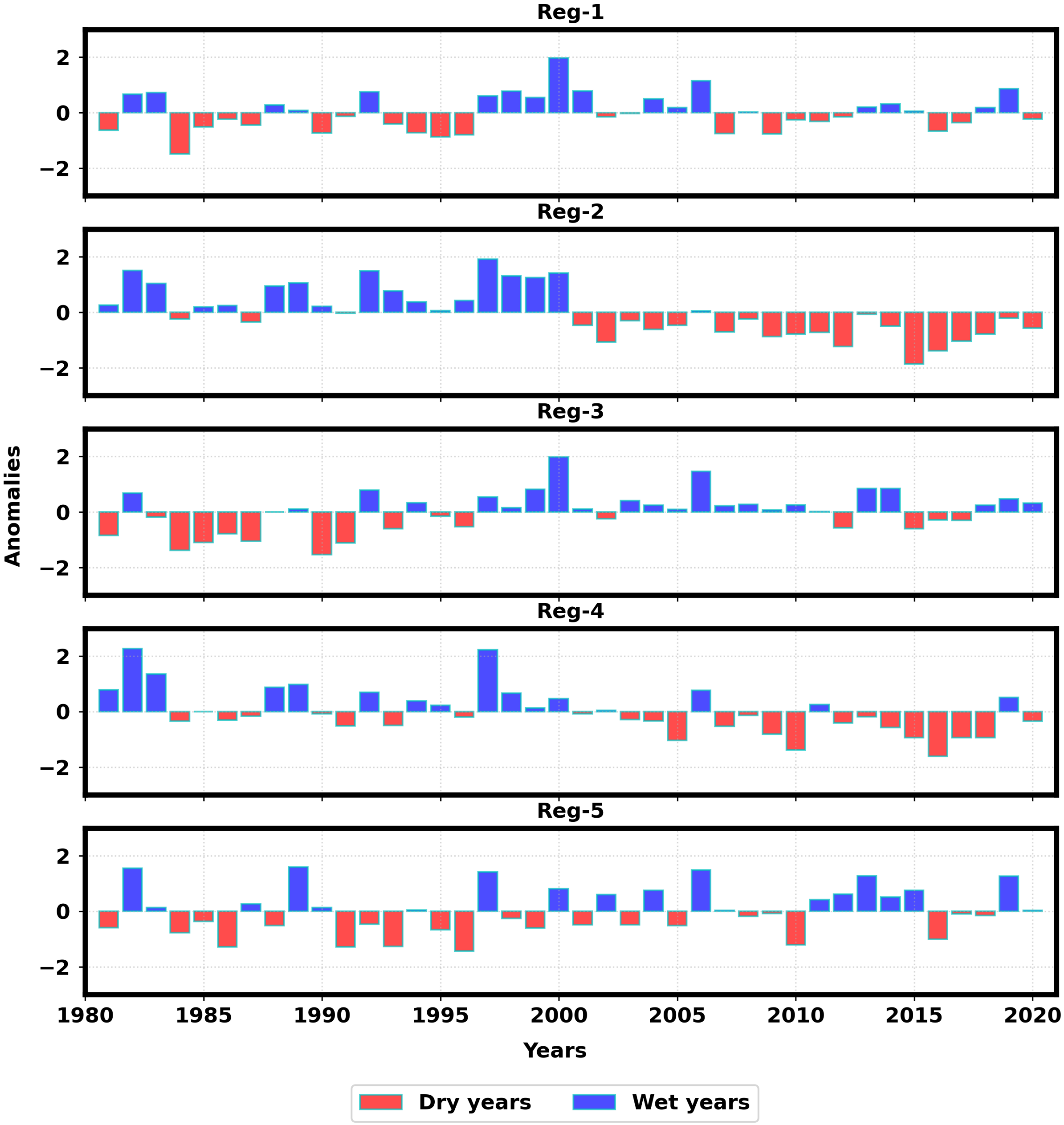

Figure 4.8.: Interannual variabilities in soil moisture within homogeneous soil moisture regions.

Figure 4.9 presents the long-term time series smoothed by a 7-year moving average for homogeneous climate regions, showcasing the decadal soil moisture trends in these regions. The figure illustrates increasing moisture trends across all regions until 1997; however, after that point, Reg-2 (trend magnitude, $\tau = -0.60$) and Reg-4 ($\tau = -0.67$) reveal decreasing trends, with Reg-2 experiencing a particularly sharp decline. Reg-1's trend continues to increase until 2003, followed by a moderate decline and subsequent increase ($\tau = 0.30$). In contrast, Reg-3 ($\tau = 0.26$) and Reg-5 ($\tau = 0.59$) consistently show increasing moisture levels. It is evident that the magnitude of seasonal decreasing trends in Reg-2 and Reg-4 is substantially high, aligning with the observations in Figure 4.9. The increase in trends in Reg-1 and Reg-3 is moderate in both seasonal and decadal time scales, while the decadal increase in trend in Reg-5 is considerably larger. On the other hand, the annual trending (as shown in Appendix B Figure B.2) is low in Reg-1, Reg-3, and Reg-5.

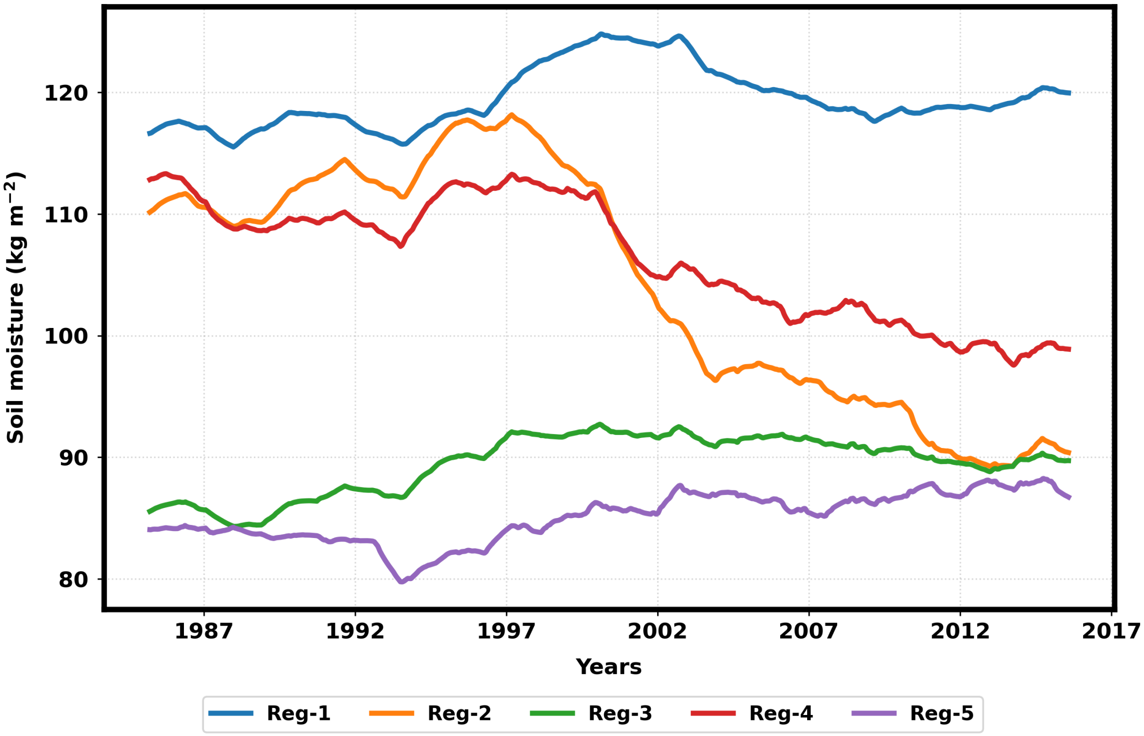

Figure 4.9.: Long-term temporal trends of residual soil moisture in homogeneous regions. The long-term time series data is smoothed on a decadal time scale (7 years) to reduce high-frequency variability.

Figure 4.10 presents the spatial and temporal densities of soil moisture levels. The spatial and temporal coverage of the range of soil moisture values are comparable in their respective homogeneous climate regions. For instance, Reg-1, Reg-2, and Reg-4 reveal a wider range of moisture levels coverage, whereas Reg-3 and Reg-5 exhibit moisture levels concentrated in a narrow band of values. Spatially, Reg-1 and Reg-2 show a moderately left-skewed distribution, while Reg-4 is a bit right-skewed, and Reg-3 and Reg-5 indicate a normal distribution. This suggests that high moisture levels are prevalent in Reg-1 and Reg-2, while the areas in Reg-4 are characterized by relatively lower moisture levels. Temporally, all regions resemble close to a normal distribution.

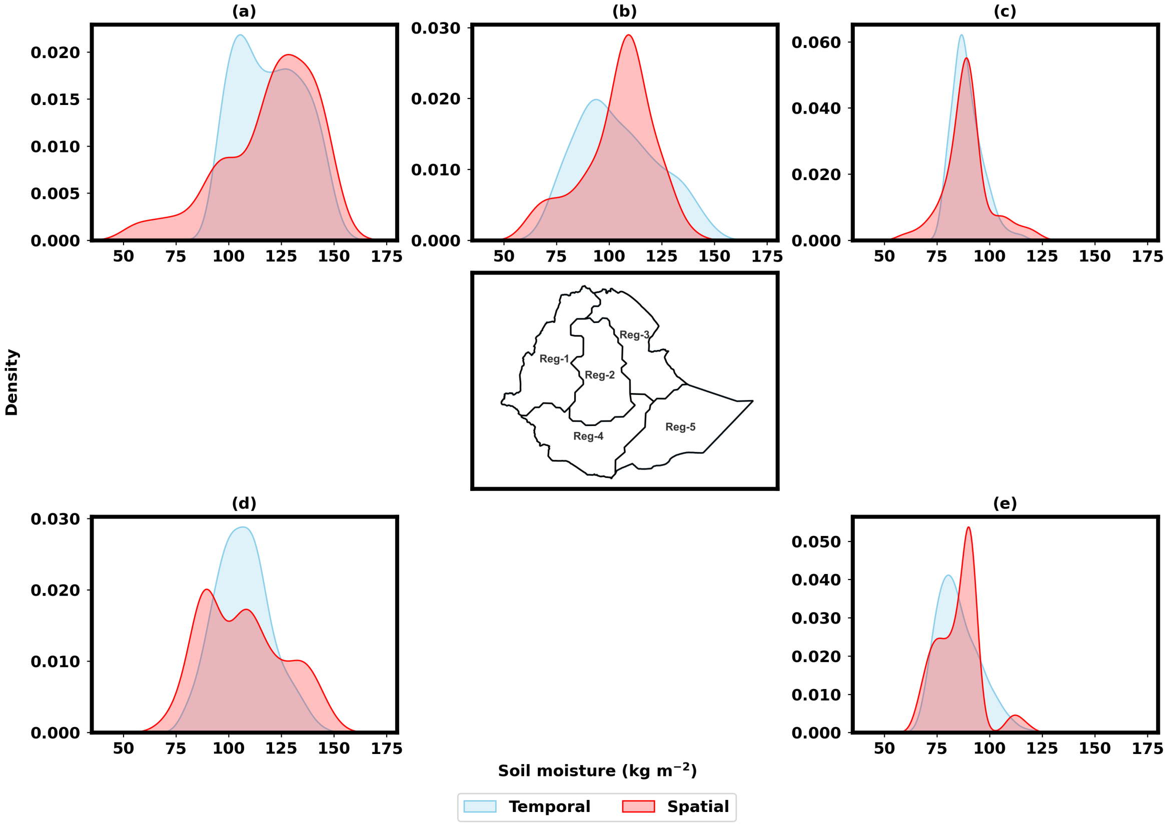

Figure 4.10.: Spatial and temporal density of soil moisture in homogeneous regions (1981-2020). The top three panels in the row presents (a) Reg-1, (b) Reg-2, and (c) Reg-3; the central panel displays a map of homogeneous regions, and the last two panels in the row correspond to (d) Reg-4 and (e) Reg-5.

As indicated in Table 4.1, 79% of the time, moisture values fall between the 10th and 90th percentiles in their respective homogeneous climate regions. It is not surprising that temporally every region's 10th to 90th percentiles of moisture values fall within the same percentages, considering we classified the homogeneous regions based on the temporal variability of the seasonal (OND) soil moisture. However, the spatial coverage of these ranges of values differs from region to region. It is also important to note that the spatial distribution of the highest moisture values in Reg-1, Reg-2, and Reg-4 covers 65.9%, 90.7%, and 48.9% of the regions' areas, respectively. Although Reg-3 and Reg-5 also exhibit a wider area coverage of moisture levels in their respective regions, the range of these values is narrower and smaller in magnitude, as depicted in Figure 4.10 (c,e).

Table 4.1.: Lower (10^{th}) and Upper (90^{th}) percentiles of soil moisture values in homogeneous regions, along with the percentages of corresponding temporal and spatial soil moisture values within the lower and upper percentiles.

Regions	**Percentiles [$10^{th} - 90^{th}$] ($kg.m^{-2}$)**	**Percentages [Temporal/Spatial]**
Reg-1	[99.13 - 141.31]	[79.74% / 65.58%]
Reg-2	[79.96 - 132.94]	[79.38% / 90.65%]
Reg-3	[80.78 - 99.210]	[79.44% / 69.85%]
Reg-4	[90.54 - 124.49]	[79.67% / 48.89%]
Reg-5	[73.49 - 99.510]	[79.25% / 80.09%]

4.4.4 Cropping assessment based on crop water requirements

Cropping strategies that can prioritize (a) utilization of residual soil moisture, (b) incorporation of drought-tolerant crops, (c) maintain a short growing season (maximum 120 days), and (d) align with crop water requirements are critical for promoting sustainable agricultural systems in water-scarce regions.

To address this need, we conducted tests on five legume crops known for their ability to withstand low water stress and which are characterized by short growing periods. Table 4.2 outlines the legume crops, their respective lengths of growing periods across three stages (initial, mid-season, and late), and their corresponding crop coefficients.

Table 4.2.: Crop types, their corresponding crop coefficients (Kc), and growth stages employed to assess crops development during the OND season, utilizing residual soil moisture.

Legume crops	**Growing stages**	**Crop coefficients (Kc)**	**Growing dates (days)**
Chickpea	• initial-stage • mid-season • late-stage	• 0.26 • 1.08 • 0.52	• 25 • 40 • >65
Fieldpeas	• initial-stage • mid-season • late-stage	• 0.50 • 1.15 • 0.30	• 50 • 35 • >85
Common bean	• initial-stage • mid-season • late-stage	• 0.40 • 1.15 • 0.54	• 40 • 35 • >75
Soybean	• initial-stage • mid-season • late-stage	• 0.50 • 1.15 • 0.50	• 30 • 40 • >75
Alfalfa	• initial-stage • mid-season • late-stage	• 0.40 • 0.95 • 0.40	• 30 • 30 • >60

Source: FAO crop database, FAO (2023) and Jabow et al. (2015).

Figure 4.11 depicts the daily water requirements for the five crops across various homogeneous regions characterized by normal, extreme dry, and wet soil moisture conditions. Under wet conditions, soil moisture levels in Reg-1, Reg-2, and Reg-4 are adequate to meet the daily water needs of these crops. Conversely, Reg-3 and Reg-5 exhibit sufficient moisture levels to support crop growth until late October, yet these regions experience water stress during the mid-season and late stages, with a deficit of approximately 5mm/day in the latter stage. In drier locations, all regions lack adequate moisture to sustain crop growth, even during the initial stage. However, at normal moisture levels, Reg-1, Reg-2, and Reg-4 demonstrate the potential to support crop water requirements if supplemented with irrigation (maximum of 4.5mm/day) during the mid-season and late growing stages.

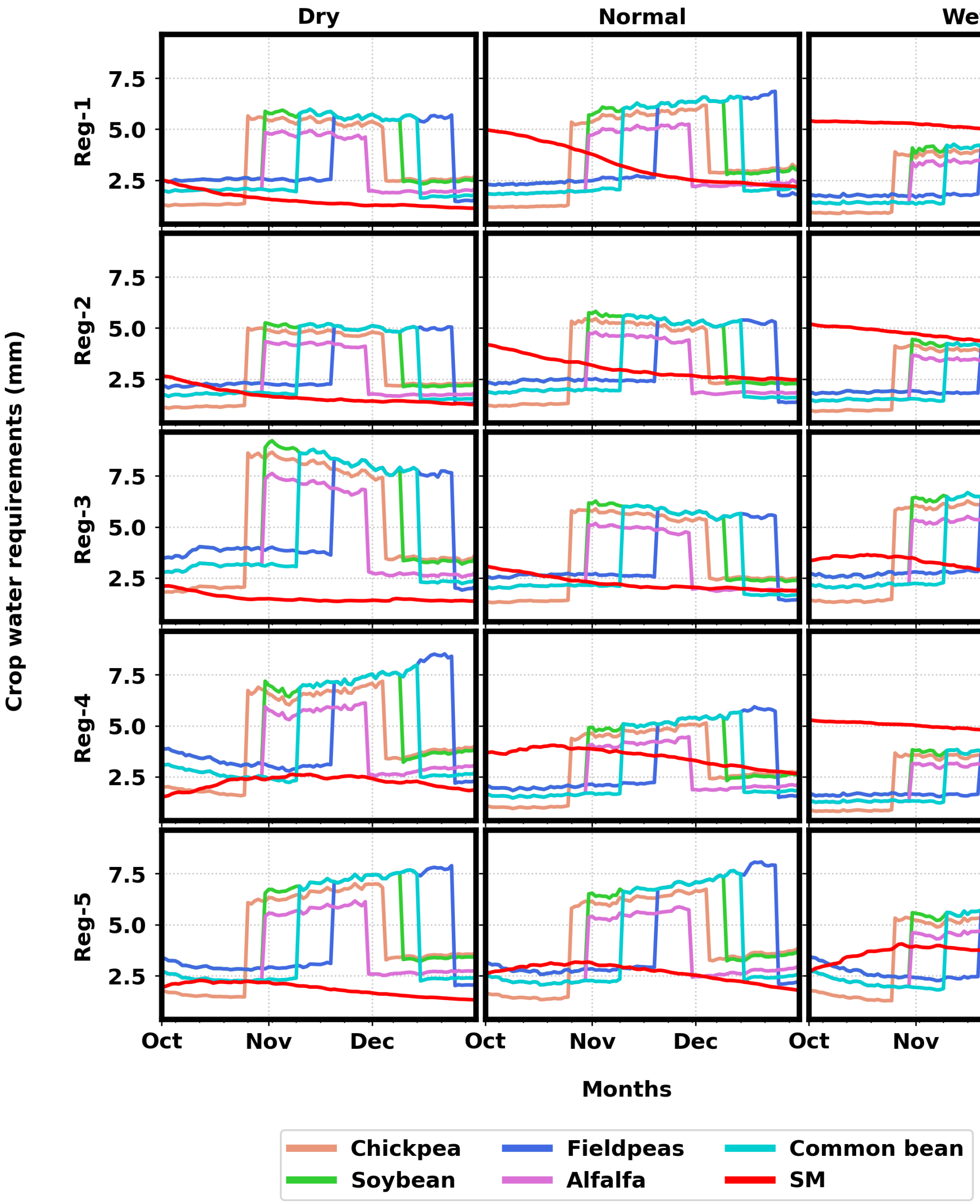

Figure 4.11.: Daily crop water requirements for chickpea, field peas, common bean, soybean, and alfalfa, alongside available residual soil moisture (SM) during the OND season. Columns represent soil moisture conditions (dry, normal, and wet) in respective regions, while rows indicate homogeneous regions (Reg-1 to Reg-5).

Figure 4.12 illustrates the spatial distribution of the difference between residual soil moisture and crop water requirements for the five crops across cropland areas in Ethiopia. Cropland covers approximately 30.1% of the total country area. At the initial growth stage, a high percentage of cropland areas (99.6% for chickpea, 94.7% for field peas, 99.4% for alfalfa, 99.4% for common bean, and 97.2% for soybean) support crop water requirements. These areas are primarily concentrated in the central and western regions of Ethiopia.

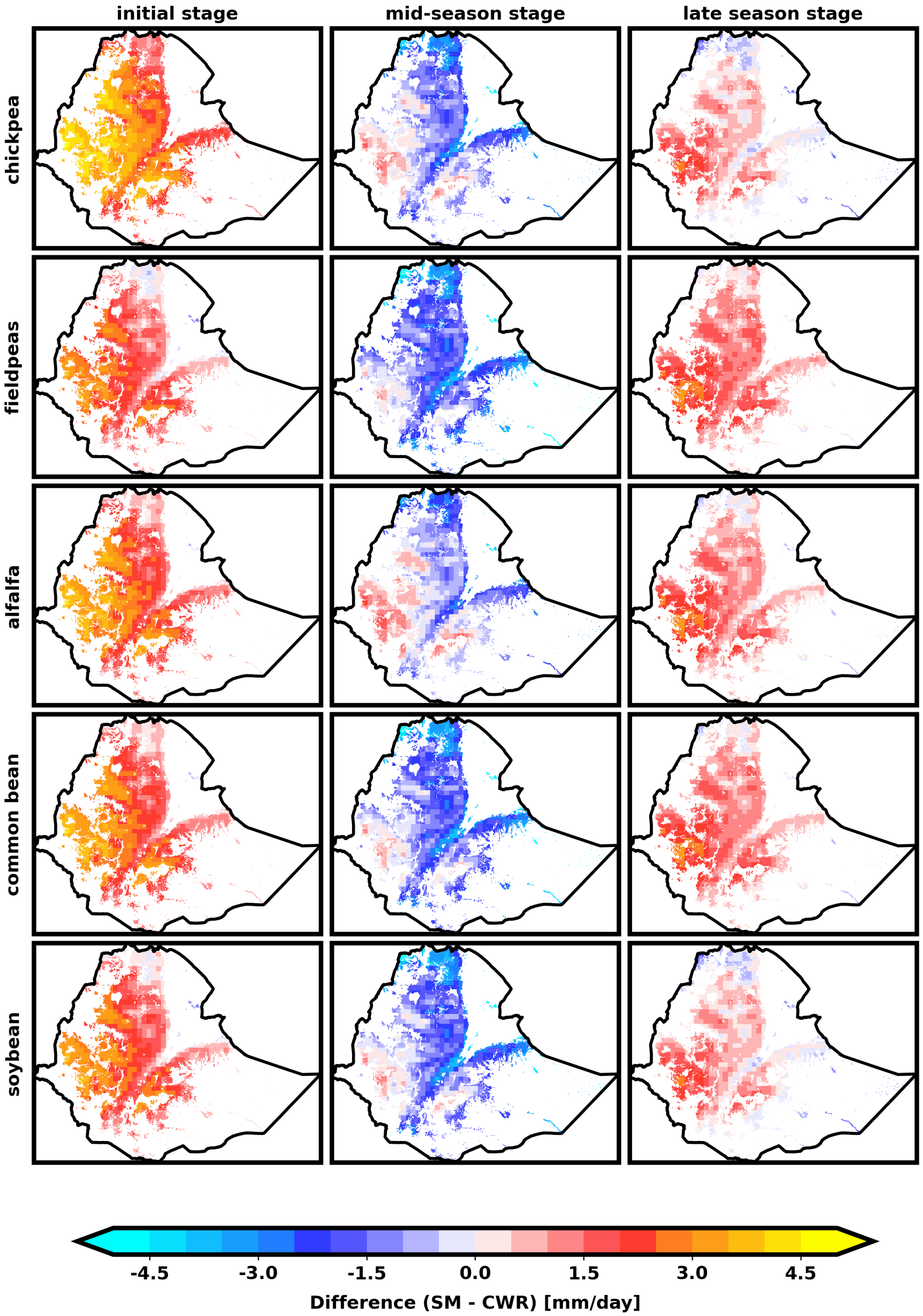

Figure 4.12.: Spatial distribution of the difference between residual soil moisture (SM) and crop water requirements (CWR) for chickpea, field peas, alfalfa, common bean, and soybean at their initial, mid-season, and late-season growth stages.

During the mid-season growth stage, the spatial coverage significantly reduces to 18.9% for chickpea, 3.6% for field peas, 29.5% for alfalfa, 7.4% for common bean, and 10.4% for soybean. Residual soil moisture in the central and eastern highlands becomes insufficient to meet mid-season crop water requirements for all crops. In addition, moisture deficits exceeding -4.5mm/day are observed in the central rift valley, eastern, and northern regions of the country. However, in most parts of the central and western highlands, moisture deficits are less than 1mm/day, which may be tolerated by crops' moisture resistance capabilities or supplemented by minimal irrigation to sustain crop growth all along this growth stage. During the late-season growth stage, crop water requirements for all crops are adequately supported by residual moisture across cropland areas, except for chickpea and soybean in the northernmost regions of the country.

4.5 Discussion

Our study investigates the spatiotemporal variability of soil moisture during the OND season in Ethiopia and its potential contribution to supporting legume-based cropping improvements in agricultural productivity. Through empirical analysis employing advanced statistical techniques, we unraveled the spatial and temporal distribution and trends of soil moisture across Ethiopia over the four decadal period from 1981 to 2020. Our primary focus was to investigate the potential of residual moisture to support post-rainy season cropping of legumes, particularly in light of adverse climate impacts on crop yield and the need for agricultural transformation to meet escalating food demand driven by population growth in the face of a changing climate.

Ethiopia's diverse topography, agroecologies, and climate variability play pivotal roles in shaping the heterogeneous distribution of soil moisture across the country. Our findings demonstrate pronounced soil moisture gradients between the eastern and western regions of Ethiopia, with the former characterized by comparatively lower moisture levels. The eastern regions of Ethiopia predominantly consist of lowlands, comprising a significant portion of the country's landscape. Characterized by arid and semi-arid agroecology, these lowland areas typically receive annual rainfall of less than 200 mm, accompanied by high temperatures reaching up to 50°C (Jimma et al. 2024; Berihun et al. 2023). This combination of climatic factors, including elevated temperatures and limited rainfall, contributes to reduced soil moisture availability in the eastern region, rendering it less conducive to post-rainy season cropping activities as already observed in other studies (Agutu et al. 2021; Temam et al. 2019).

Notably, the central region of Ethiopia, encompassing the highlands renowned for extensive agricultural practices, exhibits substantial moisture variability, imposing challenges regarding the sustainability of future agricultural activities in this crucial agricultural hub. The spatial heterogeneity of soil moisture underscores the need for tailored agricultural strategies that account for local moisture conditions, enabling farmers to spatially and temporally optimize their selection of crop species, crop varieties and management practices based on their specific agroecological context. This is becoming more important because of the protracted impacts of droughts in the horn of Africa and in Ethiopia particularly (Degefie et al. 2019), with climate projections indicating that the frequency and intensity of such droughts is likely to increase (Haile et al. 2020).

A key finding is that the eastern regions, particularly the northern and southeastern parts, are identified as particularly vulnerable to unreliable post-rainy season cropping, due to the prevalence of consecutive dry days and frequent dry spells. This finding helps to explain why agriculture is already constrained in these regions for the main season, and exhibits even more serious constraints for the post cropping period. Abera et al. (2019) indicate that the effects of climate change further compound the challenges, impacting surface water availability and exacerbating moisture deficits in these regions of Ethiopia. Conversely, the southeastern region of Ethiopia shows a promising trend with a substantial increase in moisture levels, suggesting potential opportunities for future post-rainy cropping of legume crops. The gradual decline in soil moisture in the Reg-1, Reg-2, and Reg-3 throughout the months of the season is likely explained by the withdrawal of Ethiopian summer rainfall (main rainy season) from northeast to southwest, following the trajectory of the Inter-Tropical Convergence Zone (ITCZ), as described in several studies (Gleixner et al. 2017b; Segele et al. 2009b; Segele and Lamb 2005) and the soil moisture's correlation with rainfall. The longest consecutive dry period, spanning from 2001 to 2020, is observed in Reg-2, consistent with the findings of Jimma et al. (2023), who utilized annual soil moisture data to assess trends in soil moisture across the country. These year-to-year variabilities within homogeneous climate regions are likely attributed to topographic effects, as well as local and global moisture drivers.

Our study further highlights the capacity of residual soil moisture to fulfill the water demands of selected legume crops, thereby rendering specific areas conducive to post-rainy season cropping, particularly the western, central, and southwestern regions. However, it is noteworthy that supplemental irrigation may be necessary for some crops during the mid and late growing stages in certain areas to mitigate moisture deficits and ensure optimal crop growth and yield. Furthermore, in regions that possess higher soil moisture values, such as wetter pocket areas in the southeastern region, implementation of supplementary irrigation could augment existing moisture levels, thereby enhance the potential for post-rainy cropping in the region.

Our findings have significant implications for sustainable intensification of agriculture in Ethiopia. Firstly, it underscores the potential for cultivating legume crops in non-overlapping growing seasons across different regions of Ethiopia, thereby enabling double harvesting and strengthening food security (Renard and Tilman 2021). Secondly, the availability of residual moisture presents an opportunity to incorporate legumes as secondary crops, potentially enhancing nutritional security because of their high protein content (Semba et al. 2021; Kebede 2020; Neda 2020; Assefa et al. 2011). Thirdly, the residual moisture during the OND period can contribute to soil fertility replenishment, particularly through its use for the cultivation of legumes for nitrogen fixation. Moreover, our findings bear significance for informing strategic planning initiatives aimed at agricultural transformation in Ethiopia to effectively address food security concerns in the face of a changing climate.

4.6 Conclusion

Our study provides insights into the spatiotemporal variability of soil moisture in Ethiopia and its potential for enhancing agricultural productivity. By rigorous empirical analysis, we have identified significant gradients in soil moisture levels across Ethiopia, shaped by its diverse topography, agroecology, and climate variability. These findings emphasize the importance of understanding soil moisture dynamics in optimizing post-rainy season cropping strategies.

Our research findings highlight the vulnerability of certain regions, particularly the eastern areas, to unreliable post-rainy season cropping due to moisture deficits, potentially exacerbated by climate change. However, there are promising opportunities for future legume crop production, especially in the southeastern region, where moisture levels show a notable increasing trend. Furthermore, we emphasize the crucial role of residual soil moisture in sustaining agricultural productivity, particularly in regions characterized by wetter moisture levels. By leveraging this resource and implementing supplemental irrigation where necessary, farmers can enhance their crop yields and resilience to climate variability.

Our study contributes to the broader discourse on agricultural sustainability and resilience to climate change, providing a foundation for future research and informing strategies to enhance food security and livelihoods in Ethiopia. The implications of our findings offer actionable insights for agricultural stakeholders and policymakers. By incorporating our research into decision-making processes, policymakers can formulate evidence-based policies aimed at promoting sustainable agricultural practices and ensuring food resilient cropping system in Ethiopia.

While our findings offer valuable insights for farmers, agricultural stakeholders and policymakers to optimize post-rainy season cropping strategies, we acknowledge the limitations of our study and emphasize the need for further research to deepen our understanding of the predicted crop viability in localized regions. Further research efforts employing process-based crop modeling, and incorporating soil properties and crop management strategies, combined with crop field trials across the different regions, would enhance understanding. Moreover, refining climate datasets through regional modeling approaches can provide more detailed insights by capturing fine-grained spatial variations overlooked in coarse-resolution analyses, thus improving the robustness and accuracy of our findings, and guiding more targeted interventions for sustainable agricultural development in Ethiopia.

Chapter 5

Summary of Findings, Conclusions, and Recommendations

5.1 Summary

This dissertation systematically investigates three critical dimensions: spatiotemporal soil moisture variability and its influential local and remote drivers, the coupled impacts of climate change and soil acidification on future crop suitability, and the potential of residual soil moisture to support post-rainy season cropping through comprehensive soil moisture analysis. These studies contribute essential insights to the broader goal of fostering agricultural practices that are productive, environmentally conscious, and resilient in the face of climatic uncertainties. This dissertation's findings are summarized as follows.

The second chapter investigates spatiotemporal soil moisture variability in Ethiopia, which is essential for promoting sustainable agriculture. Initially, the study validates soil moisture data from reanalysis and satellite sources against in-situ observations, revealing that FLDAS accurately captures the intricate spatiotemporal dynamics of soil moisture in Ethiopia. Using the FLDAS dataset, the study systematically outlines five homogeneous soil moisture zones in Ethiopia based on annual soil moisture levels. This was done by employing EOF analysis and the KMeans clustering algorithm. Thus, the research characterizes the spatiotemporal variability in soil moisture content within each zone, indicating significant variations across the country, with an evident gradient between Ethiopia's eastern (low soil moisture levels) and western (high soil moisture levels) regions.

The research further elucidates the dynamic nature of soil moisture in Ethiopia by analyzing the complex interplay among local factors, such as rainfall and evapotranspiration, and remote drivers like SST teleconnections utilizing CMCA. The in-depth investigation reveals unique relationships between evapotranspiration, rainfall, sea surface temperature, and soil moisture, providing detailed insights into the strength of these relationships across Ethiopia. Results indicate that rainfall patterns primarily influence interannual variabilities of soil moisture. In comparison, evapotranspiration plays a crucial role in soil moisture dynamics, particularly in the eastern part of the country. Furthermore, key findings demonstrate a strong association between major global oceanic indices, such as the Oceanic Niño Index (ONI, $r = 0.72$), Indian Ocean Dipole (IOD, $r = 0.43$), Pacific warm pool (PACWARMPOOL, $r = 0.48$), and Pacific Decadal Oscillations (PDO, $r = -0.52$), and local soil moisture anomalies observed in various regions of Ethiopia. This detailed analysis contributes to understanding the complex soil moisture patterns prevalent across the outlined homogeneous climate zones.

The third chapter examines the combined impacts of climate change and soil acidity on the future suitability of crops in Ethiopia. In addition to several natural and anthropogenic causes of soil acidity, agricultural intensification in Ethiopia may lead to unintended consequences on soil health. This intensification, aimed at meeting growing food demands, can particularly result in soil acidification. By 2050, Ethiopia is expected to experience climate shifts characterized by increased rainfall and temperatures. This climatic transformation and evolving soil acidity are projected to influence crop suitability across the country significantly.

The study focused on four key food crops in Ethiopia—teff, maize, barley, and wheat—to evaluate the combined impacts of climate change and soil acidification on their suitability using a crop suitability model. The findings indicate that climate change alone has a minimal impact on the area suitable for crops, with only marginal changes observed for maize (0.08%), barley (1.8%), and wheat (0.4%). However, there is a substantial increase in suitable land area for teff (5.1%). In contrast, the worst-case scenario, where soil pH levels decrease by 1.5, reveals significant reductions in suitable crop land area: -26.7% for teff, -8.7% for maize, -30.9% for barley, and -34.3% for wheat. These results indicate that wheat is the most affected crop, while maize is less impacted. Additionally, the central-western region of Ethiopia shows higher susceptibility to increased soil acidity.

The research highlights the necessity for balanced and sustainable approaches to minimize soil acidity, including modern farming practices and mitigating natural causes of soil acidification. These findings underscore the importance of addressing soil health alongside climate change to ensure sustainable agricultural productivity in Ethiopia.

The post-rainy season cropping period, from October to December, is pivotal for sustainable agriculture. Strengthening cropping practices during this period is important, focusing on analyzing residual soil moisture as a key strategy to utilize soil moisture resources after the rainy season. This chapter uses empirical analysis to examine the spatial and temporal evolution of residual moisture and its availability to meet crop water demands. The findings show significant variability in soil moisture levels across the central highlands, with standard deviations over 25 $kg.m^{-2}$. The western regions have high moisture levels (> 150 $kg.m^{-2}$), while the eastern regions have low levels (as low as 60 $kg.m^{-2}$). The northern and southeastern areas experience extended dry periods (> 150 days) and frequent dry spells, rendering these regions unreliable for post-rainy season cropping. The study assesses the crop water requirements of common legume crops such as chickpeas, field peas, common beans, soybeans, and alfalfa from October to December. The results reveal that residual soil moisture can support these crops in the western, central, and southwestern regions, meeting their water demands during the initial and late-season growth stages but not the mid-season development. This study underscores the potential of using residual soil moisture for post-rainy season legume cropping as a viable strategy to boost crop productivity in Ethiopia.

In general, the insight from this dissertation reveals both benefits and threats to cropping activities in Ethiopia. The studies highlight the significant potential of soil moisture for cropping in the western regions. However, the studies also inform that increasing soil acidity could undermine these benefits in the region. In addition, the projected climate change suggests an increase in rainfall across the central south-north highlands. However, findings indicate high moisture variability and decreasing trends in these regions. This moisture variability and declining trends necessitate adopting innovative, climate-resilient approaches to capitalize on the projected increase in rainfall and the anticipated improvement in crop suitability in the region. On the other hand, the central-eastern highlands are expected to benefit from the rising rainfall, declining soil pH level, and increasing soil moisture trends, positioning the region as a potential future agricultural hub. The studies also point out promising future cropping potential in the southeast region, which is indicated by increasing annual and seasonal soil moisture trends, except in the southeasternmost tips of the country.

5.2 Conclusions

i. **Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers**

Soil moisture is among the essential climate variables that play a significant role in land-atmosphere interactions, particularly in energy exchange and water balance (Dorigo et al. 2017; Wang et al. 2016; Wagner et al. 2012; Seneviratne et al. 2010). Despite its importance, Ethiopia lacks a reliable network of in-situ soil moisture stations. Hence, our research evaluated the agreement among station, reanalysis, and satellite estimates of soil moisture across Ethiopia, identifying the FLDAS dataset as the most representative. Using EOF and KMeans clustering, we classified Ethiopia into five homogeneous soil moisture zones, revealing distinct annual patterns aligned with seasonal rainfall. Rainfall and evapotranspiration strongly influence soil moisture, especially in the southern regions, where higher values are closely linked. In the southeastern part, temperature drives land-atmosphere interactions, with higher temperatures leading to increased evaporation and convection. Global SST anomalies also significantly affect Ethiopia's local soil moisture, suggesting the need for further study to understand their roles in these anomalies. These findings underscore the necessity of comprehensive soil moisture monitoring and integrating these insights into climate resilience planning for sustainable agricultural development in Ethiopia.

ii. Coupled impacts of climate change and soil acidification on future crop suitability in Ethiopia

Chapter 3 investigated the combined effects of soil acidity and climate factors on the suitability of four key crops (teff, maize, barley, and common wheat) in Ethiopia under changing climate and soil conditions. By 2050, Ethiopia is projected to experience increased rainfall and temperatures, which, along with shifting soil pH, will impact crop suitability. The study found that using default soil pH values, the suitability for maize, barley, and wheat remains unchanged for the projected climate by 2050. In contrast, teff suitability increases due to higher rainfall. The central western region of Ethiopia is susceptible to rising soil acidity that affects all crops, with wheat being the most affected. Therefore, the increased soil acidity could negate enhanced suitability benefits, highlighting the need for agricultural adaptation strategies considering soil health. Intensification measures that exacerbate soil acidity must also be avoided.

iii. Spatiotemporal dynamics of residual soil moisture and its role in legume-based cropping systems in Ethiopia

In this chapter, we comprehensively analyze residual soil moisture variability in Ethiopia and its implications for post-rainy season cropping. Analysis showed that the residual soil moisture level varies from 150 $kg.m^{-2}$ in the west to below 60 $kg.m^{-2}$ in the eastern regions. It is highly variable and exhibits a declining trend along the central highlands. It is showing an increasing trend over the western and eastern lowlands. Our findings also indicate that the western, central, and southwestern regions have the potential to sustain crop water demands. Moreover, there are promising opportunities for legume crop production in the southeastern region, where moisture levels are trending upwards. Conversely, specific regions, particularly the eastern and northern areas, are vulnerable to unreliable post-rainy season cropping due to moisture deficits, potentially exacerbated by climate change. Residual soil moisture is vital in sustaining agricultural productivity, especially in regions with higher moisture levels. By leveraging residual soil moisture and implementing supplemental irrigation where necessary, farmers can enhance their crop yields and resilience to climate variability.

5.3 Recommendations

This dissertation addresses key challenges and opportunities in Ethiopia's agricultural sector, culminating in a series of recommendations.

The recommendations derived from the studies in this dissertation aim to provide actionable insights for policymakers, practitioners, and stakeholders committed to promoting sustainable agriculture in Ethiopia. These recommendations span three critical dimensions discussed in the respective chapters and are designed to enhance the sustainable development of Ethiopia's agricultural sector.

Findings from Chapter 2 highlight patterns of soil moisture spatiotemporal variability linked to global climate indices. Understanding the interactions between large-scale circulations and local climatic variables is important. Therefore, it is recommended to recognize the impact of oceanic indices on local soil moisture and integrate these factors into long-term climate resilience planning. Incorporating the influence of global oceanic indices into climate change adaptation strategies is essential. In addition, supporting further research to assess the specific roles of other oceanic regions in influencing local soil moisture in Ethiopia will help promote climate-resilient agricultural strategies that align with the variability of these climate indices. It is also noteworthy to consider the significant impact of evapotranspiration on the eastern regions of Ethiopia, as cropping practices may require substantial amounts of water, making it resource-intensive.

Results from Chapter 3 on the combined impacts of climate change and soil acidification on future crop suitability emphasize the need to consider soil acidity in agricultural adaptation planning. Acknowledging that intensification measures leading to increased soil acidity may exacerbate existing problems is crucial. Therefore, it is recommended to adopt integrated nutrient management practices to address this issue. Developing and promoting precision nutrient management practices, such as tailored fertilizer application based on soil nutrient assessments, can help prevent imbalances that contribute to soil acidification. It is also essential to integrate soil moisture as a factor directly into the modeling approach to understand its direct implications and role in mediating soil acidity. The study also recommends considering the predicted crop suitability shifts to the central-northern and -eastern highlands; these regions could be a potential agricultural hub in the future.

This dissertation also underscores the potential of residual soil moisture for post-harvest cropping across Ethiopia. Therefore, it is recommended to capitalize on the identified regions' existing residual soil moisture potential to enhance post-rainy season cropping. Furthermore, expanding this research to evaluate other potential crops that can utilize residual soil moisture to enhance crop productivity is advisable. Implementing a comprehensive residual moisture monitoring system to establish residual moisture advisory services is recommended due to the highly variable nature of soil moisture. These services can provide farmers with real-time information and recommendations regarding optimal post-rainy season residual moisture levels, guiding them in making informed decisions and minimizing crop loss risks.

The implications of our findings likely provide actionable insights for agricultural stakeholders and policymakers. By incorporating this research into decision-making processes, policymakers can formulate evidence-based policies to promote sustainable agricultural practices in Ethiopia. Our study contributes to the broader discourse on agricultural sustainability and resilience to climate change, offering a foundation for future research.

One limitation of this study is the short duration of the soil moisture dataset used. Future research should utilize longer observational records to improve accuracy. Additionally, examining the relative importance of climate and soil factors in crop suitability using process-based models, especially the effects of soil pH, is crucial. Expanding this research to larger scales will help understand the broader implications of soil and climate interactions on crop suitability under climate change. Further studies should also focus on localized crop viability, incorporating soil properties, crop management strategies, and field trials across different regions. Refining climate datasets through regional modeling can provide detailed insights, enhancing the robustness of findings and guiding targeted interventions for sustainable agriculture in Ethiopia.

List of publications

Our research findings have been disseminated through publication in prestigious academic journals, showcasing the culmination of our efforts in the scholarly community. In addition, we are currently in the process of preparing a number of other manuscripts for publication, further extending the impact and reach of our research. The following are published and work on progress articles from this dissertation:

1. Jimma, T.B., Demissie, T., Diro, G.T., Ture K, Terefe T, Solomon D. (2023) Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers. *Theoretical and Applied Climatology.* 151, 1911–1929 (2023). https://doi.org/10.1007/s00704-022-04335-7
2. Jimma TB, Chemura A, Spillane C, Demissie T, Abera W, Ture K, Terefe T, Solomon D, Gleixner S. (2024) Coupled Impacts of Soil Acidification and Climate Change on Future Crop Suitability in Ethiopia. *Sustainability*. 2024; 16(4):1468. https://doi.org/10.3390/su16041468
3. Jimma TB, Abera W, Demissie T, Spillane C, Ture K, Solomon D, Chemura A,. Spatiotemporal dynamics of residual soil moisture and its role in resilience of legume-based cropping systems in Ethiopia. Submitted.

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Appendix A

Supplementary materials for "Spatiotemporal Variability of Soil Moisture over Ethiopia and its Teleconnections with Remote and Local Drivers.

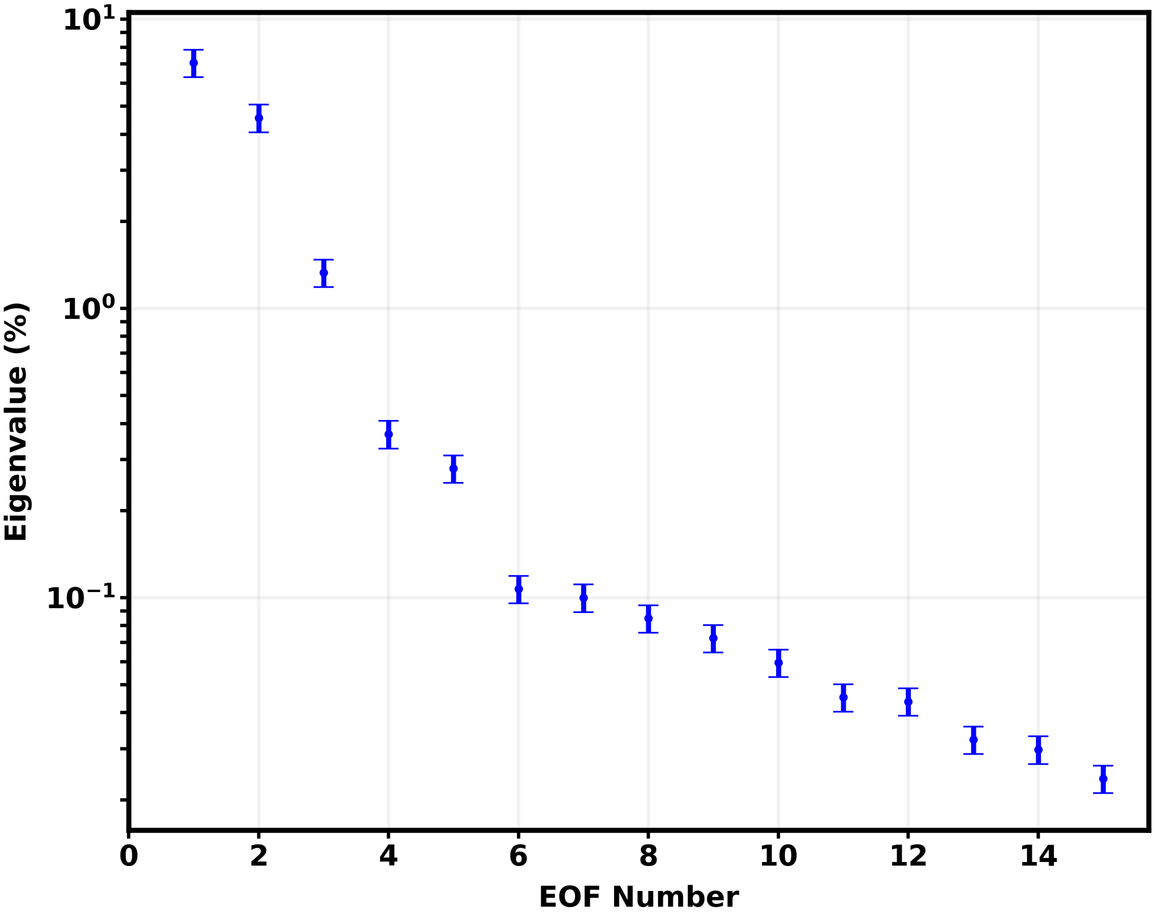

Figure A.1.: The eigenvalue spectrum graph in percent shows the first fifteen EOFs of the covariance matrix with a 95% confidence interval indicated by vertical bars. The first three EOFs that do not overlap in 95% confidence intervals indicate they are non-degenerate.

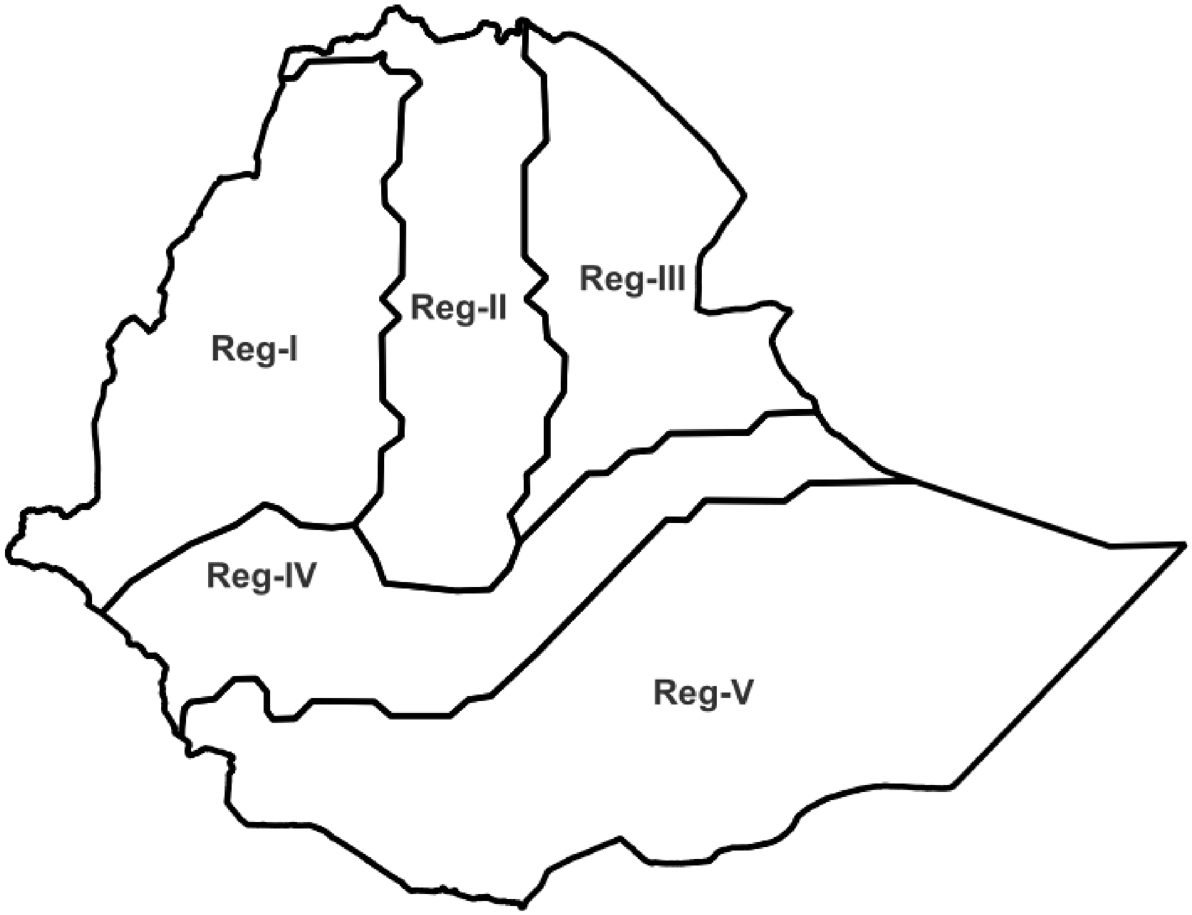

Figure A.2.: Homogeneous climate zones (Reg-I, Reg-II, Reg-III, Reg-IV, and Reg-V) based on soil moisture distribution (FLDAS dataset) across the country (1982-2020).

Appendix B

Supplementary materials for "Spatiotemporal Dynamics of Residual Soil Moisture and its Role in Legume-based Cropping Systems in Ethiopia."

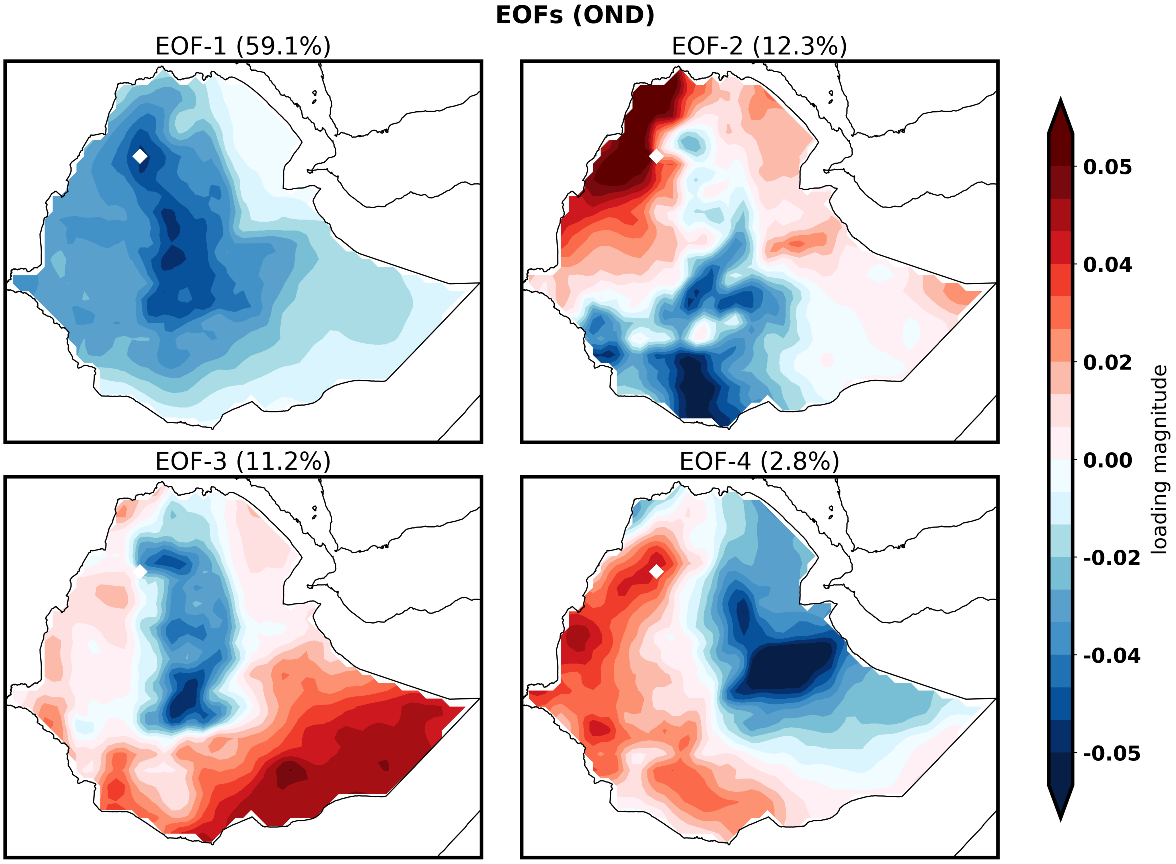

Figure B.1.: Four highest modes of EOFs explaining the spatial variability of soil moisture during the OND season in Ethiopia.

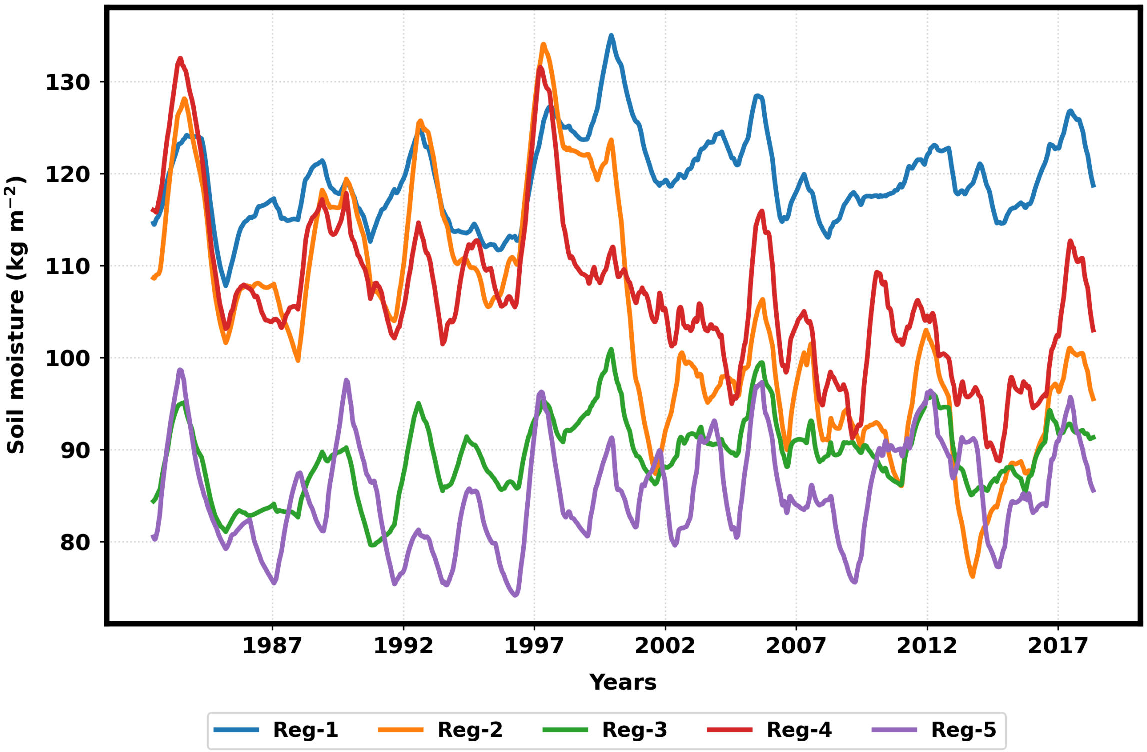

Figure B.2.: Long-term temporal trends of residual soil moisture in homogeneous regions. The long-term time series data is smoothed on a seasonal time scale (1 year).