Università degli Studi di Sassari.

Department of Agricultural Scineces

Doctoral Research Course Under the Curriculum Desertification and Land Degradation

Sustainable Solutions to Land Degradation and Rainfall Variability in Sub-Saharan Africa: Integrating Traditional Water Management, Agricultural Intensification, and Machine Learning Approaches

A Thesis Submitted for the Degree of

Doctor of Philosophy

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Foreword

This thesis consists of five manuscripts: 4(four) have been published, and one is currently under review and the fifth was presented as a poster at the AGU Conference 2024. The research was conducted as part of my PhD studies in the Department of Agricultural Sciences, specializing in Desertification and Land Degradation. This work was fully supported by the EWA-BELT Project, funded by the European Union's Horizon 2020 research and innovation program (Grant Agreement No. 862848). My studies were carried out at the University of Sassari, Italy, from October 2021 to October 2024, under the guidance of Professor Giovanna Seddaiu and Professor Ing. Alberto Carletti.

Abstract

This thesis examines sustainable agricultural practices designed to tackle the challenges of land degradation, climate variability, and food insecurity in sub-Saharan Africa, with a specific emphasis on rainfed agricultural systems. As the region grapples with the effects of erratic rainfall, soil degradation, and limited access to advanced technologies, this research explores solutions that blend traditional knowledge with machine learning and remote sensing. It investigates how climate variability impacts agricultural productivity and underscores the need for adaptive strategies. The thesis highlights traditional water harvesting techniques, such as stone bunds and in-situ water conservation methods, to improve soil moisture retention, reduce runoff, and boost crop yields. Furthermore, it integrates remote sensing and machine learning to enhance soil moisture predictions and inform more effective water management strategies. By combining age-old practices with innovative technologies, this research offers valuable contributions toward building resilient agricultural systems that improve productivity and sustainability in the face of climate change, providing practical insights for policymakers, practitioners, and researchers working towards lasting solutions for food security in sub-Saharan Africa.

Keywords: Land Degradation, Rainfall Variability, In-situ water harvesting (IS_WH), Machine Learning, Soil Moisture and Sub-Saharan Africa.

Declaration

I, the undersigned Meron Lakew Tefera, declare that this dissertation is the original report on my doctoral research at the University of Sassari, it has been written by myself and has not been submitted or presented, in whole or in part, for the award of any other academic degree or diploma elsewhere.

Meron Lakew Tefera

(February, 2024)

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Finally, I would like to express my deepest gratitude to Francesco Bonechi for his constant love and encouragement, which have been a source of strength, and to my family, his family, and all those who have walked this path with me. Each of you has contributed in some way to the realization of this work, and for that, I am truly thankful.

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List of Abbreviations

CI	Confidence Interval
CO_2	Carbon dioxide
ENSO	El Niño-Southern Oscillations
ETa	Actual Evapotranspiration
ETo	Evapotranspiration
FAO	Food and Agriculture Organization
GHG	Greenhouse Gas
ICTA	International Centre for Tropical Agriculture
IDW	Inverse Distance Weighted
I^2	Heterogeneity Statistics
Ks	Saturated Soil Hydraulic Conductivity
IS_WH	In-Situ Water Harvesting
ITCZ	Intertropical Convergence Zones
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NDVI	Normalized Difference Vegetation Index
NRD	Desertification Research Centre
NSE	Nash Sutcliffe Efficiency
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
SIAP	Sustainable Agricultural Intensification Practices
SMAP	Soil Moisture Active Passive
SMD	Standardized Mean Difference
SPI	Standardized Precipitation Index
TE	Treatment Effect
SPEI	Standardized Precipitation Evapotranspiration Index
SSA	Sub-Saharan Africa
UNCCD	United Nations Conventions to Combat Desertification
VWC	Volumetric Water Content

General Introduction

Sub-Saharan Africa, particularly West Africa, is highly vulnerable to the impacts of climate variability, which significantly affects agricultural productivity. In many areas where agriculture is predominantly rainfed, fluctuations in rainfall patterns and the increasing frequency of droughts exacerbate the challenges faced by farmers, leading to reduced yields and food insecurity. The unpredictability of rainfall, combined with limited data availability, complicates effective agricultural planning and water resource management. These climatic uncertainties, along with the adverse effects of climate change, such as shifting precipitation patterns and more frequent droughts, make it essential to develop adaptive strategies that ensure the sustainability of agriculture in the region.

Among the strategies that have gained attention is the role of soil conservation practices, which are increasingly recognized for their potential in managing water resources and enhancing agricultural productivity. This thesis aims to address the challenges posed by land degradation, climate variability, drought, and the lack of sufficient data for soil moisture estimation in semi-arid regions of West Africa, particularly in Ghana and Burkina Faso. The complexity of these challenges requires a multi-methodological and multi-scale approach that integrates field evaluations, remote sensing data, and advanced modeling techniques.

By combining these methods, this study seeks to create a comprehensive understanding of the impacts of land degradation and climate variability on agricultural systems. This integrated approach also enables the development of practical, scalable strategies that can be applied across different levels—from local to regional offering adaptable solutions to improve agricultural sustainability and resilience in sub-Saharan Africa.

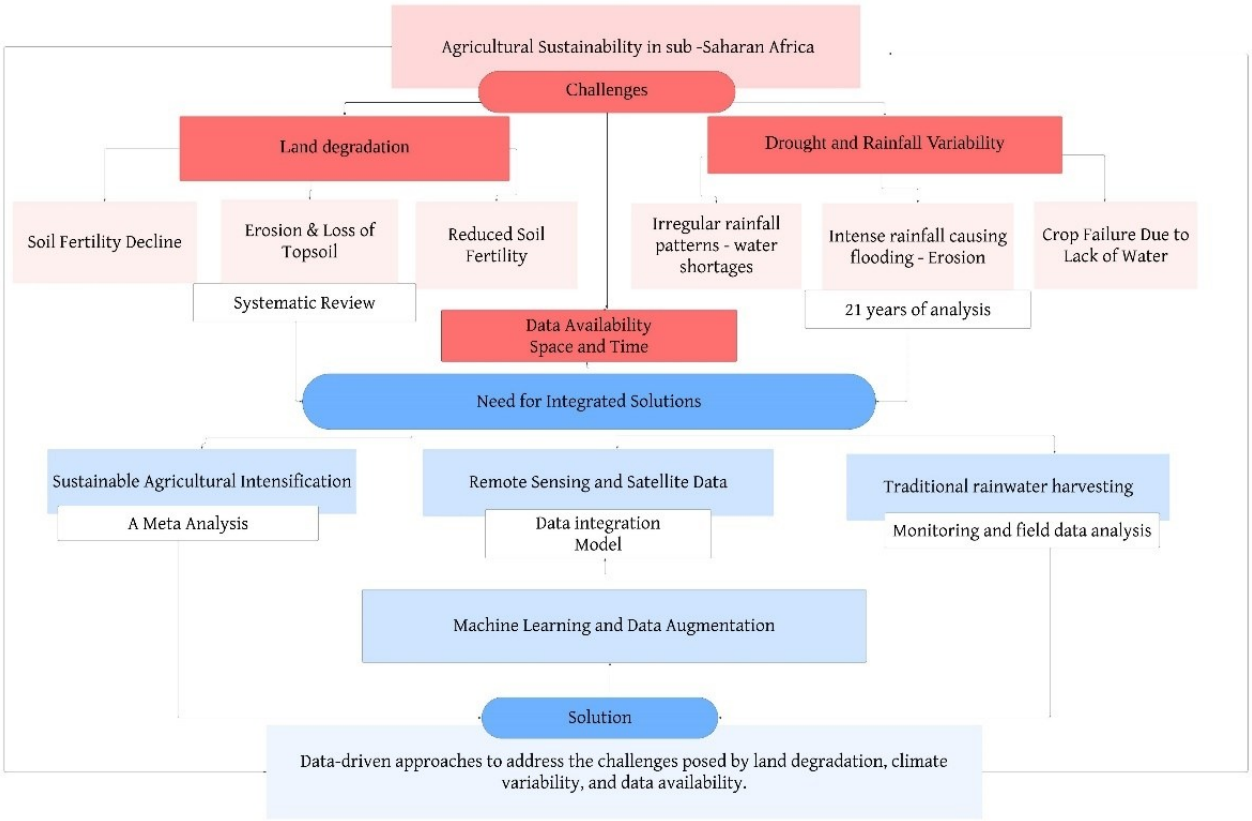

Figure 1. Integrated Solutions to Challenges Impacting Agricultural Productivity and Sustainability in Sub-Saharan Africa_ thesis flow chart

Hypothesis

The primary hypothesis of this study is that integrating traditional soil and water conservation practices with modern technological approaches, including remote sensing and machine learning, can significantly enhance soil moisture retention, improve agricultural productivity, and contribute to sustainable land management in semi-arid regions of sub-Saharan Africa. Specifically, it is hypothesized that:

- Traditional water harvesting practices, such as stone bunds, improve soil moisture retention and reduce soil erosion at the field scale, leading to enhanced crop yields and overall agricultural resilience in Ghana and other similar regions.
- Climatic variability, particularly changes in rainfall patterns and drought occurrences, negatively impacts agricultural productivity and water management in Ghana and Burkina Faso, requiring localized adaptation strategies to mitigate these effects.
- The combination of systematic reviews and meta-analyses of traditional water harvesting techniques across sub-Saharan Africa will demonstrate the region's potential for scaling up these practices as part of broader sustainable agricultural strategies.
- Advanced machine learning models, when integrated with field data and remote sensing technologies, can effectively predict soil moisture levels in semi-arid regions, providing accurate and timely information to improve water management and enhance agricultural productivity over larger areas.
- The integration of traditional and modern approaches will offer a scalable and adaptable framework for overcoming data scarcity challenges, enabling farmers to better manage water resources and adapt to climate variability at local and landscape levels across West Africa.

Significance of the Study

The significance of this study lies in its comprehensive, multi-methodology, and multi-scale approach to addressing some of the most pressing challenges faced by sub-Saharan Africa, including land degradation, water scarcity, and food insecurity. By integrating traditional agricultural practices with modern technological solutions, the research provides actionable insights and scalable strategies that can enhance agricultural sustainability and resilience. The study employs a combination of systematic reviews, meta-analyses, field evaluations, and advanced modeling techniques, allowing for a holistic understanding of the issues at hand. This multi-methodology approach ensures that diverse perspectives are incorporated into the solutions, while the multi-scale framework—ranging from regional assessments to local field evaluations—ensures that findings are applicable at both broader policy levels and on-the-ground interventions. The research highlights the importance of both indigenous knowledge and advanced methodologies in improving soil and water management, promoting sustainable farming practices, and ensuring long-term food security. Moreover, it bridges the gap between local-level interventions and larger-scale policy frameworks, offering practical solutions to help farmers and policymakers adapt to the effects of climate variability and data limitations. Ultimately, this study contributes to the development of more adaptive, resilient, and data-driven agricultural systems that can better withstand the challenges posed by changing environmental conditions in the region.

- Structure of the Thesis

The subsequent chapters present each study in detail, beginning with the systematic review of land degradation and sustainable intensification. Each chapter is framed within the broader context of this

introduction, with a concluding synthesis chapter that integrates the findings and discusses their implications for sustainable development in sub-Saharan Africa.

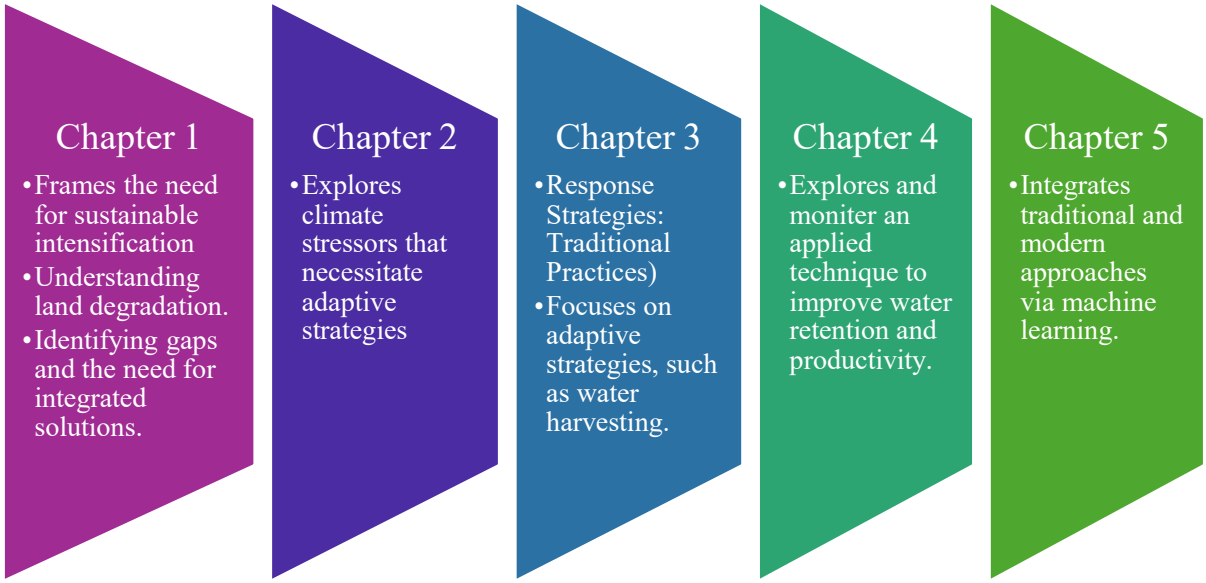

Figure 2. The chapters

Objective

The overarching objective of this thesis is to evaluate and enhance sustainable agricultural practices to combat land degradation, improve water management, and ensure food security in sub-Saharan Africa. Through a combination of systematic reviews, meta-analyses, field evaluations, and advanced modeling techniques, the study aims to bridge the gap between traditional knowledge and modern technological solutions, providing actionable insights and scalable strategies for resilient agricultural systems in the face of climate variability and data limitations. Specific Objectives by Chapter:

Chapter 1: Assessing the Role of Sustainable Agricultural Intensification in Combating Land Degradation and Ensuring Food Security in Sub-Saharan Africa

Scale: Sub-Saharan Africa (Regional level)

Objective: Establish a broad foundation for the thesis by conducting a systematic review to evaluate the role of sustainable agricultural intensification practices in addressing land degradation and improving food security across sub-Saharan Africa. This chapter aims to provide a regional overview, highlighting trends, challenges, and opportunities for scaling up sustainable practices to inform policy and national-level strategies.

Chapter 2: Investigating the Impacts of Climatic Variability on Agricultural Productivity and Water Management

Scale: Ghana and Burkina Faso (National level, with focus on specific countries)

Objective: Explore the impacts of a 21-year period of climate variability in Ghana and Burkina Faso, assessing the impact of changes in rainfall patterns, and droughts on agricultural productivity. It provides country-specific insights that can guide national-level adaptation strategies, contributing to a deeper understanding of how climate change affects agricultural systems in West Africa.

Chapter 3: Evaluating the Effectiveness of Traditional In-Situ Water Harvesting Practices in Improving Soil Moisture Retention and Enhancing Crop Yields

Scale: Meta-analysis across Sub-Saharan Africa (Regional level)

Objective: Conduct a meta-analysis to assess the regional effectiveness of traditional in-situ water harvesting practices across sub-Saharan Africa. Building on the themes of sustainability and climate resilience from Chapters 1 and 2, this chapter quantifies the role of these indigenous techniques in improving soil moisture retention and crop yields.

Chapter 4: Field Evaluation of Stone Bunds on Water Retention and Soil Erosion Reduction in Ghana

Scale: Field evaluation in Ghana (Local level)

Objective: Transition from theoretical assessments to practical validation by conducting field-scale evaluations in Ghana. This chapter investigates how stone bunds improve soil moisture retention and reduce soil erosion, providing real-world evidence that supports and enhances the findings from previous chapters.

Chapter 5: Integration of Field Data, Remote Sensing, and Machine Learning for Soil Moisture Estimation in West Africa's Semi-Arid Environments

Scale: Large agricultural areas (Local to landscape level)

Objective: Address the challenge of data availability by integrating field data, remote sensing, and machine learning to develop a predictive soil moisture model. This chapter leverages insights from earlier chapters to propose a scalable framework for quantifying the impact of traditional soil and water conservation practices, enabling sustainable water management and agricultural resilience over large areas in West Africa.

CHAPTER 1

1. Land degradation and the upper hand of sustainable agricultural intensification in sub-Saharan Africa – A systematic review

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Land degradation and the upper hand of sustainable agricultural intensification in sub-Saharan Africa - A systematic review

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Abstract
Sub-Saharan Africa (SSA) faces severe land degradation, driven by a combination of human and natural factors. Deforestation, inadequate land management practices, and unsustainable farming methods are the primary causes. The historical trends reveal the impact of soil erosion and nutrient depletion on 70% of the soil and 65% of its total land area. Unchecked degradation poses a critical threat to economic growth and poverty reduction initiatives. The region's food security is intricately linked to the complex interplay between land degradation and a rapidly growing population. Escalating demand for agricultural resources raises concerns about the ability to meet the needs of SSA's population. The adoption of sustainable agricultural intensification practices (SIAP) emerges as a crucial strategy to address land degradation and enhance food security. SIAP involves innovative and ecologically sensitive techniques, such as agroforestry and organic farming, targeting to optimise resource use and minimise negative impacts on soil health. The interconnectedness between factors of land degradation, food security, and the contribution of SIAP underscores the urgency of adopting sustainable practices to ensure a balanced relationship between agricultural productivity and environmental conservation in SSA. However, while SIAP holds promise, several challenges hinder its widespread adoption. These include socio-economic barriers, such as limited access to financing, *inadequate knowledge*, and *low adoption rates*, as well as contextual variations in local conditions and farmer needs. Additionally, the *limited availability and reliability of data, climate variability*, and land use further complicate the successful implementation and monitoring of SIAP, creating a significant hurdle for policymakers and practitioners. Addressing these challenges requires continuous support, context-specific policies, and robust data systems to ensure the long-term success of sustainable agricultural practices across the region..

Keywords – Agriculture, Food Security, Poverty, Soil Erosion, Sustainable Land Management

1.1. Introduction

Land is an essential resource (IPCC, 2019) and land degradation is commonly defined as the deterioration of the productive capacity of land (AbdelRahman, 2023; Pacheco et al., 2018). Land degradation stands out as one of the most persistent and pressing global challenges (Stocking, 2001). Sub-Saharan Africa (SSA) accounts for 20% of the value of ecosystem services of the terrestrial biomes and 16% of the world's land area (Nkonya et al., 2008; Nkonya et al., 2016). The region accounts for 14.97% of the world population in 2022 (UN, 2022) and is expected to account for 35% by 2100 (Ezeh

et al., 2020). Smallholder farms account for more than 80% of all farms, and farmers provide up to 90% of the food supply in the region (Goedde et al., 2019; Hlophe-Ginindza et al., 2021). However, the region bears the most considerable portion (22%) annual cost of land degradation in the world (Nkonya et al., 2016). The world's most serious land degradation has been occurring in SSA during the past ten years (Byaro et al., 2023). Unsustainable agricultural practices and deforestation are the leading causes (Zingore et al., 2015). Nearly 70% of the region's soil resources are affected by soil erosion and nutrient depletion (Nkonya et al., 2008). 40% of the soils in SSA are characterized by low nutrient reserves (Tully et al., 2015), which is attributed to low suitability for agricultural production. The demand for adequate, cheap, and nutritious food in the region is being challenged by land degradation (Giller, 2020). As a consequence of degradation and climate change by 2050, about 86 million people will tend to migrate within their own countries making it the region with the highest number of internal refugees (WBG, 2021). Furthermore, the negative impacts of land degradation on human society are likely to become more prevalent, and undoubtedly SSA will be among the most affected areas by these impacts (Nkonya et al., 2016).

Responding to these challenges, researchers have increasingly focused on sustainable agricultural intensification practices (SIAP) in recent years. This shift reflects the recognition of the pressing need for effective solutions to mitigate the consequences of land degradation. Civil society organizations, governments, and nongovernmental programs are also a part of this approach in SSA (Hossain et al., 2021). SIAP has been reported to improve sustainable production (Kansiime et al., 2021), increase natural capital (Pretty et al., 2014), and help smallholder farmers to achieve higher yields on the same amount of land (Kassie et al., 2015; Oumer et al., 2020). Simultaneously, sustainable agricultural intensification serves as a vital strategy for reducing the strain on natural resources (Dalezios, 2017; Yahaya et al., 2018) and enhancing the resilience of agricultural systems in SSA, where dependence on natural resources for livelihoods is pronounced.

In SSA, there is a notable gap in the literature regarding the relationship between land degradation and food security. While various studies exist on this topic, a comprehensive synthesis is lacking, particularly in evaluating the effectiveness of sustainable agricultural intensification practices in addressing land degradation and improving food security. Moreover, limited exploration of the factors hindering the contribution of these practices to addressing land degradation further underscores the need for a systematic review. Addressing this gap, this study aims to provide a comprehensive summary of existing literature on the topic, focusing on assessing the impact of sustainable agricultural intensification practices as a solution to combat land degradation and improve food security in SSA. Specifically, this research endeavours: a) Review and evaluate the current state of land degradation in SSA, examining indicators, causes, and impacts; b) Assess the effectiveness of sustainable agricultural intensification practices in mitigating land degradation and their implications for food production systems in the region; and c) Identify factors limiting the contribution of SIAP to addressing land degradation in SSA, offering insights to inform strategies for overcoming these constraints.

1.2. Methodology

This systematic review methodology involved structured approach to identify, select, critically appraise, and synthesize relevant research studies aligned with our objectives. It involved predefined criteria for study selection, systematic search strategies across multiple databases, transparent data extraction processes, and quality assessment of included studies.

1.2.1. Search strategy

The search strategy for this review was meticulously developed to ensure a systematic and focused approach. It involved selecting key terms, specifying databases, setting a publication timeframe, and applying selection criteria based on relevance and methodology. These inclusion/exclusion criteria encompassed factors such as relevance to the research question, publication type, date, geographic scope, language, intervention/exposure, and outcome measures aligned with the research objective. Following the Problem, Intervention, Comparison, Outcome (PICO) framework paradigm, the essential concepts and relevant scientific literature related to the research goal were identified, articles with the potential to answer the research questions were selected (Aromataris et al., 2014), and components suitable for achieving optimal results were determined (Cumpston et al., 2020; Foo et al., 2021; Mengist et al., 2020). The framework also guided decisions regarding the time range for the review, databases searched, search techniques employed, and methodologies for data extraction and analysis, ensuring a comprehensive and robust synthesis of the literature.

1.2.2. Search terms and strings

The scientific literature search was conducted using Web of Science and Google Scholar as primary sources. Furthermore, official reports and databases international research organisations including, the Food and Agriculture Organization (FAO), United Nations Conventions to Combat Desertification (UNCCD), European Soil Data Centre (ESDAC), International Centre for Tropical Agriculture (ICTA), and Consultative Group on International Agricultural Research (CGIAR) addressing similar findings aligned with the research objectives were consulted and reviewed to ensure comprehensive coverage. To streamline the search process, keywords, and connectors were employed systematically. The following lists detail the keywords and connectors utilised during the search: land degradation, sustainable intensification, SSA, AND erosion OR climate change OR soil fertility OR natural resource management, OR agroforestry OR soil conservation OR conservation agriculture (CA) OR pull-push OR zero tillage OR soil conservation OR water conservation OR manure OR organic fertilizer OR compost OR desertification OR water harvesting OR deforestation OR overgrazing OR salinization OR alkalization OR soil compaction OR poor land management OR continuous cultivation OR land OR degradation OR intensification OR sustainability. Additionally, advanced search tools of the Web of Science were used to refine the search following the categories: environmental science, environmental studies, plant science, green, and sustainable technology, water resources, agronomy, remote sensing, forestry, agricultural economics, and policy.

1.2.3. Overview of the structure and typology of the reviewed paper

The examined papers were distributed across 25 countries within SSA, the general distribution accounts for 47% of West Africa (Benin, Burkina Faso, Cape Verde, Ivory Coast, Ghana, Mali, Niger, Nigeria, Senegal and Togo), 31% of East Africa (Djibouti, Ethiopia, Eritrea, Kenya, Malawi, Mozambique, Rwanda, Tanzania and Uganda), 16% of Southern Africa (Namibia, South Africa and Zimbabwe), and 6% of Central African countries (Cameroon, The DR of the Congo). More than 80% of the articles were published after the year 2010. The publications search related to the topic of smallholder farmers at different scales yielded publications focusing on field and farm scales, as well as watershed scales, encompassing both qualitative and quantitative empirical studies, along with mixed findings at the land scale. However, articles not clearly expressing and referring to the topic and the search terms were excluded from the result. These data were then assessed for objectives, components, outcomes, requirements, and limitations and were extracted solely from a total of 143 shortlisted articles (Figure 3). The extracted data were then analysed and synthesised to address the research question, with findings interpreted in context.

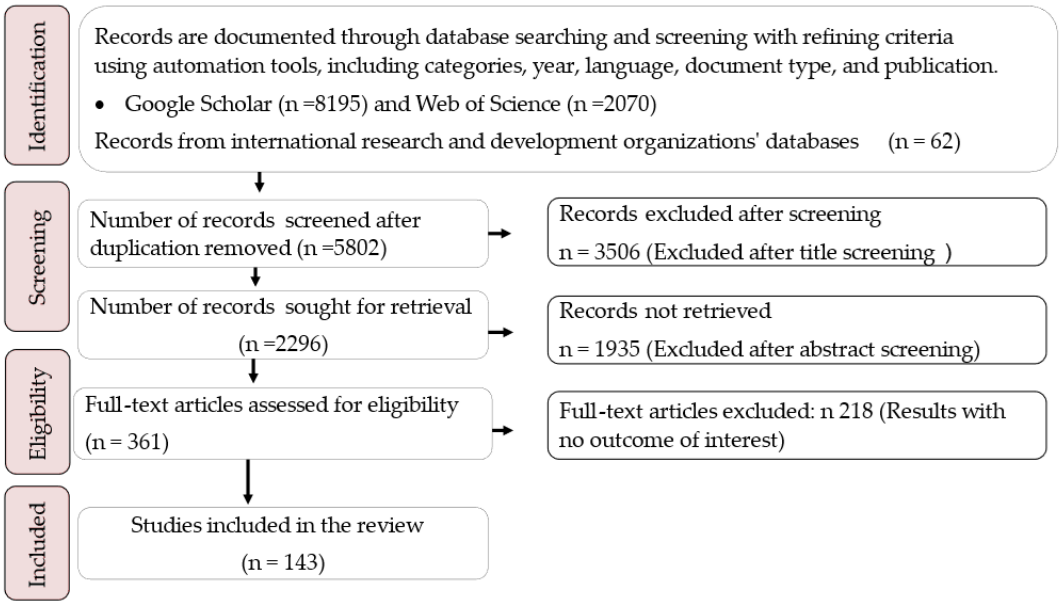

Figure 3. Study flow diagram (adopted from Page et al. (2021))

1.3. Results

1.3.1. Land degradation and food security in sub-Saharan Africa

Land degradation in SSA is an issue, impacting rural livelihoods and environmental stability (Nkonya et al., 2008). According to different scholars, 60 to 73% of Africa's topsoil is degraded; 24% of which is due to agricultural practices, 49% to overgrazing, 13% to overexploitation, and 14% due to deforestation particularly for fuelwood (Verso, 2015). The significant percentages highlight the various human activities contributing to the degradation of topsoil. Moreover, soil erosion washed away 60% of topsoil, which ultimately ended up in rivers, streams, and lakes. which escalates the risk of flooding and increasing pesticide and fertilizer runoff, thereby contaminating water bodies (Mulvihill, 2021). This difficulty poses a substantial challenge to enhancing the sustainability of agricultural systems, particularly within SSA (Annappa et al., 2023; Wakweya, 2023). Alarming predictions indicated that by 2020, over 75% of SSA's arable land had been expected to be degraded (Snapp et al., 2018), with projections suggesting that by 2050, as much as 90% would be at risk (UNCCD, 2022). Figure 4 illustrates extensive land degradation across Southern Africa, Southeastern, Eastern, Partly Western, and Central African regions, depicted in white to signify absence and black to indicate presence (Nkonya et al., 2016).

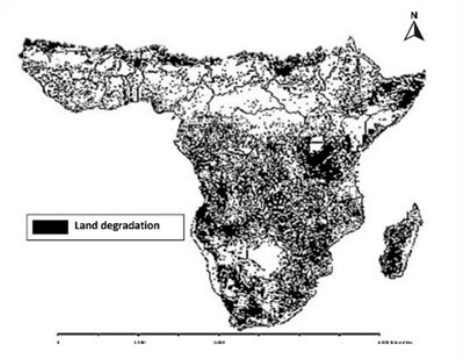

Figure 4. Extent of land degradation in SSA, adopted from Nkonya et al. (2016) and Gibbs et al. (2015)

Land degradation in SSA is a multifaceted issue with significant environmental, social, and economic implications (Eni, 2012). Natural factors such as climate variability and extreme weather events, combined with human activities like deforestation, unsustainable agricultural practices, and urbanization, contribute to the degradation of land and natural resources in the region (Becerril-Piña et al., 2021; Pelser, 2000). The consequences of land degradation are far-reaching, affecting food security, water resources, biodiversity, and the livelihoods of millions of people who depend on the land for their sustenance. Understanding the root causes and major impacts of land degradation is crucial for sustainable land and natural resource management (Morales et al., 2019). To visually support the preceding discussion, Figure 5 presents a summary of the main driving factors and adverse impacts of land degradation in SSA (Qi et al., 2020).

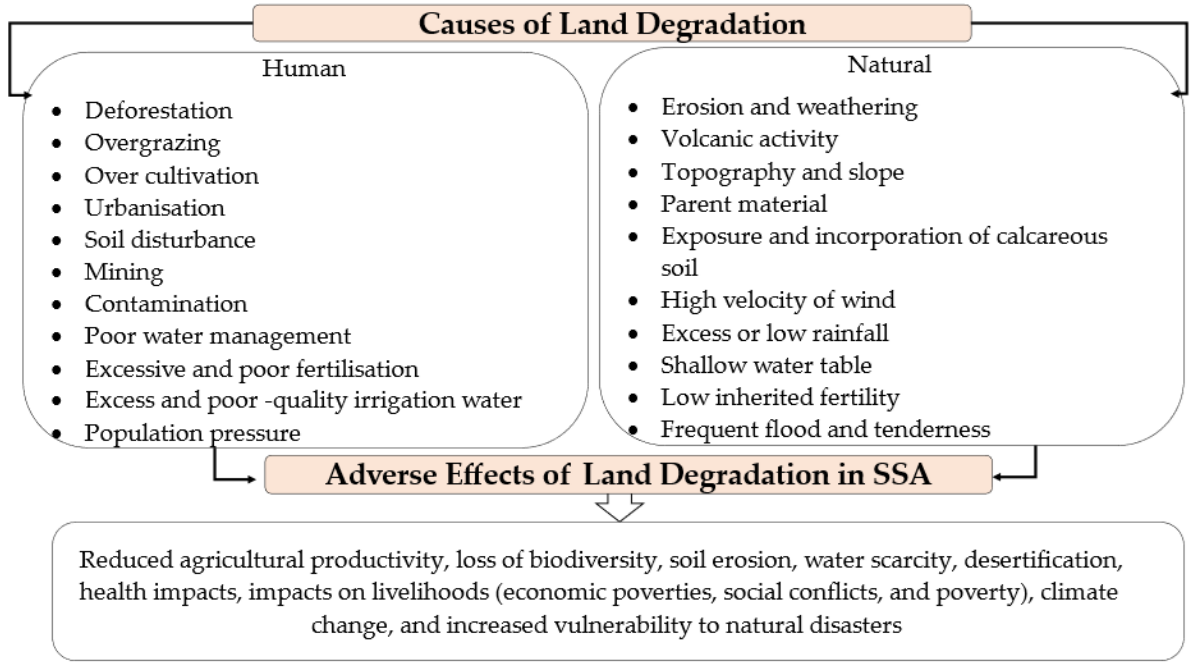

Figure 5. Summary of driving factors and impacts of land degradation in SSA (compiled by the author).

The fundamental issue of food security in SSA is intricately linked to the complex interplay between land degradation and the region's rapidly growing population (Weldeghaber et al., 2006). The demand for agricultural resources and land (FAO, 2022), driven by population growth of around 3% per annum (UNEP, 2015). Agriculture, a cornerstone of SSA's economy, is crucial for ensuring food security (Claire, 2014; Utuk, 2015), mainly for small farms (El-Ramady et al., 2014; Kavoi et al., 2014). It is well reported that growth generated by agriculture is several times more effective in reducing poverty than growth in other sectors in SSA (Claire, 2014). However, intensive agricultural practices have led to substantial soil fertility decline in various parts of the region (Gupta, 2019). 39% of households in SSA are classified as severely food insecure (Fraval et al., 2019), and the region faces four times more land degradation than any other global area (Bjornlund et al., 2022a; FAO, 2017b). This degradation exacerbates the challenge of feeding a growing population and intensifies the strain on natural resources, including increased demand for fuelwood (Maja et al., 2021), leading to land degradation, desertification, climate change and subsequent food insecurity (Frelat et al., 2016). Deforestation driven by agriculture significantly contributes to greenhouse gas (GHG) emissions in SSA, with the majority originating from land-use change, forestry, and the agricultural sector as of 2020. This sector alone accounts for approximately 43% of CO_2 emissions in SSA. Poverty, greenhouse gas emissions, and land

degradation are interconnected challenges, each exacerbating the other in a complex cycle of environmental and socioeconomic vulnerability. Despite strides in agricultural research and development efforts to improve yields and incomes, these impacts and their interconnectedness have not been commonly realized (Thornton et al., 2011). The failure to prioritize sustainable food production, rural welfare, land protection, and soil fertility regeneration could perpetuate a cycle of food insecurity in SSA for years to come.

1.3.2. Land degradation: A comprehensive review of indicators, causes, and impacts

In the realm of understanding land degradation, indicators emerge as pivotal tools, offering specific, measurable metrics to evaluate the land's health and track changes over time. These indicators, highlighted in numerous studies (FAO, 2003), not only serve as early warning signs but also provide crucial information for monitoring, analysis, and decision-making. However, the widespread use of indicator-based methodologies is not without conflicting perspectives (Kairis et al., 2014), particularly concerning their application in monitoring land degradation (Morales et al., 2019). The selection and interpretation of indicators demand caution, considering the diverse local conditions and underlying relationships influencing land degradation. Indicators, instead of simply indicating deterioration or progress, may authentically spotlight variations in the natural condition (FAO, 2003). Previous research has employed a spectrum of indicators to gauge land degradation, encompassing aspects related to soil water (Imbrenda et al., 2013), land cover (Abdelfattah, 2009; Al-Awadhi et al., 2005; Kosmas et al., 2014), vegetation (Sharma, 1998), hydrology, runoff, sediment yield (Vanmaercke et al., 2011), and groundwater resources (Eswaran et al., 2019). Some studies even delve into the use of implemented regulations or policies as indicators of resource development and ecological sustainability, acknowledging their protective role against degradation (Salvati et al., 2016). The literature further uncovers that indicators reflecting human pressure, institutional factors, social dynamics, and tourism contribute to assessing land vulnerability (Kosmas et al., 2014; Pace et al., 2023). Table 1 serves as a comprehensive summary, outlining the most prevalent factors and indicators of land degradation derived from existing research. Factors are variables that contribute to a phenomenon or situation. They are often broad categories that involve various aspects. Each factor has multiple indicators that help assess and measure diverse aspects within that broader theme. Understanding both factors and indicators is crucial for gaining insights into the complex dynamics of land degradation, as factors provide the overarching framework within which indicators operate, helping to identify the root causes and drivers of degradation.

Factor	Indicator	Citation
Climate	Air temperature, rainfall, aridity index, potential evapotranspiration, and rainfall seasonality & erosivity (Extreme weather, too much or too little rainfall, high precipitation - soil erosion, drought - low rainfall amount, flooding – sedimentation).	(Sharma, 1998; Sivakumar et al., 2007; Webb et al., 2017; WMO, 2005)
Water and water use	Quality and quantity, groundwater exploitation, water demand, irrigation %, runoff water storage, water consumption per sector and water scarcity (low salinity, sodium adsorption ratio, conductivity, decreased area of water bodies, advanced runoff, declined groundwater resources, reduction in recharge rate in the hydrological area, reduction in surface, runoff volume, irrigation land area, and water consumption/year).	(EU, 2018; Noble, 2012; Nyssen et al., 2009; Oliveira et al., 2021; Pereira, 2005)
Soil	Drainage, parent material, rock fragments, slope aspect, soil texture, water storage capacity, and organic matter content, reduction or restricted segregation of soil elements the depth of hydromorphic features (Fe, Mn waterlogging, lack of oxygen and affects groundwater depth, compaction, decreased rainwater infiltration, redaction in the amount of water stored	(Akbari et al., 2020; ESDAC, 2020; Eswaran et al., 2019; EU, 2018; Nelson, 2009; Noble, 2012;

	in soil & availability for plant growth, landfilling & accelerated soil erosion, flooding of low land and bedrock exposure on the soil surface, wind and water erosion, reduction in % of plant material, salinization, land productivity).	Nyssen et al., 2009; Oliveira et al., 2021; Pereira, 2005; Sharma, 1998; Sivakumar et al., 2007)
Vegetation	Effective land use and urban area, vegetation cover type, plant cover, grazing intensity & deforested area, land abandonment, land-use intensity, period of existing land use and fire frequency, fire risk, a burned area, & fire protection (Vegetation loss, Increase the application of fertilizers and pesticides, decreased land productivity, land use land cover change, overgrazing and uncontrolled grazing, deforestation, and low protection).	(Barbier et al., 2018; Bensel, 2008; Bishaw et al., 2013; Borrelli et al., 2020; Dimobe et al., 2015; Sengupta, 2013)
Land management and water runoff	Drainage density, flooding frequency, impervious surface area, reclamation of affected areas, soil erosion control measures, soil water conservation measures and terracing presence/absence (length of streams, size of water bodies, changes in land use, urbanization, soil sealing, industry, transport, and waste disposal, deteriorated groundwater resources, erodible soil, flooding of low-land and dam sedimentation).	(Gardner et al., 2009; Gessesse et al., 2014; Kairis et al., 2014; Kosmas et al., 2014; Niang et al., 2015; Sharma, 1998; Stroosnijder, 2007; Zainuddin, 2023).
Agricultural and cultivation-related	Farm ownership, farm size, parallel employment, net farm income, tillage (operations, frequency, depth, directions), mechanization index (A decline in total land in hector and total income from the farm for each family, Soil disturbance and compaction tillage depth and frequency, Soil erosion, intensified agriculture and cultivation practices with slopping, waterlogging- mechanization related to soil disturbance and compaction, monocropping and excessive use of agrochemicals).	(Akbari et al., 2020; Hossain et al., 2020; Mortimore, 1993; Priya, 2021; Salvati, 2011; Salvati et al., 2016; Wolde et al., 2021)
Social	Human poverty index, aging index, population density, growth rate, and distribution (Low level of human pressure on natural resources and farm income, increases population that impacts long-term sustainability of natural resources).	(Barbier et al., 2018; Baye, 2017; Mortimore, 1993; Salvati, 2011; Salvati et al., 2016; Taddese, 2001; Wolde et al., 2021)
Institutional	Subsidies, protected areas, and policy enforcement, access to market (Low and unsustainable restoration works, low level of biodiversity conservation and cultural heritage, and the absence of agricultural and land-use policies).	(Chapman et al., 2019; Ding et al., 2021).
Tourism	Tourism intensity and tourism change (Soil erosion, pollution, natural habitat damage, and endangered species).	(Ekonomou et al., 2023; Sahota, 2016; Ștefănică et al., 2021).

Table 1. Summarizes factors and indicators of land degradation in agricultural land of Sub-Saharan Africa.

1.3.3. The underlying causes and impacts of land degradation on sub-Saharan Africa's agriculture

The extent of land degradation in SSA may vary across studies (Gomiero, 2016), but the underlying factors and impacts consistently mirror global patterns. A study by Tindwa et al. (2023) demonstrates that 36 out of the 80 countries affected by soil degradation worldwide are located in SSA. This comprehensive review identifies causes ranging from improper agricultural practices to deforestation and institutional challenges, revealing the intricate nature of the issue. Supported by extensive data, the impacts include concerns such as soil acidity, nutrient loss, and declines in vegetation cover (Qi et al., 2020). Alarming statistics reveal significant percentages of land affected by water and wind erosion,

deforestation, as well as improper irrigation practices, driving changes in the landscape that negatively affect land quality and functionality. Extensive research on Table 2 highlights the extent and severity of these impacts. On average, approximately 39.9% of land in SSA experiences low nutrient capital reserves, and 45 to 67% of the land is affected by desertification, while over 25% of SSA's productive lands are degraded due to mining activities. Identified causes of land degradation impacts signify observable consequences, providing insights into the severity and extent of environmental, ecosystem, biodiversity, and human well-being changes. Regional disparities highlight the urgency of addressing these challenges, and the review emphasizes the interconnectedness between land degradation and societal well-being, citing issues like food insecurity, low income, and biodiversity loss. Table 2 serves as a valuable resource to identified causes of land degradation in SSA and serving as a valuable tool for decision-making, policy development, and advocacy efforts aimed at promoting sustainable land management practices and environmental conservation. The meticulous citation of sources enhances the 15 cited paper's credibility, forming a robust foundation for subsequent research and policy interventions.

Identified causes of land degradation	Impacts on agricultural land and its extent (Estimated affected land in %) in SSA	Citation
Improper agricultural practices and Soil loss by water and wind, poor land management, and Insufficient use of organic inputs.	Impacts: Soil acidity & alkalinity toxicity, physical degradation loss of soil nutrients, loss of topsoil, nutrient depletion, and decreased water-holding capacity. Decline of soil properties - physio-chemical and biological properties, increased fertilizer uses and poor agricultural productivity, high soil erosion, soil fertility deterioration/ organic matter content, high soil erosion. Extent: Soil erosion- 46% by water and 38% wind erosion, unsustainable agricultural practices (24%). - irrigation (4.5% salinization of cropland) and a decline in agricultural productivity of 2–40%.	(Kirui et al., 2014; Tamene et al., 2015; Tindwa et al., 2023; Tully et al., 2015; Vlek et al., 2010; Zingore et al., 2015)
Deforestation (Uncontrolled Charcoal, land cleaning and wood production) and Overgrazing,	Impacts: Land degradation, land use/ land cover change, decline in vegetation cover, salinization, soil erosion/soil loss and nutrient depletion, dropping in rainfall amount and distribution, deterioration of soil nutrients, loss of biodiversity, declining vegetative health, loss of habitat, poor agricultural productivity. Extent: 67% of land because of deforestation SSA - About 51% in Tanzania, 41% in Malawi, 23% in Ethiopia, and 22% in Kenya, only between the 1982 and 2006 periods. (16%) and 24%,15%,18%, and 10% in light, moderate, severe, and very severe by severity level, and in some cases in worse condition and beyond reclamation. 50% overgrazing of all soil degradation in semi-arid and arid areas of Africa.	(Bot et al., 2000; Kelatwang et al., 2006; Vlek et al., 2008)
Population density, expansion and intensification of agriculture, Land cover change/ Urbanization/	Impacts: Physical surface selling, soil compaction, chemical - nutrient depletion, dispersion (alkalization, toxic contaminations & salinization), biological- depletion in organic matter, loss of biodiversity, and depletion of plant, animal, and microbial biomass, relocated rural residents, food	(Tully et al., 2015; Vlek et al., 2010)

Infrastructural expansion	insecurity and low nutritional levels, low household incomes, and poverty low rate of fertilizer use. Extent: 39.94 % of land in SSA goes through low nutrient capital reserves, 24.94% al toxicity, 6.70 % calcareous reaction, and 2.21 % alkalinity, respectively.	
Extreme weather (Desertification), Topography, and slope.	Impacts: Soil erosion and, soil nutrient depletion, stagnant or declining agricultural productivity, Unproductive lands, and Reduced plant growth. Extent: Between 45% and 70% of all land is impacted by desertification, with approximately 20% of this being severely degraded agricultural land.	(Nkonya et al., 2008; Obalum et al., 2012)
Institutional, Governance, and land tenure insecurity	Impacts: Biodiversity loss, soil fertility decline, food insecurity, low income, and low adoption of sustainable land management practices. Extent: 28% of the land and 22 % of people are living/farming on degraded land.	(Nkonya et al., 2016)
Mining	Impacts: Contamination, depletion of soil organic matter, accelerated erosion, acidification, salinization and lack of plant nutrients, loss of nutrients and soil organic carbon, food and nutritional insecurity, and environmental degradation. Toxic chemicals and heavy metals leached from abandoned waste rock and tailings contaminate soil surfaces and groundwater. Extent: ≥25% of SSA's productive lands degraded.	(Jones, 2013; Tindwa et al., 2019; Tindwa et al., 2023)

Table 2. A comprehensive overview of the identified causes of land degradation in sub-Saharan Africa (SSA), their impacts on agricultural land, and the extent of affected land as estimated by various scholarly sources.

1.3.4. Sustainable agricultural intensification to combat land degradation and food insecurity in sub-Saharan Africa

In SSA, agriculture plays a crucial role in sustaining the food and income of smallholder farmers (Bilsborrow, 1992). However, poor farming practices often lead to land degradation and resource loss (Struik et al., 2017). SIAP emerges as a promising strategy for enhancing land productivity amidst degradation, addressing both food production increase and environmental challenges associated with land degradation in the region (UNDP, 2022). SIAP enhances environmental health (Fischer et al., 2020) and increases economic benefit from the unit of land (Piñeiro et al., 2020). Practices like agroforestry, crop rotation, soil conservation, organic farming, integrated soil fertility management (ISFM), water harvesting, conservation agriculture (CA), and climate-smart agriculture are widely recognized for improving land productivity (Giller et al., 2020; Kuyah et al., 2019; Mwaura et al., 2021; Olarinde et al., 2012; Wawire et al., 2021; Wolka et al., 2018). Specific SIAP practices such as ISFM and CA improve biodiversity, increase soil water infiltration by over 44%, reduce runoff by 30%, and minimize soil erosion by 33% (Kihara et al., 2020). Additionally, SIAP replenishes soil and other natural resources like water and air, ensuring sustainable food production systems and supporting ecosystem maintenance (FAO, 2023). Furthermore, SIAP reduces climatic vulnerability and desertification. A study spanning from 1999 to 2007 highlights SIAP's significant impact on drought reduction (Knutson et al., 2011), while a survey in southern Africa's Chi-Nyanja Triangle demonstrates SIAP's ability to enhance land productivity even under climate change (Makate et al., 2017). Further

studies indicate that implementing SIAP enhances productivity, supports ecosystem preservation, strengthens adaptation to climate change, extreme weather, drought, and flooding, and improves land and soil quality over time (Sieber et al., 2015). SIAP technologies also reduce reliance on forest resources, energy, pesticides, and inorganic fertilizers while managing greenhouse gas emissions through eco-friendly methods and nature-based solutions (Ahmadpour, 2016; Milestad et al., 2003; Wang, 2009). Further demonstrated by Kim et al. (2021), citing three studies, when implementing CA, the emissions of nitrous oxide (N2O) per unit of crop yield are significantly reduced, ranging from 19% to 88% lower compared to conventional practices. Although, studies show that farmers can adapt to environmental changes using agronomic strategies at the crop, farm, and landscape levels (Dubey et al., 2020).

Over the next five decades, there will be an increasing need to address land degradation, particularly soil health, and to secure land and water resources for food production (Zdruli et al., 2010). Sustainable agriculture plays a crucial role in enhancing productivity despite land degradation (Ussiri et al., 2019). However, the synthesis of 47 articles result on table 3 shows that the adoption rates and yield impacts of sustainable agricultural practices in SSA vary widely, ranging from 0.8% to 68%, and 3.7% to 81%, respectively, depending on the specific approach implemented and adoption. This variation is largely influenced by the diversity of practices implemented, such as agroforestry, conservation agriculture, organic farming (Pretty et al., 2011), soil conservation measures, and water harvesting technologies. Tailoring these practices to the specific needs, ecological conditions, and socio-economic contexts of each region is essential for maximizing their effectiveness and ensuring successful implementation. At first, adoption trends in SSA are encouraging if they are backed by incentives, empirical sustenance, and information access. A study revealed that 53 % of the technology adoption is influenced by the lack of empirical support related to information, wealth, social capital, and land tenure (Arslan et al., 2022). The institutional arrangement, including access to inputs, finance, markets, and agricultural value chains to improve farm productivity and sustainability has been considered vital for implementing successful SIAP practices in SSA (Godfray et al., 2014). This approach involves conducting thorough site assessments, understanding local farming practices, engaging with communities, and providing targeted technical support and resources to promote adoption and optimize yield impacts.

Approaches	Practices	Impacts	Countries	Signs of adoption and yield impact in SSA	Citations
Agroforestry	Trees on farmland Scattered trees Alley cropping Windbreak and shelterbelts Home gardens Silvopastoral systems Multipurpose trees	Reduce deforestation (Source of fuel, fodder, and food products Reduce overgrazing as a source of animal fodder. Minimize soil erosion-Improve soil cover and groundwater recharge. Supplying habitat for associated species. Additional income - lower poverty.	Burkina Faso, Ethiopia, Benin, Ghana, Niger, Nigeria, Mali, Senegal, South Africa	Positive (+) An estimated 1.2 billion individuals rely on it. 5 million ha of cropland with a mixed cropping system. Increased livestock product yields by 68%. Mean yield impact - 68 to 81%.	(Arslan et al., 2022; Chamsham a et al., 2009; Doberman n et al., 2020; Duguma et al., 2018; Franzel et al., 2001; Iiyama et al., 2014; Kuyah et al., 2021; Kuyah et al., 2019; Sheppard

	Plantation-crop combinations				et al., 2020; Zerihun, 2020)
Conservation agriculture (CA)	Minimal tilling (minimum soil disturbance) Permanent soil cover Crop rotation and (or intercropping with legumes) Mulching with crop residues	Improve soil organic matter - improve agronomic performance. Protect agroecosystems. Reduce soil erosion and soil compaction by tillage. Improve family nutrition (legumes to cereal) and income. Reduce fertilizer cost and impacts of climate change. Improve nutrient intake of the plant and enhance food security.	Benin,Botswana, Burkina Faso, Cameroon, Côte d'Ivoire, Ethiopia, Eritrea,Ghana, Lesotho, Malawi, Mali, Namibia, Niger, Nigeria, Sudan,Tanzania, Uganda, Zimbabwe	Positive (+) Adopted – 0.8 to 1% In 933 studies from 16 countries, the average yields > conventional tillage. Decrease soil erosion (28–500%) and runoff (28–50%). Improve soil cover. Decrease GHG emissions. Mean yield impact - 3.7 to 37.6%.	(Assefa et al., 2020; Chinseu et al., 2021; Corbeels et al., 2015; Descheemaeker, 2020; Galani et al., 2021; Kim et al., 2021; Salustro, 2016; Wekesah et al., 2019)
Organic farming (OM)	Biological pest and disease control Crop rotation, mechanical weed control Leguminous crops (nitrogen fixation) Green manure crops Use of compost/ organic manure	A healthy food production system and sustainable soil health imply people's health. Sustainable ecosystems - Reduce GHG emissions, improved ecological processes, biodiversity, Boost productivity & farm income, decrease poverty and hunger by 2030(Prediction). A study (Ghana & Kenya) has shown 292% increase in gross margins and over 144% higher yields compared to conventional farms.	Most SSA countries Benin, Ethiopia, Ghana, Kenya, Nigeria, Mali, Malawi, and Tanzania, Uganda,	Positive (+) Adoption - 11 to 68% Adoption rate (13 to 68% 127–308% yield for coffee, and maize in Ghana & Kenya. 11% income per capita, 55% reduction household food gap. Mean yield impact – 8 % and 78%.	(Arslan et al., 2022; Daadi et al., 2021; Giller et al., 2020; Kuyah et al., 2019; Milestad et al., 2003; Mwaura et al., 2021; Schader et al., 2021; Wei, 2020)

Soil conservation measures (SWC)	Agronomic, vegetative, structural, and management measures, like strip crops, terraces, Contour. Soil and stone bunds Planting pits (zaï or Tassa) Bunds, slop barriers, cross-slope farming, vegetable covers, etc.	Reduce runoff velocity and soil erosion and reduce soil loss. Direct impact on crop yields due to the retention of nutrients and moisture and improve soil health. Normalize water flows. Boost soil biodiversity & greenhouse gases and influence ecosystem services positively. Increasing infiltration (>44).	Burkina Faso, Ethiopia, Ghana, Kenya, Mali, Niger, West Africa	Positive (+) Adoption - 25.4 to 64%. increases total crop yield by 17-24% per household. 22-33% income in smallholders. Reduce runoff by 13 – 71% and soil loss by 39 – 83%. > 86% of studies found increased yield with nutrients and moisture. Mean yield impact – 7 to 66%.	(Abdulai et al., 2013; Asfaw et al., 2018; Bashir et al., 2017; Judith, 2011; Kihara et al., 2020; Olarinde et al., 2012; Reij, Smale, et al., 2009; Reij, Tappan, et al., 2009; Stewart et al., 2020; Tilahun, 2019; Wolka et al., 2018)
Water harvesting technologies (WHT)	Zai pits (In situ reservoir water harvesting techniques). Securing more rainwater and storing it (improving water accessibility) Using the available water (increasing water productivity)	Improve the water-holding capacity of soil. Overcoming droughts (water for families, livestock, and crops will have a greater chance). Reduce soil loss. Improved yields and helped a change to high-value crops. Recharge groundwater. Water retention in farmers' fields improved. alleviate water stress and enrich soil fertility. Enhancing food security and livelihood.	Burkina Faso, Ethiopia, Kenya, Niger, South Africa, Sudan, Rwanda, Zimbabwe, Tanzania	Positive (+) Adoption – 3 to 67 %. 16.5% sorghum and 9% labor -Burkina Faso. 17-106 and 12-30% in income - Ethiopia. Ndiva (Tanzania) – increase yield 22 and Food security 70% and Zaï, grass strips, and bunds in Burkina Faso - 100–200% yield and 70% organic matter content. Increase productivity in 74-82% Household ponds) Zai pits - 250 and 83% (sorghum and maize yield). Mean Yield impact – 12 % and 84% increase in yield, depend on the SWC type	(Bouma et al., 2012; Critchley et al., 2013; Gebru et al., 2020; Gowin et al., 2013; ISPC, 2019; Karpouzoglou et al., 2014; Kim et al., 2021; Muchai et al., 2020; Snelder et al., 2018)

Table 3.Sustainable agricultural intensification approaches' role and signs of adoption in SSA, compiled by author and adopted from table Garzón Delvaux et al. (2020).

1.3.5. Sustainable agricultural intensification practices: addressing food insecurity in sub-Saharan Africa

Sustainable agricultural intensification practices are essential for combating land degradation and food insecurity in SSA, in line with global poverty eradication and ecosystem preservation goals (Martin et al., 2018). Land degradation, caused by factors such as soil erosion, nutrient depletion, and loss of biodiversity, poses a significant threat to food security. Degraded soils have reduced fertility and water-holding capacity, leading to lower crop yields and food production. Additionally, land degradation can exacerbate food insecurity by reducing the availability of arable land for cultivation, increasing vulnerability to climate change, and undermining rural livelihoods. SIAP offers a multifaceted approach to improving land sustainability and enhancing food security (Smith et al., 2020; Tittonell et al., 2013). Agroforestry systems, for instance, promote biodiversity, enhance soil structure, nutrient content, water retention and soil fertility, and provide a buffer against climate variability (Garrity et al., 2010). CA complements agroforestry by emphasizing minimal soil disturbance, cover cropping, and crop rotation (Gowing et al., 2007), thereby contributing to improved soil health (Garrity et al., 2010; Pretty et al., 2011). Water harvesting technologies further enhance this synergy by capturing and efficiently utilizing rainwater for irrigation, mitigating water-related soil degradation (Rockström, 2009). Concurrently, soil conservation measures, such as terracing and contour ploughing, prevent erosion and sustain overall soil integrity (Lal, 2001). Biological control and integrated plant protection, integral to organic farming, contribute to pest and disease management, aligning with the principles of ecological balance (Altieri et al., 2003). Integrated soil fertility management reinforces these efforts by emphasizing nutrient cycling and organic matter incorporation, fostering sustained soil fertility (Pimentel et al., 2005). Generally SIAP, with its focus on efficient resource use, plays a pivotal role in reducing land degradation by optimizing inputs (Kassam et al., 2011). According to (Pretty et al., 2011), from the 1990s to 2000s SIAP has been implemented in 20 SSA countries across more than 40 projects. The focus of these projects and programs were to implement eco-friendly technology and land management practices for sustainable intensification, promoting environmental conservation and increasing land productivity. The widespread implementation of SIAP across SSA countries in past decades reflects a growing recognition of the importance of sustainable agriculture in achieving food security and environmental sustainability. The interconnection of these practices within SIAP forms a holistic and synergistic approach that not only addresses land degradation but also promotes sustainable ecosystems, safeguarding the long-term productivity and health of the land. Similarly, recent study in Northwestern Ghana showed that community participation in SIAP reduced household access to food insecurity by 2.95% (mean) compared to business-as-usual, with a decreasing amount of 11% (Yahaya et al., 2018). These practices, when strategically implemented, contribute to increased crop yields, subsequently addressing food insecurity concerns. Productivity is influenced by various factors, including the integration of different practices. Research suggests that the more these practices are integrated, the greater the potential yield advantage (Pretty et al., 2011). This integration allows for synergies between different techniques, leading to improved soil health, nutrient retention, pest control, and overall crop resilience. The past success of SIAP initiatives suggests that there is potential for continued adoption and expansion of these practices in SSA (Table 3). By interconnecting sustainable agricultural intensification practices (Figure 6), SSA can simultaneously improve land productivity, promote food security, and advance the region towards a sustainable agricultural future.

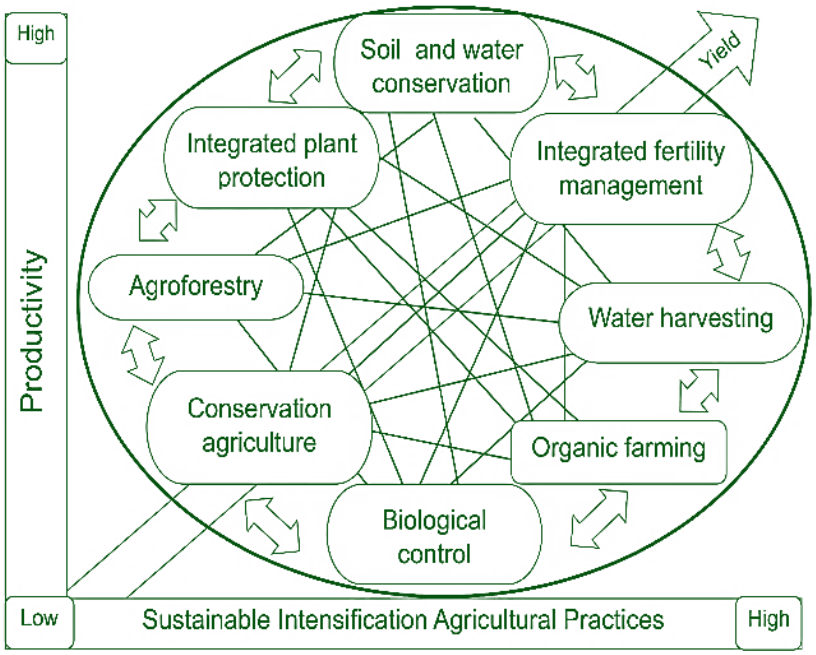

Figure 6. SIAP Intervention impact on productivity and their interaction, the more these practices are integrated, the greater the potential yield advantage (compiled by the author).

1.4. Discussion

1.4.1. Balancing yield and conservation: Sustainable intensification of agriculture practices as a key solution in sub-Saharan Africa

The factors contributing to land degradation in SSA are diverse and interconnected, spanning environmental, socio-economic, and institutional dimensions. Land degradation, food security, and the contribution of Sustainable Intensification of Agricultural Practices (SIAP) to enhancing land sustainability are all interdependent, which highlights the complex interaction among agricultural productivity, environmental well-being, and food availability. Shifting focus to SIAP in SSA is vital for addressing both land degradation and food insecurity. Agriculture being the primary source of food and income, improving production systems is crucial for enhancing food security. SIAP offers practical methods to boost land productivity despite degradation challenges, emphasizing innovative and eco-friendly techniques like agroforestry and organic farming. Practices such as crop rotation and cover cropping are highlighted for soil fertility restoration. Sustainable intensification maintains a balanced approach between productivity and environmental conservation, providing a practical solution to counteract land degradation. Adoption rates and yield impact data from SSA countries support the effectiveness of these practices (Bashir et al., 2017; Gachene et al., 2019). SIAP provides farmers with a promising opportunity to achieve better yields. The evidence from various reviewed studies emphasizes that SIAP is highly effective in enhancing soil quality, nutrient cycling, organic matter, soil carbon sequestration, moisture retention, temperature regulation, productivity, and nutritional value (Abbadiko et al., 2018). Furthermore, farmers, in general, have gained valuable income and profits by implementing SIAP. The reviewed studies highlight the essential role of sustainable practices in promoting a healthy society and a better income (Osidoma et al., 2021). Techniques like agroforestry and integrated soil fertility management continue to support native vegetation growth, facilitating natural processes and aiding in quick rebounds from environmental changes. SIAP not only contributes to healthier household diets but also ensures more sustainable agricultural productivity (Table 3). The

interdependence between factors of land degradation, food security, and the contribution of SIAP to improving land sustainability is illustrated in Figure 7.

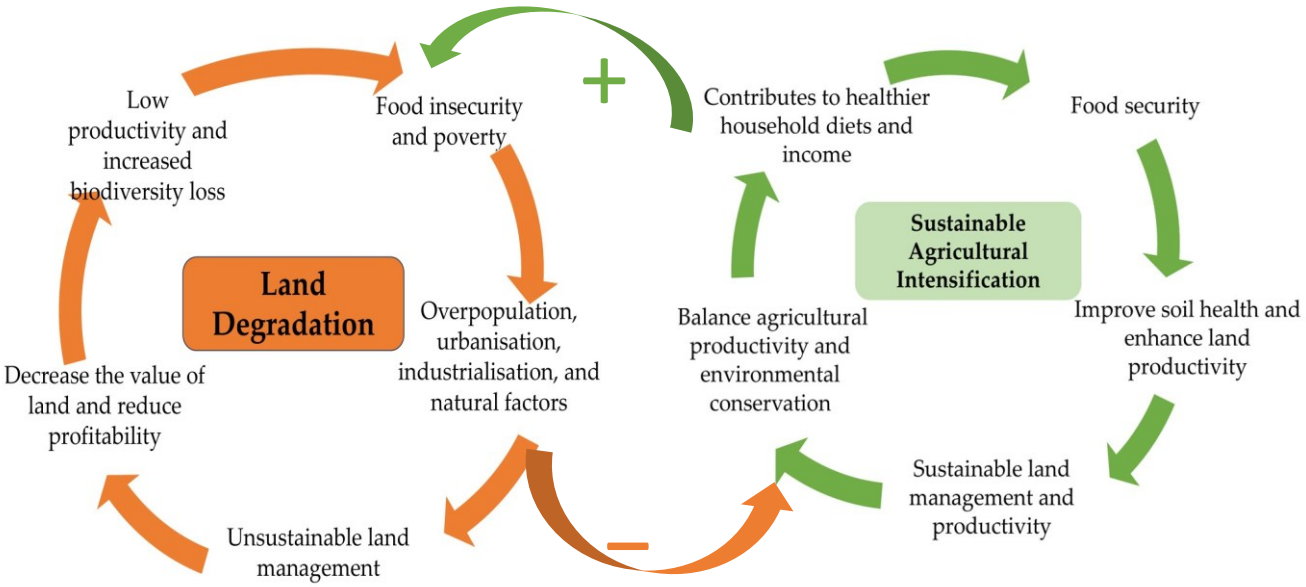

Figure 7. The interdependence between factors of land degradation, food security, and the contribution of SIAP to improving land sustainability, where red colour indicates the negative impact and green colour the positive. (compiled by author).

1.4.2. The concerned view - Factors limiting the contribution of sustainable intensification of agriculture practices to addressing land degradation

Despite the promising potential of SIAP in bolstering agricultural sustainability, several obstacles hinder their effectiveness in addressing land degradation. Socio-economic barriers, low adoption rates, and inadequate implementation of SIAP techniques present significant challenges to achieving sustainable land management. Moreover, contextual variations in agroecological conditions and a lack of institutional support further complicate the success of SIAP across different regions. The literature point out the crucial role of robust policy frameworks in addressing declining agricultural production, natural resource depletion, and inappropriate land use in SSA. However, policymakers often overlook the importance of preserving land and soil health, which limits the conversion of native ecosystems to agricultural land. There is a pressing need for more studies and reliable data for accurate land degradation assessment, with a call for policy frameworks to support the contributions of land policy designers. Additionally, large-scale land degradation assessment is deemed inaccurate due to several complex factors (Kopittke et al., 2019; Mengist et al., 2020; Ziadat et al., 2021). The myriad challenges, including socio-economic barriers, low adoption rates, implementation gaps, contextual variations, insufficient institutional support, technological and educational gaps, market dynamics, and environmental variability, collectively underscore the complexity of promoting successful SIAP implementation in SSA. Continuous support for scaling up SIAP principles and practices (Mulale et al., 2014), along with the creation of an enabling environment through well-designed policies and strategies, holds promise for sustainable land conservation in the region (Gomiero, 2016).

1.5. Conclusions

Failure to recognize the impacts of unsustainable natural resource management and land degradation without adhering to sustainability principles could have immediate repercussions on SSA agricultural

production and ecosystem services. Therefore, it's imperative to take sustainable action to safeguard land and ensure an adequate food supply for the rapidly expanding population in SSA. This entails recognizing the consequences of land degradation, sharing knowledge and information with smallholder farmers, and implementing effective measures to tackle the issue. Additionally, tailoring SIAP is crucial to ensure their efficacy and applicability in diverse socio-economic and ecological contexts. This customisation enables the adaptation of agricultural techniques to specific local conditions, including soil types, climate patterns, and resource availability. By tailoring SIAP practices, stakeholders can effectively address the unique challenges and opportunities present in each region, thereby maximizing their positive impact on agricultural productivity, environmental sustainability, and food security. This review emphasizes the potential of SIAP in mitigating and reversing land degradation within the context of SSA.

1.6. A way forward

A comprehensive approach is needed to address the complex challenges of land degradation and food insecurity in SSA. This approach should encompass policy support and institutional strengthening to promote sustainable land management practices, coupled with capacity building and awareness initiatives to educate farmers about the benefits of adopting SIAP. Providing financial and technical support can help overcome barriers to SIAP adoption, while improving market access and value chain development can create economic opportunities for smallholder farmers. Research and innovation are essential for developing context-specific SIAP techniques that address the unique challenges faced in the region. By implementing these strategies in a coordinated manner, stakeholders can work towards overcoming the barriers to SIAP adoption and promoting sustainable land management practices, ultimately contributing to food security, environmental conservation, and rural livelihood improvement.

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CHAPTER 2

2. Rainfall Variability and Drought in West Africa: Challenges and Implications for Rainfed Agriculture



Abstract

This research investigates rainfall variability and drought patterns in West Africa and its consequential impacts on rainfed agriculture, with a particular focus on vulnerability linked to weather extremes. Utilizing NASA POWER/Agro-climatology data, cross-validated against observed meteorological records in the targeted countries, this study spans the years 1981 to 2021, with a particular focus on Ghana and Burkina Faso. The Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and different statistical methods were employed to evaluate the variations in rainfall, including intensity and frequency, as well as analyze drought patterns in the study areas. Despite increased rainfall in the last decade, seasonal and decadal shifts have been noticed, and drought and irregular patterns still threaten the study areas. Temporal analysis reveals fluctuations in temperature and rainfall. SPI and SPEI results indicated a decline in drought frequency, aligned with global trends, though the monthly scale showed no evident decline. The spatial analysis highlights regional variations in rainfall and drought dynamics. The study emphasizes the importance of region-specific mitigation and adaptation strategies, providing valuable insights for informed decision-making in West Africa's agriculture and water resource management under climate change. *The findings underscore the continued threat of irregular rainfall patterns and drought, emphasizing the need for tailored approaches* to address these challenges.

Keywords: Rain Intensity, Climate - Change, Ghana, Burkina Faso, SPI and SPEI

2.1. Introduction

Climate change manifests in a spectrum of effects, including shifts in weather patterns, global temperatures, and an increase in the frequency and intensity of extreme weather events (Mechiche-Alami et al., 2020; Sylla et al., 2016). Droughts are categorized into four types: meteorological, agricultural, hydrological, and socio-economic (Li et al., 2024). Meteorological droughts, marked by insufficient precipitation, can rapidly evolve and serve as precursors to subsequent drought categories, leading to deficits in soil moisture and decreased streamflow, which in turn trigger water supply shortages (Fowé et al., 2023; Le et al., 2019; Li et al., 2024). Climate change intensifies drought conditions through changes in rainfall patterns, evaporation rates, and water cycles (Konapala et al., 2020). As temperatures rise, soil and water bodies lose moisture making the environment drier (Condon

et al., 2020; Findell et al., 2019; Snyder et al., 2011). While the relationship between climate change and drought is complex (Mukherjee et al., 2018), it is important to note that climate change does not directly cause droughts. However, it does make it intense, long-lasting, and widespread (Naumann et al., 2021; Sultan et al., 2016). Altered climatic patterns disrupt rainfall distribution, leading to prolonged dry spells in some regions, while potentially increasing rainfall and flooding in others (Ostroff et al., 2017). On the other hand, climate change can also result in rainfall and increased flooding in specific areas (Tabari, 2020). Various sectors, including agriculture, water resources, and ecosystems bear the brunt of drought impacts (Zhang et al., 2021). Reduced water availability negatively affects crop production by decreasing yields and increasing competition for resources (Santini et al., 2022). Droughts heavily impact various sectors, notably agriculture, water resources, and ecosystems, with diminished water availability adversely affecting crop production, heightening resource competition, and exacerbating food security concerns (FAO, 2017a; Santini et al., 2022; Zhang et al., 2021).

In West Africa, where rainfed agriculture dominates (Sylla et al., 2018), agricultural productivity is highly sensitive to changes in rainfall intensity and volumes (Pauline et al., 2023) and the increasing frequency of dry spells during the rainy season (Lèye et al., 2021). Water scarcity, particularly acute during the dry seasons, remains a pressing issue in the region (Ndehedehe, 2019). Both drought and irregular rainfall patterns exert substantial impacts on crop production and food security (Leal Filho et al., 2021). Intense rainfall events can lead to soil erosion, surface runoff, and topsoil depletion (Zhao et al., 2021), while heavy rains may cause nutrient leaching and restrict oxygen availability for plant roots, adversely affecting crop growth and development, and resulting in significant yield losses (Li et al., 2020). Conversely, insufficient rainfall during critical growth stages subjects crops to water stress, inhibiting their development and diminishing yields (Das et al., 2019; Hayashi et al., 2018; Quenum et al., 2019; Reed et al., 2022). Prolonged drought or sub-average rainfall periods can cause crop failure, food scarcity, and economic hardship for farming communities (World Bank, 2022). The distinct wet and dry seasons of West Africa emphasize the critical role of rainfall timing and distribution (Leal Filho et al., 2021), as disruptions to planting schedules and changes in crop cycles can significantly affect agricultural productivity (Sylla et al., 2018). Analyzing the changing climate patterns and their impacts on agriculture, including assessing drought severity, duration, and spatial distribution, is crucial for understanding risks and planning adaptive strategies such as crop diversification, enhanced water management, and the implementation of climate-resilient sustainable water management practices (Acevedo et al., 2020; Conway et al., 2014; Srivastav et al., 2021; Todisco et al., 2012). Furthermore, the identification of areas with water surplus or deficits through understanding rainfall intensity and distribution is essential for informed decisions on water allocation for agricultural purposes (Garg et al., 2022).

The Standardized Precipitation Evapotranspiration Index (SPEI) and the Standardized Precipitation Index (SPI) serve as crucial drought indices, providing valuable insights into drought conditions (Mohammed et al., 2022). SPEI incorporates both water supply (precipitation) and demand (evapotranspiration), making it a comprehensive tool for drought monitoring and analysis (Amare et al., 2019; Tirivarombo et al., 2018a) In contrast, SPI focuses exclusively on precipitation, measuring deviations from the long-term average across different time scales (Pei et al., 2020). This focus allows for comparisons across various locations and periods, facilitating the identification of drought occurrences and their severity. Moreover, both SPI and SPEI primarily rely on meteorological data, neglecting other essential factors for a thorough assessment of drought conditions, such as soil moisture, groundwater levels, and the potential impacts on runoff and water availability (Keyantash, 2021). Despite these limitations, numerous studies have utilized SPI and SPEI to explore drought patterns and their associations with large-scale climate drivers, demonstrating their utility in global drought variability research (Fuentes et al., 2022; Pyarali, 2022; Sein et al., 2021; Vicente-Serrano et al., 2010),

These indices remain vital tools for researchers aiming to understand and predict drought dynamics effectively.

The need for comprehensive data and accurate spatiotemporal representation is critical in drought and agriculture-related studies. In the realm of drought analysis, reliable meteorological data is indispensable for monitoring conditions, assessing severity, and forecasting impacts on agricultural productivity. Spatiotemporal analysis enhances our understanding of drought progression over time and across landscapes (Goor et al., 2016; Vrieling, 2014). However, the scarcity of such data presents a significant hurdle, particularly in West Africa (Chason et al., 2022; Dinku et al., 2022; Menezes et al., 2022). To mitigate these challenges, researchers increasingly rely on satellite-derived meteorological data (Magloff, 2023; Serifi et al., 2021). Satellite-based products, reanalysis, and multi-source products from sources such as NASA, CHIRPS, and provide widely used data that represent spatial variability by combining satellite data with ground-based observations (Copernicus., 2021; Dinku et al., 2022; Garcia, 2019; NASA, 2021, 2023). These datasets offer high-resolution estimates in regions where ground data is limited (Funk et al., 2015). Numerous studies on global climate modelling have utilized these sources, underscoring their reliability and extensive use (Hagemann, 2017; Zscheischler et al., 2018).

This research delves into the complex dynamics of rainfall patterns and drought occurrences in West Africa, with a particular focus on Ghana and Burkina Faso, areas critically impacted by climate variability (Fowé et al., 2023). These countries have been chosen due to their significant reliance on rainfed agriculture, making them highly vulnerable to fluctuations in rainfall and drought conditions. Unlike conventional approaches relying on common drought indices, our research incorporates daily analyses of changes in rainfall event intensity changes across the region to better understand drought conditions. The specific objectives of this research are: 1) Conducting a thorough analysis of historical rainfall data in Ghana and Burkina Faso to identify long-term trends and spatial variability in rainfall patterns. 2) Evaluating the characteristics of drought events in Ghana and Burkina Faso, including factors such as frequency, duration, and intensity. 3) Furthermore, exploring the spatial and temporal distribution of drought events, using established drought indices that combine rainfall intensity analysis to reveal how daily rainfall intensity changes over time and its implications for drought in rainfed agriculture in the studied area.

2.2. Material and Methods

2.2.1. Study area

The study area covers Ghana and Burkina Faso, countries in West Africa (Figure 8), characterized by a climate influenced by intertropical convergence zones (ITCZs), African monsoons, and El Niño-Southern Oscillations (ENSO). Ghana is situated on the southern coast of West Africa, bordered to the east by Togo, to the west by Côte d'Ivoire, to the north by Burkina Faso, and to the south by the Atlantic Ocean, specifically the Gulf of Guinea, just a few degrees north of the Equator, experiences a warm climate throughout the year (Ampofo et al., 2023; Maier, 2023). It has a tropical climate with a dry season in winter and a rainy season in summer, attributed to the West African monsoon (Asante et al., 2014). The eastern coastal belt of Ghana is warm and relatively dry, while the southwest is hot and humid, and the northern region is hot and dry(Asante et al., 2014; Owusu et al., 2009). On the other hand, Burkina Faso encounters a Sahelian, warm tropical climate characterized by distinct seasons of rainfall and dryness

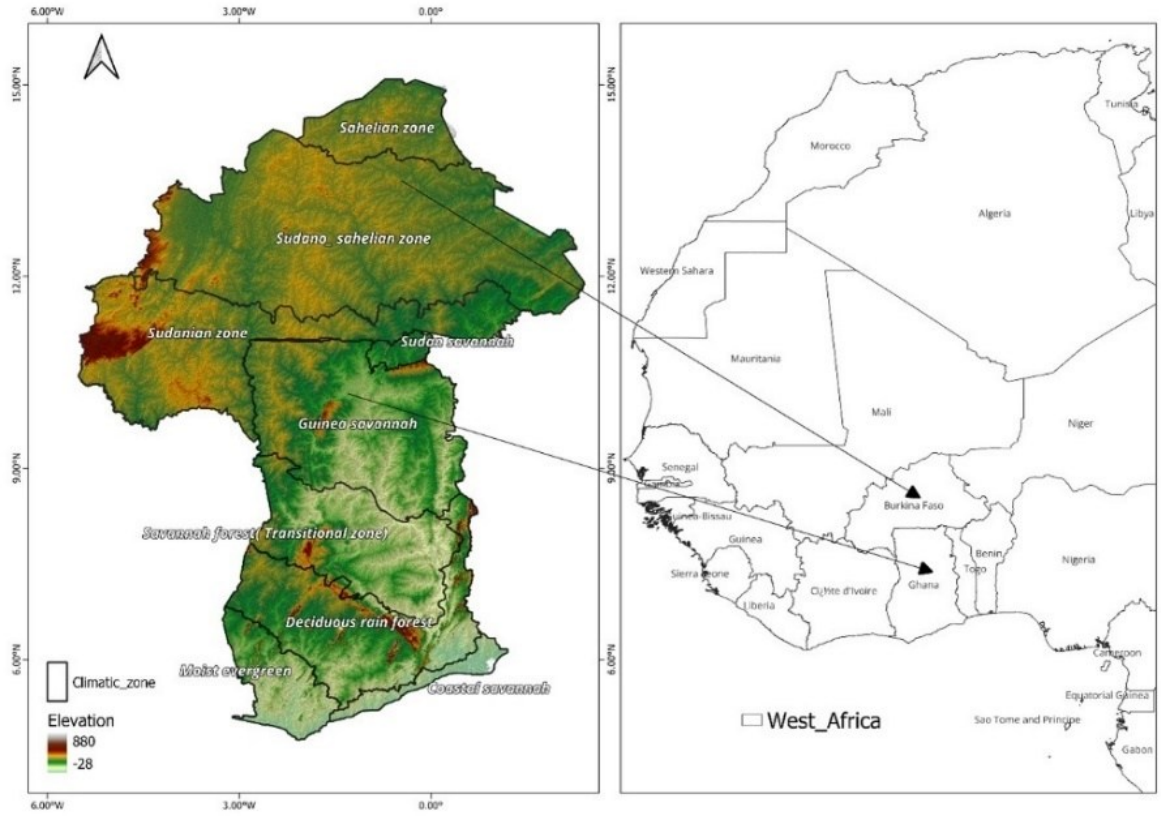

Figure 8. Geographic overview of the study area - elevation and west African country boundaries. Elevation data sourced from ALOS world 3d - 30m (aw3d30), provided by the Japan aerospace exploration agency (JAXA), based on ALOS satellite imagery.

Ghana and Burkina Faso heavily rely on rainfed agriculture, where crops are predominantly grown using rainfall. The rainfall distribution in the nine climatic zones of the area varies significantly. In Ghana, from 1981 to 2022, the highest mean annual rainfall was recorded in the Moist Evergreen zone with 1497.5 mm, followed by the Transitional (Savannah-Forest) zone at 1286.3 mm, Deciduous rain forest at 1240.0 mm, Guinea savannah at 1073.8 mm, Coastal savannah at 1021.3 mm, and Sudan savannah at 975 mm. In Burkina Faso, during the same period, the Sudanian zone received the most rainfall with 1003.6 mm, followed by the Sudano-Sahelian zone with 758.3 mm, and the Sahelian zone with 434.3 mm. The rainfall distribution across the climatic zones highlights a vital link between precipitation, agricultural productivity, and drought sensitivity. Irrigated farmland constitutes a mere 1.7% of the total agricultural area in Ghana (Baldwin et al., 2022), and less than 0.091% in Burkina Faso, highlighting minimal utilization of irrigated agriculture in both countries (FAOSTAT, 2024). Farmers in Ghana and Burkina Faso often follow specific crop calendars (Table 1), which outline optimal planting, cultivation, and harvesting times based on historical rainfall patterns and local agroecological conditions. However, climate variability and changing rainfall patterns present significant challenges to rainfed agriculture and crop calendars in these countries. This is highlighted in the studies conducted by (Nkrumah, 2019) in Ghana and (Traoré, 2018) in Burkina Faso. The primary rainfed crops grown in the region have planting and harvesting schedules from March to December. Among these months, May to September emerge as critical periods that merit closer examination in the area's drought analysis context. Table 4 presents the crop calendar for the main crops grown in the two countries. This study defines the period from May to October as the wet season and November to April as the dry season, aligning with the mean monthly rainfall distribution.

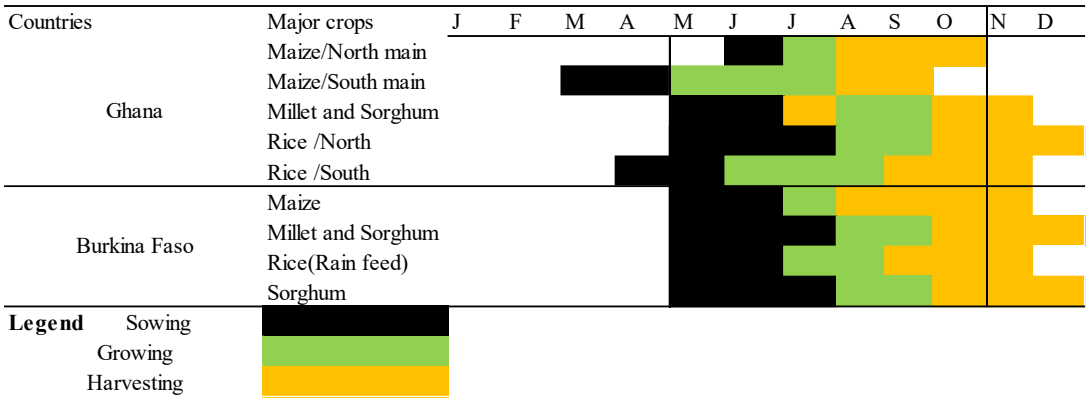

Table 4. Crop calendar for rainfed agriculture in Ghana and Burkina Faso, planting and harvesting periods. Data sourced from FAO (https://cropcalendar.apps.fao.org/#/home).

2.2.2. Data collection

To achieve the first objective of analyzing historical rainfall data, daily rainfall and temperature data were collected from 1981 to 2021 across nine agroecological zones in Ghana and Burkina Faso (Figure 9). This approach aligns with climatic zoning techniques used by Abbam et al. (2018), Ibrahim et al. (2012), and Lienou (2016) for the region. Daily data at a 0.5° spatial resolution were retrieved from the NASA POWER/Agro-climatology archive *(POWER | Data Access Viewer (nasa.gov)* for 36 selected grid points from January 1981 to December 2021 (41 years or 492 months). This dataset was selected due to its alignment with our study's requirement to analyze climatic trends over four decades across varied ecological zones. The data were considered adequate for capturing long-term trends in the study area. Additionally, the grid points were chosen based on their alignment with existing weather station locations, ensuring a representative distribution across the precipitation gradient in the study area. This method facilitates the contextualization of satellite-derived data with ground-truth observations from these stations. NASA POWER data were utilized due to their comprehensive integration of meteorological variables and suitability for long-term climatic analysis across large spatial scales. Derived from MERRA and supplemented by products like IMERG, NASA POWER data provide a valuable mix of solar and meteorological measurements suitable for our application. This dataset has been used by various scholars for similar applications, showcasing its broad applicability in environmental and agricultural research (Akkraoui, 2023; Asilevi et al., 2024; Attih, 2023; Jed et al., 2022; Monteiro et al., 2017; Ndiaye et al., 2020; NOAA, 2023; Rodrigues et al., 2021; Tan et al., 2023; Tayyeh et al., 2023). Data extracted included daily retrievals of precipitation, maximum and minimum temperature, and solar radiation at a 0.5° spatial resolution. we compared the NASA POWER/Agro-climatology data with daily precipitation and temperature records from eight ground-based meteorological stations provided by the National Meteorology Services of Ghana and Burkina Faso. This comparison was crucial for validating the satellite-derived data against observed ground data.

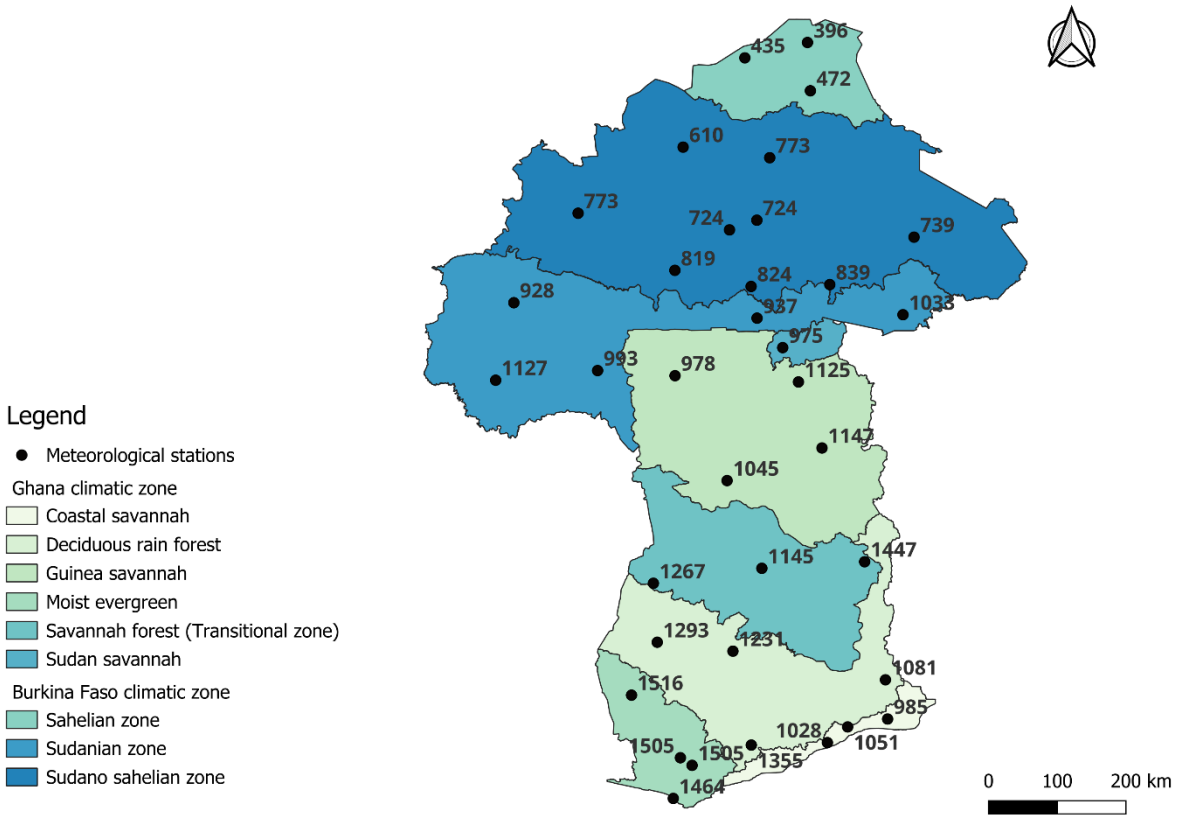

Figure 9. Geographic distribution 36 meteorological station points along with their corresponding annual mean rainfall (1982–2021) across various climatic zones in Ghana and Burkina Faso (Adelaïde et al., 2018; Nyadanu et al., 2015). the names and coordinates of each station are detailed in annex 1.

2.2.3. Data analysis

To achieve the objectives of evaluating drought characteristics and exploring the spatial and temporal distribution of drought events, various analytical methods were employed.

- Data accuracy evaluation

The accuracy of the satellite-derived data (NASA POWER) was validated using ground-based observations from 8 meteorological stations across the study areas, covering the period from 1981 to 2021. These stations were selected because they had comparatively more extensive data coverage for the study period, ensuring a representative sample across various agroclimatic zones. The validation process involved comparing the satellite data with ground-based observations using statistical metrics such as root mean square error (RMSE), mean error (ME), coefficient of determination (R^2), and Nash-Sutcliffe efficiency coefficient (NSE) (Hodson, 2022; Piñeiro et al., 2008; Singh et al., 2007). R "*Metrics*" and "*hydroGOF*" package (Hamner, 2018; Zambrano-Bigiarini, 2020) was used to apply and carry out various statistical methods. According to Piñeiro et al. (2008) , the following equation is used to calculate the coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \widehat{O})^2}$$

where $O_i, \widehat{O}$, and P_i stand for the measured values, measured average values, and satellite values, respectively. In addition, n is the number of measurement variables used for analysis. The R^2 values

range from 0 to 1, with values higher than 0.5 typically being accepted (Liew et al., 2003; Santhi et al., 2007). Higher values denote a better fit of the model and lower error variance.

The NSE provides information about the mean square error (MSE = $RMSE^2$) in relation to the variance of the observed data (Legates et al., 1999). The ideal value is NSE = 1.0, which represents a perfect match between measured and observed values (Nash et al., 1970). The Nash-Sutcliffe efficiency (NSE) ratio is calculated as:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$

The Root Mean Square Error (RMSE) (Willmott, 2005) and Mean Absolute Error (MAE) (Hodson, 2022; Legates et al., 1999) were calculated using obtained by the following equations:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2$$

Additionally, given the importance of detecting long-term climatic trends in rainfall and temperature for Ghana and Burkina Faso, we employed the Mann-Kendall trend test to analyze our dataset. This non-parametric test is particularly suitable for environmental data analysis, as it does not require the assumption of normal distribution and is robust against outliers and missing values. By comparing the rankings of data points over time, the test effectively identifies whether significant trends exist in the observed climatic variables (Chatfield, 2003; Mann, 1945; Shumway et al., 2017).

The Mann-Kendall trend statistic is defined as:

$$\tau = \frac{\sum_{i-1}^{n-1}\sum_{j=i+1}^{n} sgn(x_j - x_i)}{n(n-1)/2}$$

Where: x_i and x_j are data points in time series i<j, n is the number of data points, and *sgn* is the sign function, which is 1 if $x_j - x_i > 0$, -1 if $x_j - x_i < 0$, and 0 if $x_j = x_i$.

This test helped identify any upward or downward trends in rainfall patterns over the study period. By examining the temporal distribution of rainfall, we analyzed the frequency and intensity of rainfall events, observing seasonal fluctuations and extreme weather occurrences such as droughts and heavy rainfall periods.

To analyze the data and understand variations over time, we also calculated the running mean and standard deviation.

- Rainfall and temperature

To address the critical issue of drought analysis, our study incorporates an in-depth examination of rainfall patterns and intensity. This methodology is rooted in the understanding that the characterization of rainfall in terms of quantity, distribution and intensity.

Rainfall patterns analysis: The rainfall patterns denote the distribution and variability of rainfall within a specific area, influenced by factors such as geography, climate, and seasonality. These patterns can include characteristics such as rainfall amount, frequency, intensity, and duration (Nayak, 2015; Panagos et al., 2017). The assessment of rainfall patterns began with collecting historical daily rainfall data for the area. These data were then organized into periods, such as months, seasons, and years. Statistical measures were calculated from these data, including total rainfall (the sum of measurements over a designated time frame, e.g., from 1981 to 2022), average rainfall as an estimate of typical rainfall (total rainfall divided by the number of observations), and rainfall variability as an insight into regional variation (determined by the standard deviation of measurements). A histogram or frequency distribution was used to visually represent rainfall distribution, facilitating comprehension of

precipitation patterns over the studied regions. Temporal distribution analysis examined rainfall event frequency and intensity over time, identifying trends, seasonal fluctuations, and extreme events like droughts or heavy rainfall periods. Historical data from previous years or decades was then compared to the derived rainfall patterns to identify notable alterations or anomalies.

Rainfall intensity analysis: Rainfall intensity was assessed using percentiles, a measure of the relative frequency and occurrence of rainfall events, as outlined by Wilks (2011). Historical daily rainfall measurements for each of the 36 locations were collected and organized by station. Mean values were computed for each of the nine climatic zones during the study period from 1981 to 2022. Rainfall measurements were sorted in ascending order, and rainfall distribution was determined by associating the cumulated percentage rain amount and the cumulated percentage number of rain days (rain frequency) for various percentiles, ranging from the 5th percentile to the 99th percentile. We considered starting at 5th for outlier exclusion, focusing on the central data, and reducing the impact of skewness. Higher percentiles indicate more extreme or intense rainfall events that occur less frequently.

Temperature changes were assessed using monthly and yearly average temperature values (T_{Av}), with a reference temperature (T_{Ref}) calculated for comparison. The temperature change (ΔT) is calculated by subtracting T_{Ref} from the average value for each time ($\Delta T=T_{Av}-T_{Ref}$).

- Drought indices

To compute the Standardized Precipitation Index (SPI), we first aggregated daily precipitation data from each station into monthly totals. This data was then fitted to a gamma distribution to align with SPI's computation requirements, which is distinct from merely using standard deviation for normalization. The SPI is calculated by transforming the cumulative precipitation into a standardized index through the gamma probability function. This transformation allows us to assess the intensity of wetness or dryness relative to a long-term precipitation record. We calculated SPI across various timescales—1, 3, 6, and 12 months—to comprehensively capture both immediate and extended patterns of precipitation anomalies. (Guttman, 1999; Keyantash, 2021; Keyantash et al., 2002; McKee, 1993; Tirivarombo et al., 2018a; Vicente-Serrano et al., 2010). In this paper, SPI is expressed as follows:

$$SPI = (X - \mu)/\sigma$$

where X is the transformed precipitation data, μ is the mean, and σ is the standard deviation of the fitted gamma distribution.

SPEI is an index calculated based on the likelihood of the climate water balance described by Equation (2). This calculation depends on the disparities between precipitation (P) and potential evapotranspiration (ET_o), which are adjusted using a three-parameter log-logistic distribution, taking into account the occurrence of negative values (Vicente-Serrano et al., 2010). The Hargreaves-Samani equation (Hargreaves, 1982) was used to obtain ET_o. This equation requires few parameters as the minimum, maximum, and mean temperatures (T_{min}, T_{max}, and T_{mean}), along with extraterrestrial radiation (R_a), which is a function of latitude and the day of the year (Allen, 1986).

$$ET_o = 0.23(0.408)(T_{mean+17.8})(T_{max} - T_{min})^{0.5} R_a$$

Where ET_o represents the reference evapotranspiration(mm/day), 0.23 and 0.408 are empirical coefficients, T_{mean} is the mean daily temperature, T_{max} and T_{min} denote the daily maximum and minimum temperatures (°C) respectively, and Ra signifies the extraterrestrial radiation (MJ/m²/day).

The Standardized Precipitation Evapotranspiration Index (SPEI) utilizes a three-parameter distribution to effectively account for negative deficit values, which are more likely to occur in arid and semiarid regions. In contrast to two-parameter distributions, as utilized in the SPI, where the variable 'x' is bounded from below at zero ($0 > x < \infty$), meaning it can only take positive values, three-parameter distributions employed by SPEI allow 'x' to vary within the range ($\gamma < x < \infty$), implying that 'x' can

encompass negative values (Tirivarombo et al., 2018b). In this context, γ serves as the origin parameter of the distribution, as introduced by Vicente-Serrano et al. (2010).The SPEI is derived by standardizing the water balance using a three-parameter log-logistic probability distribution. It was computed over each station point for each dataset for 1 month, 3 months, 6 months, 9 months, and 12 months as follows. Let D_n represent the difference between P and ET_o for the month 'n' (Eq. 3).

$$D_i = P_n - ET_{o\,n}$$

These calculated D_n values were aggregated over different timescales using Eq. 4, where 'k' represents the timescale in months, and 'n' denotes the specific month for which the climate water balance is computed.

$$D_n^k = \sum_{i-0}^{k-1} . P_{n-1} - ET_{o\,n-1}$$

The log-logistic probability density function for SPEI, as defined in Eq. 5, depends on the three parameters of the distribution: α (scale), β (shape), and γ (origin), where $\gamma > D < \infty$.

$$f_{(x)} = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} \left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-2}$$

The probability distribution function for the D series is then given in Eq. 6.

$$f_{(x)} = \left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-1}$$

Finally, the SPEI can be obtained as the standardized values of $f_{(x)}$ according to the method of (Abramowitz, 1964) as:

$$SPEI = W -$$

$$\text{and } W = 2In(P)$$

Where, for $P \leq 0.5$, P is the probability of exceeding a determined D value, $P=1-f(x)$ and for $P > 0.5$, P is replaced by $1-P$, and the sign of the resultant SPEI is reversed. The constants are: $C_0=2.515517$, $C_1=0.802853$, $C_2=0.010328$, $d_1=1.432788$, $d_2=0.189269$, $d_3=0.001308$.

Additionally, the characterization of drought events was performed by analyzing their duration, intensity, and frequency. Drought duration was defined as the number of consecutive months where the SPI or SPEI value remained below a certain threshold. Drought intensity was calculated as the cumulative deficit of SPI or SPEI values below the threshold during a drought event. The frequency of drought events was determined by counting the number of drought occurrences within the study period. Table 5 presents the classification of drought events based on SPI and SPEI values, ranging from extremely wet to extremely dry, with each category corresponding to specific SPI or SPEI values.

S.N.	Categorization	SPI or SPEI values
W3	Extremely Wet	≥ 2
W2	Severely Wet	1.5 ≤ to < 2
W1	Moderately Wet	1 ≤ to < 1.5
W0	Mildly Wet	0.5 < to < 1
	Normal	−0.5 ≤ to ≤ 0.5
D0	Mildly Drought	−1 < to < −0.5
D1	Moderately Drought	−1.5 < to ≤ −1
D2	Severely Drought	−2 < to ≤ −1.5
D3	Extremely Drought	To ≤ −2

Table 5.Classification of moisture levels based on SPEI and SPI, following the methodology proposed by Zhang et al. (2023).

o Characterization of Drought Events

In addition to identifying drought events using the SPI and SPEI indices, it is essential to characterize these events in terms of duration, intensity, and frequency to fully understand their impact and to develop effective mitigation strategies.

a) Drought Duration

To determine the duration, we count the number of consecutive months where the SPI or SPEI is below a specific threshold (e.g., SPI < -1 for moderate drought). This provides insight into how long an area experiences drought conditions.

b) Drought Intensity

Drought intensity is calculated as the cumulative deficit of SPI or SPEI values below the threshold during a drought event. This measure helps in understanding the severity of the drought by considering the total amount of precipitation deficit over the drought period.

$$Drought\ Intensity = \sum_{i=1}^{n} SPI_i \quad \text{(Eq. 14)}$$

where SPI_i is the SPI or SPEI value for month *i* during the drought event.

c) Drought Frequency

Drought frequency is determined by counting the number of drought occurrences within the study period. This gives an indication of how often drought events occur in a given area, which is crucial for planning and resource management

o Spatial Visualization

In this section, we present the spatial visualization of our data, illustrating patterns and trends across different geographical regions. We employ various techniques, such as maps and interpolation methods, to effectively represent the spatial distribution. These visualizations are crucial for understanding spatial relationships and aiding in decision-making processes related to climate and environmental management. This study employs the Inverse Distance Weighted (IDW) interpolation method to estimate spatial data for rainfall regimes using data from 36 points at a 0.5° resolution. IDW is based on the principle that the influence of a known point on an unknown point decrease with distance. This method calculates the value at an unknown location by averaging the known values, weighted inversely by their distance. The IDW formula estimates the value Z at a location (x_0, y_0) as follows:

$$Z(x_0, y_0) = \frac{\sum_{i-1}^{n}\left(\frac{1}{d_i^p}\right)z_i}{\sum_{i-1}^{n}\frac{1}{d_i^p}}$$

Where d_i is the distance from each known point *i* to the unknown point, and p is a positive exponent that determines how quickly influence decreases with distance.

2.3. Result and discussion

2.3.1. Data validation and comparison

To enhance our analysis and ensure greater reliability, we used this validation to compare the satellite-derived data with the observations from the 8 ground-based stations (Akinyemi et al., 2019). This integration revealed strong agreements across different timescales for both precipitation and mean temperature (T_{mean}), consistent with findings from a recent study by K. H. Tayyeh et al. (2023). For precipitation, the daily correlation demonstrated an R^2 value of 0.72, an RMSE of 2.80 mm/day, an MAE of 1.37 mm/day, and a bias of -0.22 mm/day (Figure 10a). The monthly correlation exhibited an R^2 value of 0.86, an RMSE of 34.39 mm/month, an MAE of 24.57 mm/month, and a bias of -6.77

mm/month (Figure 10b). Yearly data displayed a strong correlation, with an R^2 value of 0.77, an RMSE of 186.12 mm/year, an MAE of 148.39 mm/year, and a bias of -81.28 mm/year (Figure 10c). For T_{mean}, the daily correlation showed an R^2 value of 0.87, an RMSE of 0.73°C, an MAE of 0.54°C, and a bias of -0.01°C (Figure 10d). The monthly correlation presented an R^2 value of 0.88, an RMSE of 0.62°C, an MAE of 0.46°C, and a bias of -0.01°C (Figure 10e). The yearly correlation, while slightly lower, still demonstrated reasonable agreement, with an R^2 value of 0.70, an RMSE of 0.37°C, an MAE of 0.30°C, and a bias of -0.01°C (Figure 10f). Our analysis indicates significant agreement between satellite and ground-based data across various timescales for both precipitation and T_{mean}. This correlation suggests that satellite data can provide an accurate representation of ground conditions. The strong correlations found in our study support the use of satellite data as a complementary tool to ground-based observations, enhancing the comprehensiveness of climatic studies. This is particularly valuable in regions with sparse ground data, such as West Africa, where satellite data can fill in critical gaps and provide reliable climate information (Dinku et al., 2013; Maidment et al., 2014; Maidment et al., 2017).

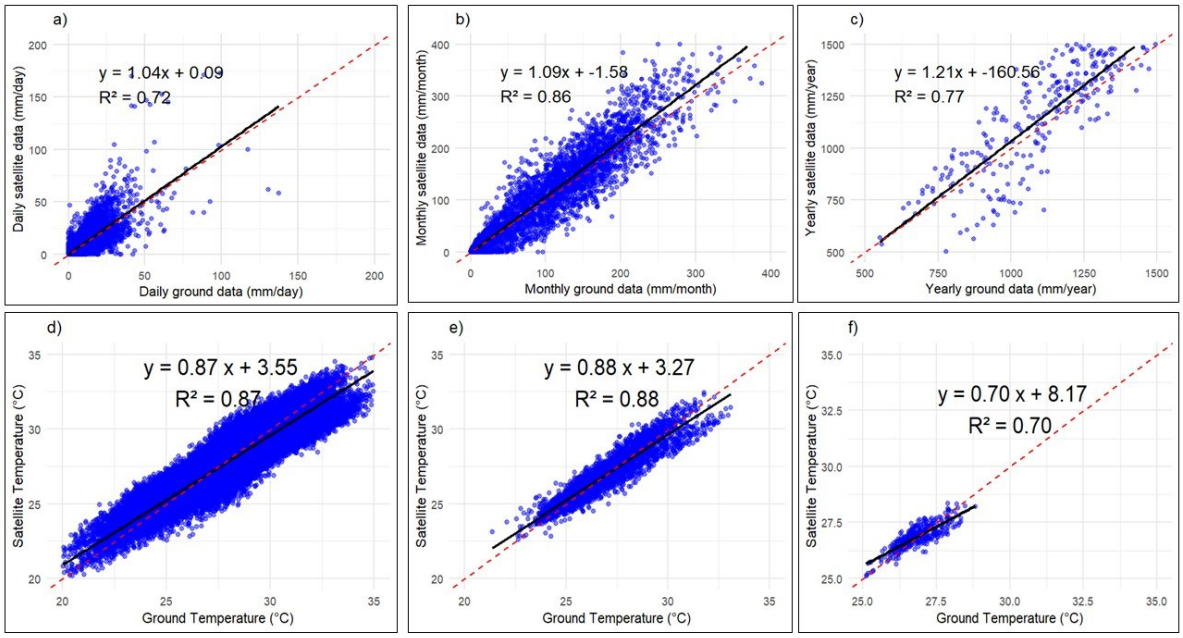

Figure 10. Comparison between satellite-derived data and ground-based measurements for precipitation (mm) and mean temperature (°C) across different timescales. Subfigures (a) to (c) represent daily, monthly, and yearly precipitation correlations, respectively, while subfigures (d) to (f) show daily, monthly, and yearly mean temperature correlations. The black lines are the regression lines and the red dashed lines are the 1:1 line.

2.3.2. Rainfall and temperature dynamics

The analysis of rainfall and temperature dynamics between 1981 and 2021 reveals significant variations and trends in both Ghana and Burkina Faso. Ghana exhibited a mean daily rainfall of 3.57 mm and a mean temperature of 26.9°C. The Mann-Kendall trend test revealed a significant upward trend in both rainfall (Tau: 0.0288, p-value: $1.1921e^{-07}$) and temperature (Tau: 0.212, p-value: $< 2.22e^{-16}$). Figure 11 illustrates these trends, showing the deviations in precipitation (blue, in mm) and temperature (red, in °C) from 1981 to 2022 for both Ghana and Burkina Faso. Seasonal decomposition of temperature indicated moderate variability and a clear increasing trend over the study period. These results demonstrate significant climatic changes in both countries, with increasing trends in temperature and rainfall aligning with global climate change patterns. Specifically, Ghana's mean temperature increased

by 0.4°C from the 1980s to the 1990s, remained stable through the 2000s, slightly increased by 0.1°C in the 2010s, and decreased by 0.2°C in the 2020s. Meanwhile, rainfall increased by approximately 19.7% in the 2020s. In Burkina Faso, the mean temperature increased by 0.3°C from the 1980s to the 1990s, further increased by 0.3°C in the 2000s, decreased by 0.4°C in the 2010s, and slightly increased by 0.1°C in the 2020s, with rainfall showing a substantial increase of approximately 25.9%. Nicholson (2005) highlighted significant rainfall fluctuations in West Africa, noting a partial recovery after the 1970s and 1980s droughts, which aligns with the recent rainfall increase in Burkina Faso. Nouaceur et al. (2020) linked increasing temperatures in Ghana and Burkina Faso to regional climate indices, reflecting broader multi-decadal trends. Additionally, Descroix et al. (2020) emphasized the regional impacts of these climatic shifts on water resources and agriculture, stressing the importance of adaptive strategies in light of the substantial rainfall increases observed in both countries in the 2020s.

Daily analysis using running means and standard deviations for rainfall and temperature supports these findings, revealing both seasonal patterns and long-term trends. Ghana and Burkina Faso exhibit increasing rainfall, with Ghana showing complex temperature trends and Burkina Faso demonstrating stable temperature patterns with notable seasonal fluctuations. These results underscore significant decadal variations and provide valuable insights into climate variability in these regions. Ghana and Burkina Faso exhibit increasing rainfall, with Ghana showing complex temperature trends and Burkina Faso demonstrating stable temperature patterns with notable seasonal fluctuations. These results underscore significant decadal variations and provide valuable insights into climate variability in these regions. This aligns with recent studies, such as Efon et al. (2022), which highlight increased precipitation and runoff as significant challenges in West and Central Africa. Nicholson (2013) also identified significant variability in rainfall patterns in the West African Sahel, noting periods of drought and increased rainfall. Similarly, Sultan et al. (2016) emphasized the impacts on agriculture in West Africa, predicting increased climatic variability and the need for adaptation strategies.

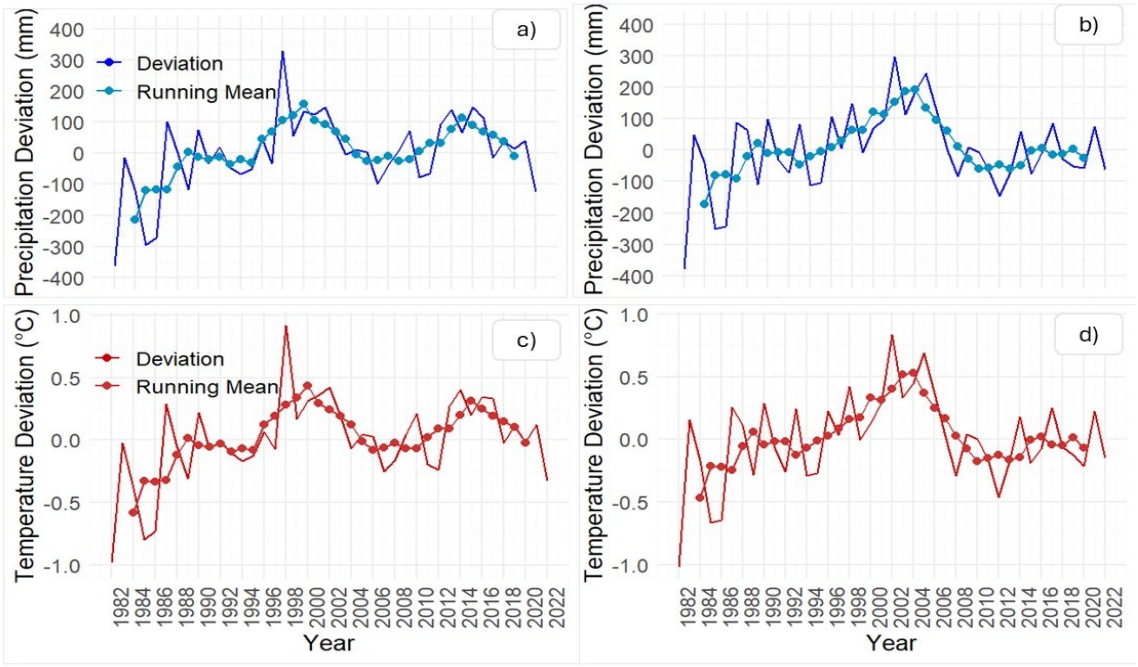

Figure 11. Trends in precipitation deviation (blue in mm) and temperature (red in °c) represented (a and c) for Ghana and Burkina Faso (b and d) from 1981 to -2022. The running means were calculated using a 365-day window, the trend lines and ribbons demonstrate the overall direction and variability of rainfall and temperature over the period.

2.3.3. Rainfall intensity and the frequency distribution

The study period from 1981 to 2021 highlighted distinct trends in rainfall intensities and distribution across Burkina Faso and Ghana. The correlation matrix represents that while lower percentiles (5th to 40th) generally showed negative correlations with total annual rainfall, suggesting that less intense rainfall events inversely affect the annual totals, higher percentiles (60th to 99th) demonstrated positive correlations both among themselves and with total annual rainfall (Figure 12).

This indicates that higher rainfall events significantly contribute to increased annual totals, aligning with global observations of intensifying precipitation extremes under current climate trends. This pattern is supported by literature indicating that the intensity and frequency of extreme rainfall events are increasing under current climate trends, which contributes to higher annual rainfall amounts. Tabari (2020) confirmed that extreme rainfall intensities are rising uniformly across various climatic regimes in Africa, aligning with the observed data in the study region. Pérez Bello et al. (2022) further support this by noting that global extreme rainfall intensity is expected to rise due to increasing temperatures, corroborating the trends noted in this study.

Percentile	5	10	20	30	40	50	60	70	80	90	99	Annual rainfall(mm
5	1											
10	-0.59	1										
20	0.20	0.57	1									
30	-0.13	0.39	0.63	1								
40	-0.54	0.10	0.34	0.66	1							
50	-0.59	-0.14	0.16	0.46	0.78	1						
60	-0.72	-0.26	-0.06	0.20	0.61	0.77	1					
70	-0.63	-0.26	-0.05	0.21	0.54	0.74	0.86	1				
80	-0.61	-0.48	-0.24	-0.02	0.36	0.59	0.84	0.83	1			
90	-0.67	-0.50	-0.24	-0.10	-0.01	0.18	0.47	0.43	0.64	1		
99	-0.16	-0.34	-0.36	-0.54	-0.51	-0.45	-0.20	-0.28	-0.03	0.53	1	
Rainfall(mm)	***0.24***	-0.12	-0.17	-0.21	-0.43	***-0.35***	-0.39	-0.47	-0.38	-0.06	***0.28***	1

Figure 12.The correlation matrix between mean annual rainfall and percentiles (5th to 99th) and between the different percentiles during the study period.

In Burkina Faso, the 99th percentile showed a strong positive correlation with total rainfall ($r = 0.88$, $p < 0.001$), indicating that extreme rainfall events significantly contribute to the annual rainfall total. This correlation suggests that years with higher total rainfall are predominantly influenced by extreme rainfall events. The 50th percentile exhibited a moderate negative correlation ($r = -0.60$, $p < 0.05$), while the 10th percentile displayed a negligible and statistically insignificant correlation ($r = 0.20$, $p > 0.05$), underscoring that typical and lower rainfall events have less impact on the annual totals. Conversely, in Ghana, the 99th percentile also showed a significant positive correlation with total rainfall ($r = 0.90$, $p < 0.001$), reinforcing the global trend where extreme weather events are becoming more influential on annual rainfall metrics. The 50th percentile correlation was slightly positive but less pronounced ($r = 0.45$, $p < 0.01$), and similar to Burkina Faso, the 10th percentile showed a minimal and non-significant correlation ($r = 0.15$, $p > 0.05$) (Figure 13a). These findings align with observed climatic shifts, suggesting an increasing role of extreme rainfall events in shaping annual rainfall profiles in both countries.

The correlation analysis between rainfall percentiles and year revealed a significant upward trend in the 99th percentile for both countries, indicating a rising pattern in extreme rainfall events over the decades. This trend was statistically significant in Burkina Faso ($r = 0.77$, $p < 0.001$) and Ghana ($r = 0.82$, $p < 0.001$), highlighting a concerning increase in extreme weather phenomena.. In contrast, the 50th and 10th percentiles showed no consistent trends with year, suggesting that the typical and lower extremes of rainfall are not exhibiting a similar increase (Figure 13b). These insights are critical for regional planning and adaptation strategies, as they suggest a growing frequency and intensity of extreme rainfall events, necessitating enhanced infrastructural and agricultural resilience measures in both Burkina Faso

and Ghana. This observation aligns with Panthou et al. (2014), who reported an increase in the proportion of annual rainfall associated with extreme events in the Central Sahel, even as the overall number of rainy days has decreased. This trend underscores the need for enhanced infrastructural and agricultural resilience measures in both Burkina Faso and Ghana, as the region experiences a more extreme and variable climate. This is consistent with the findings of Fowler et al. (2022), that extreme rainfall events have been increasing in recent decades, and are expected to increase more in the future due to global warming. Furthermore, another study by Myhre et al. (2019) indicates that extreme rainfall events may undeniably be influenced by climate change, reinforcing the urgency of addressing these shifts within the wider context of climate dynamics. This phenomenon underlines the increased total rainfall observed in recent decades is mainly attributable to extreme rainfall events in the region as reported by CarbonBrief (2023) and Adegoke (2019) in West Africa. WWAO, (2023) and OCHA (2023) report also considered the recent regional floodings in West Africa as a major outcome of rainfall intensity and climate change.

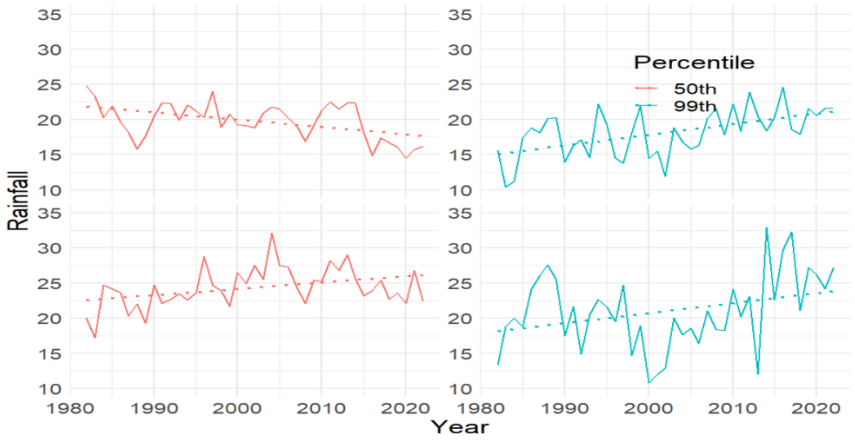

Figure 13. The provided graphs for Burkina Faso (a) and Ghana (b) illustrate the 50th, and 99th percentile rainfall events over the years. the graphs include a line for the trend and variability.

The seasonal rainfall variability was analysed by examining the correlation between the number of rainy days (>0.1 mm) and the average cumulative seasonal rainfall. The dry season exhibits a slight positive correlation of 0.07 with 290 mm of rainfall over 100 rainy days, indicating some degree of seasonal variability and shifts in trends; however, this correlation was not statistically significant (t-value: 0.43, p-value: 0.668). This minor positive correlation might suggest a slight tendency towards increasing rainfall totals and the number of rainy days, potentially due to seasonal shifts affecting rainfall distribution over the years. Conversely, in the wet season, the correlation coefficient of -0.33 was statistically significant (t-value: -2.15, p-value: 0.038). This significant negative correlation could be due to more intense rainfall events occurring over fewer rainy days. This pattern implies that despite an increase in the number of rainy days, the total rainfall may not necessarily increase, likely due to the intensity of the rain events. For instance, Feng et al. (2013) also showed that shifts in the amount, timing, and length of seasonal rainfall in tropical regions of Africa led to an increase in rainfall variability.

Furthermore, the heatmap (Figure 14) illustrates the distribution of rainfall events across different agroclimatic zones in Ghana and Burkina Faso, categorized by the 99th, 50th, and 10th percentiles. In Burkina Faso, the Sudano Sahelian Zone (SSZ) and Sudanian Zone (SDZ) exhibit a high frequency of extreme rainfall events (99th percentile), while the Sahelian Zone (SHZ) shows a moderate frequency of extreme rainfall events. Median rainfall events (50th percentile) are consistently moderate across all zones in Burkina Faso, whereas the low rainfall events (10th percentile) are infrequent, indicating a significant disparity between extreme and low rainfall occurrences. In Ghana, the Transitional Savannah Forest (TSF), Sudan Savannah (SV), Guinea Savannah (GS), and Deciduous Rain Forest (DRF) zones demonstrate a high frequency of extreme rainfall events. The Most Evergreen (MEG) and Coastal

Savannah (CS) zones display a moderate number of extreme rainfall events. Median rainfall events are consistently moderate across all zones in Ghana, mirroring the patterns in Burkina Faso. Low rainfall events remain infrequent across all agroclimatic zones, emphasizing the disparity between high and low rainfall frequencies. Comparing the two countries, Ghana generally exhibits a higher frequency of extreme rainfall events across more agroclimatic zones than Burkina Faso. Specifically, Ghana's TSF, SV, GS, and DRF zones all show a high number of extreme rainfall events. This implies as described in Figure 14 that rainfall events in Ghana generally tend to be more intense which is in line with the study of Padi et al. (2021) that found rainfall in Ghana to be more frequent and intense in a study period from 1981 to 2019. Overall, the data indicate that extreme rainfall events are prevalent across the agroclimatic zones in both Ghana and Burkina Faso, with Ghana experiencing a higher frequency of these events across a broader range of zones. Median rainfall events are moderately distributed, while low rainfall events are relatively rare in both countries. Our findings resonate with those presented by (Sylla et al., 2016), who highlighted the impending climatic shifts expected in West Africa. Specifically, Sylla emphasizes that most countries in the region will likely face shorter rainy seasons coupled with predominantly arid conditions, extended dry spells, and an increase in the intensity of extreme precipitation events. This projection aligns with our observed trends in Burkina Faso and Ghana, where extreme rainfall events show a significant correlation with annual rainfall totals, despite the overall increase in aridity and the reduction in moderate rainfall events.

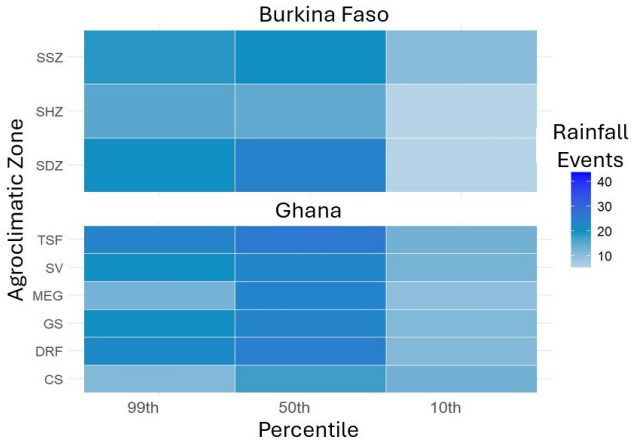

Figure 14. Heatmap of the number of rainfall events at different percentiles (99th, 50th, and 10th) across various agroclimatic zones in Ghana and Burkina Faso. The colors represent the number of rainfall events, with darker blue indicating a higher number of events and lighter blue indicating fewer events. The agroclimatic zones are coded as follows: in Burkina Faso, SSZ stands for Sudano Sahelian Zone, SHZ stands for Sahelian Zone, and SDZ stands for Sudanian Zone; in Ghana, TSF stands for Transitional Savannah Forest, SV stands for Sudan

2.3.4. Temporal variation of drought occurrence and frequency

The assessment of the temporal variation of drought occurrence and frequency using SPEI and SPI revealed fluctuations caused by seasonal patterns and variations across the 1, 6, and 12-month time scales (Figure 15). The annual and seasonal analysis showed a slight positive trend for both indices; however, SPI index indicated a higher trend of change from dry to wet climate. This could be, as mentioned by several researchers, because SPEI is more responsive to changes in drought conditions as it accounts for evapotranspiration (Liu et al., 2021; Wang et al., 2020). The annual shift can be further observed particularly after 2001, where the trend was significantly higher in the late 20 years (2001-2021) in comparison to 1981-2000. However, regarding the monthly analysis, there was no evident trend for both indexes. Although, both the indices were able to detect different dry and wet periods over the study period, they showed different sensitivity for detecting drought and wet periods. This was

manifested in the annual seasonal and monthly data e.g., an extreme drought was identified by SPI^{12} from 1983 to 1984 while the $SPEI^{12}$ indicated a very dry 1983 and moderately dry 1984. These events were even confirmed by other studies that reported 1983 and 1984 as severe drought years in West Africa (Bader et al., 2011; Bontogho et al., 2023; Masih et al., 2014; Quenum et al., 2019). This drought can be explained by the relatively small amount of rainfall received during 1983. However, the drought in 1994 was not the case, since the rainfall amount was within the range of normal rainfall but with much higher extreme events (Figure 15). The dry and wet event identifications were significantly affected by the time scale used. This can be seen over the years except in 1983, e.g., the severe drought in 2014 detected by monthly indices was not identified by the seasonal and annual scale and the extreme drought identified in 1987 seasonal scale was not identified by the annual scale. Furthermore, the monthly results from SPI and SPEI analyses showed the frequent occurrence of mild drought in most of the years. The drought experienced in 1984 (SPI) and 1983 (SPEI) October were the most extreme dry, with peak negative values of -4.894 and -3.38. In both indexes, the years 1983 (October), 1989 (January and February), 1998 (March and February), 2000 (December), 2001 (February and March), and 2004 (March), along with the more recent years of 2014 (April), 2015 (May), 2017 (June), 2019 (August) and 2020 (June) exhibit the highest negative indices. The shift from negative indices appearing predominantly in October to March in the earlier years to April to June and August in recent years shows a temporal change in the pattern of drought conditions. This highlights the importance of the time scale for this type of analysis. Selecting the right time scale of drought analysis is extremely important for mitigation and adaptation for climate change in agriculture since extreme events of drought and wet events can usually impact the crop calendar as well as the overall agricultural productivity of the region. As highlighted by Hendrawan et al. (2023), different timescales have distinct impacts on how crops respond to drought conditions. This understanding is pivotal for addressing challenges associated with global food security and agricultural sustainability.

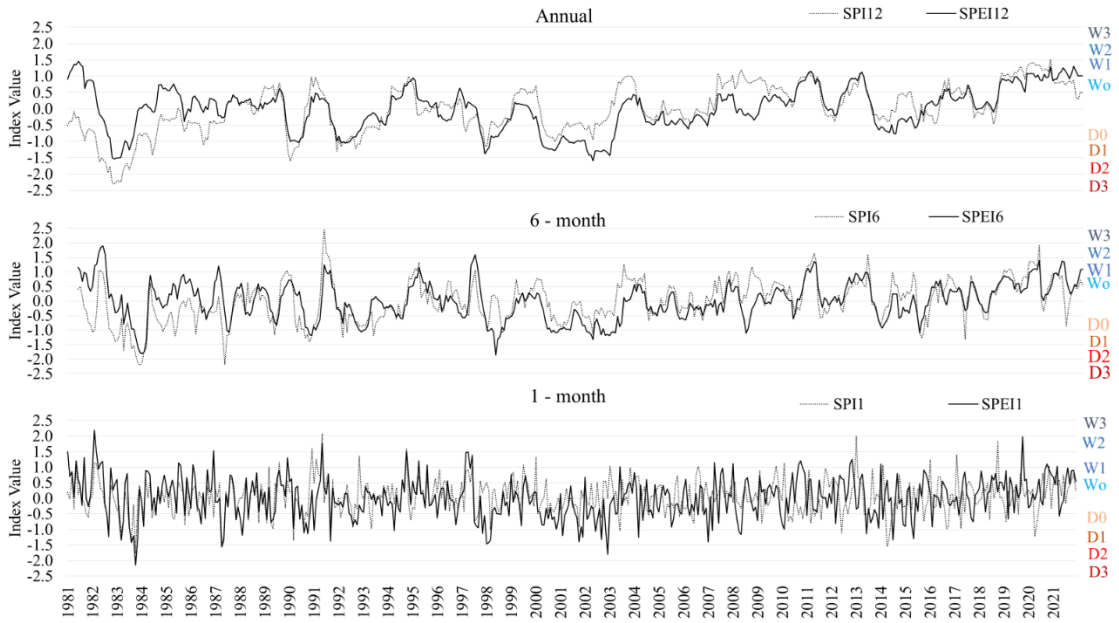

Figure 15. Temporal variation of drought in the study area at annual (12), seasonal (6), and monthly (1) time scales using SPEI and SPI. severity indices include w3 (extreme wet), w2 (severe wet), w1 (moderate wet), w0 (mild wet), d3 (extreme dry), d2 (severe dry), d1 (moderate dry), and d0 (mild dry).

2.3.5. Spatial variation of drought occurrence and frequency

The frequency and occurrence of drought patterns across the region, examining different time scales and over the whole region based on the mean average value over the entire study period (1981-2021) are illustrated in Figure 16. The analysis reveals that severe drought conditions are more frequently detected in monthly data compared to 6-month and annual data. This suggests a prevalence of more moderate conditions overall, aligning with the findings in Figure 16, where trend analysis across various time scales indicates a reduction in positive trends from larger to smaller scales. These observations highlight the importance of detailed temporal analysis. While both seasonal and annual analyses indicated wetter conditions, this trend was not observed on the one-month scale. This discrepancy can be attributed to the cumulative nature of precipitation for the SPI and SPEI indices, which may not accurately reflect the real dynamics of events or provide indications of changes in event intensity. The implication is that higher temporal resolution in our analysis yields greater accuracy in reflecting climatic conditions. It is crucial to note that a positive trend in annual and seasonal indices does not necessarily signify a decrease in drought events in the region. Instead, it indicates that the temporal scale is capturing changes in rainfall intensity.



Figure 16. frequency and occurrence of drought patterns across the region at different time scales and sensitivity levels

Following the above finding, we use the monthly data to illustrate the spatial distribution of drought over the study area. Figures 17 and 18 illustrate the intensity of drought and the frequency and occurrence of drought patterns across the region, examining a monthly time scale and spanning the nine climatic zones. The analysis is based on the mean average value over the entire study period (1981-2021). Within the study area, the values showed in Figure 15 range from 2 (extremely wet) to -2 (extremely dry). The figure 17 shows that the Northern region had more negative SPEI and SPI values, indicating relatively dry conditions, while the southern part's positive SPEI and SPI values suggest periods of relative wetness. The drought intensity map mirroring this precipitation gradient indicates that areas with lower rainfall are more prone to experiencing drought conditions. This connection was easy to understand, as regions with less precipitation are likely to face challenges related to water scarcity and drought stress (Konapala et al., 2020). The magnitude of the values on the map can provide more information on the severity of wet or dry conditions. The annual and the wet season distribution maps show there is a difference between the two indices with more affected drought areas in the SPEI in annual and the dry season. Among the study climatic zones, the Sahelian, Sudanian Burkina Faso towards Sudan Savannah, and Guinea savannah zones are more affected by drought compared to the other zones in both SPEI and SPI with more impact in the dry season during the study period. The fact that the frequency and occurrence of droughts coincide with the dry and wet seasons highlights the enduring influence of these meteorological events. In regions dependent on agriculture, as in our study case Ghana and Burkina Faso, positive values could be favorable for crop growth, while negative values might signal potential drought stress on crops. Given that the wet season is a crucial period for agricultural activities, such heightened severity can have adverse effects. Understanding climatic trends in extreme detail is achieved possible by the combination of the annual monthly drought analysis and the maps of the wet and dry seasons. This broad comprehension facilitates the adoption of proactive measures to address the issues posed by drought, not just in Burkina Faso but also in Ghana, by enabling decision-making.

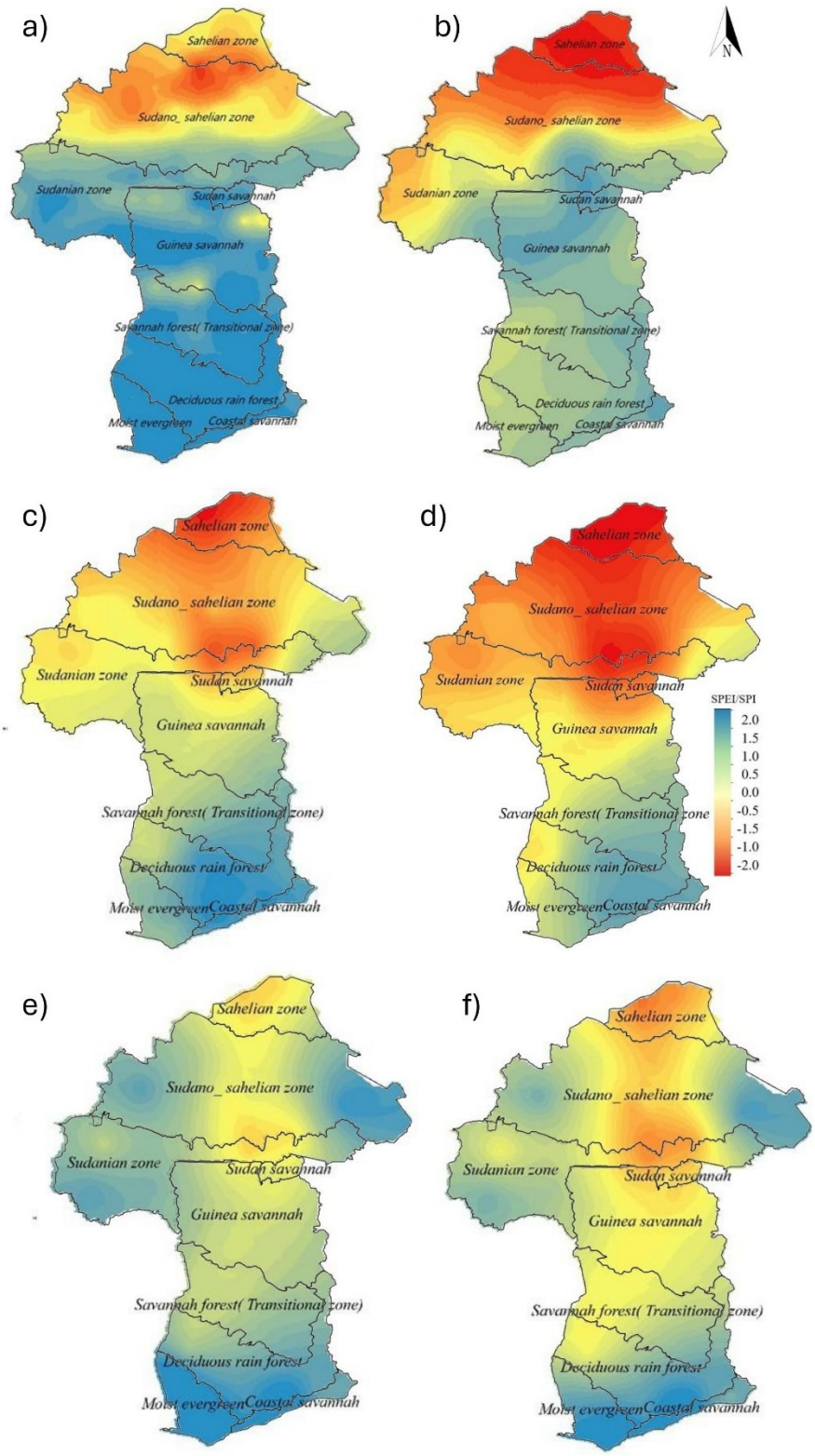

Figure 17. Annual and seasonal variation of drought distribution over the region from 1981 to 2021 across agroclimatic zones. this figure illustrates the spatial distribution of the standardized precipitation index (SPI) and the standardized precipitation-evapotranspiration index (SPEI) across various agroclimatic zones. the maps are presented for different seasons: overall, dry season, and wet season., (a) SPI full season, (b) SPEI full season, (c) dry season SPI (d) dry season SPEI, (e) wet season SPI and (f) wet season SPEI values.

This part of the study examines the frequency and distribution of droughts in the region, providing insights into the variability and concentration of drought occurrences in various locations. In the context of climatic zonal analysis for the nine climatic zones in Burkina Faso and Ghana, the examination of spatial frequency and occurrence of drought revealed heightened severity and extreme conditions, particularly evident through the SPEI. For Ghana, there is a difference between the two indices Moist Evergreen and Deciduous Rain Forest and transitional zones. SPEI is identifying higher occurrence of sever and extreme droughts. Our results conform to the finding of Pei et al. (2020) showing that SPEI is more sensitive in detecting drought occurrence compared to the SPI. The findings on the higher occurrence of drought events in the Sahelian zone of Burkina Faso align with the expected climate patterns in that region according to other scholars (Epule et al., 2013; Noureldeen et al., 2020). The monthly scale for the whole region was not enough to see the specificities of each climatic zone, while the overall monthly indices indicated a high concentration of moderate events that was not the case in all the climatic zones of the region, particularly in the Burkina Faso climatic zones and the Guinean Sudanian savannah. This highlights the importance of down scaling the spatial analysis to the level that can reflect the particularities of each zone which are affected by different frequency, intensity, and duration of drought events. (Aitkenhead et al., 2021) highlighted the importance of region-specific strategies to address extreme drought risks. This emphasizes the need for zone-specific water management strategies to compact drought more importantly on rainfed agriculture. Figure 18 illustrates the frequency of moderate, severe, and extreme droughts during the study period between 1981 and 2021. Moderate droughts were the most prevalent type, occurring frequently with a range of 12 to 19 times during the years. Both SPEI and SPI analyses showed the same distribution, but with higher intensity in the SPEI, indicating moderate dry season for extended periods. The spatial distribution of moderate drought frequency indicates that a significant area has been affected during the study period, with higher frequency in the northern part of Burkina Faso and across the entire study region, unlike severe and extreme droughts. The spatial distribution map of severe drought occurrences provides insight into the extent of drought severity throughout the study period, which was predominantly concentrated in Burkina Faso, with the most severe drought conditions observed in the northern Sahelian zone and Sudano-Sahelian climatic zone of the country. Conversely, the Evergreen climate zone in Ghana has remained relatively unscathed by drought, indicating a marked contrast in climatic conditions within the country. The study underlines the wide-reaching impact of drought on the region, as severe drought conditions were also experienced in the western and northern parts of Ghana at the border of Burkina Faso. These findings emphasize the urgent need for comprehensive and site-specific drought mitigation strategies. Efforts to address these challenges must take into account the distinct climatic zones and their unique vulnerabilities, with a focus on sustainable water resource management and adaptive agricultural practices.

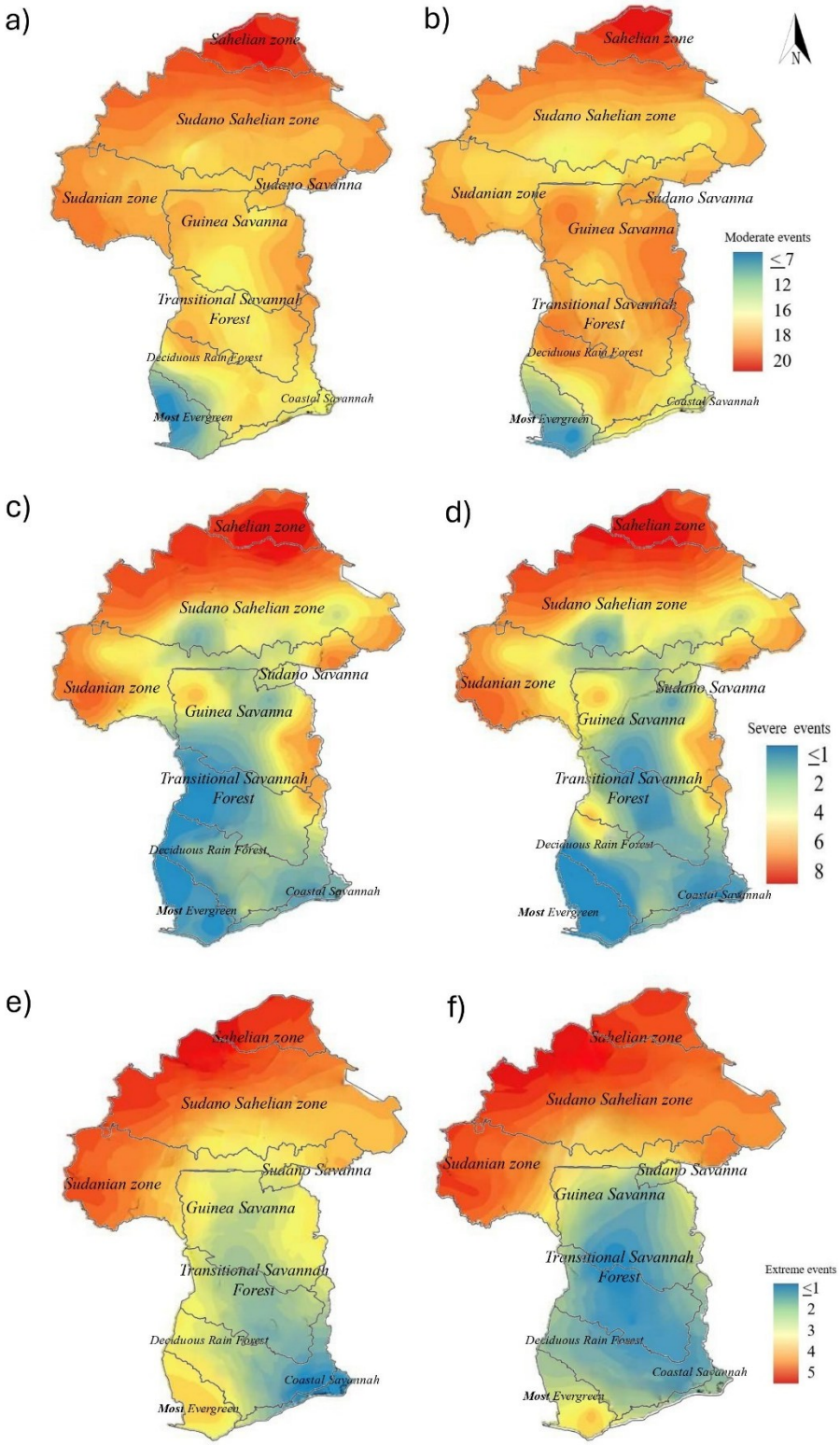

Figure 18. Frequency of moderate, severe, and extreme droughts (1981-2021), with SPI on the right and SPEI on the left. each panel represents the frequency of drought events using the standardized precipitation index (SPI) and the standardized precipitation-evapotranspiration index (SPEI). the panels are numbered and described as follows: (a) moderate drought events (SPEI), (b) moderate drought events (SPI), (c) severe drought events (SPEI), (d) severe drought events (SPI), (e) extreme drought events (SPEI) and (f) extreme drought events (SPI).

2.3.6. Implications for Agricultural Practices

In our analysis of climate data from 1981 to 2021, we observed significant shifts in rainfall patterns and temperature trends across Ghana and Burkina Faso, which have profound implications for agricultural systems reliant on predictable climatic rhythms. The increasing trend in rainfall intensity and frequency, notably a 19.7% increase in Ghana and a 25.9% increase in Burkina Faso in the 2020s has escalated the prevalence of extreme weather events in recent years (Padi et al., 2021; Sylla et al., 2016). These meteorological changes have led to more frequent and severe flooding incidents, adversely affecting crop yields through enhanced soil erosion and nutrient leaching, underscoring the need for robust drainage and flood management systems (Fowler et al., 2021). Moreover, the variability in precipitation, coupled with intense dry spells, indicates a heightened frequency of drought conditions, which disrupt water availability during critical crop growth stages, potentially leading to suboptimal agricultural outputs(Masih et al., 2014). Such variability necessitates a recalibration of agricultural calendars to adapt planting dates and crop varieties to the shortened growing seasons and erratic rainfall patterns (Padi et al., 2021).

The analysis of rainfall variability and its direct implications on drought patterns reveals intricate interactions that significantly impact the frequency, intensity, and duration of drought events. The upward trend in temperature and variability in rainfall, particularly the increase in extreme rainfall events, underscores a complex dynamic where higher mean rainfall does not necessarily mitigate drought conditions. On the contrary, the increase in rainfall intensity often leads to shorter, more intense wet periods followed by prolonged dry spells. This pattern is evident from the correlation analyses where higher percentile rainfall events correlate strongly with increased annual totals, suggesting that while total annual rainfall may appear stable or increasing, the distribution and intensity of rainfall are becoming more erratic. This erratic distribution contributes to the soil's reduced capacity to retain moisture, thereby exacerbating drought conditions during dry periods. Our findings show that droughts are indeed occurring more frequently and with increasing intensity, as reflected by the significant upward trends in the SPI and SPEI indices at the 99th percentile of rainfall events. The temporal analysis using these indices highlights a clear shift towards more severe and extended dry periods, particularly evident in the last two decades of the study period. For the SPI, an upward trend at the 99th percentile means more frequent and intense rainfall than usual, indicating a shift towards more extreme wet conditions and For the SPEI, an upward trend at this percentile not only reflects more intense and frequent rainfall but also implies that these conditions are becoming more common despite potential increases in evapotranspiration (likely due to warmer temperatures). An upward trend in these indices during extreme rainfall events might indicate not just more frequent and intense rains but also potential shifts in climate patterns, which could include more pronounced dry periods between rainfall events. This increase in drought frequency and intensity, linked to changes in rainfall patterns, calls for urgent adaptation strategies in water management and agricultural practices to buffer these more extreme climatic conditions and ensure sustainable agricultural productivity and water security.

To mitigate these impacts, policymakers and agricultural planners must devise adaptive strategies that not only revise crop calendars but also invest in infrastructural developments that accommodate increased rainfall variability. These strategies should aim to bolster the resilience of rain-fed agriculture against the backdrop of climate variability, ensuring that agricultural practices can dynamically adjust to changing conditions (Pei et al., 2020). Furthermore, the implementation of region-specific agricultural and water management strategies is crucial to address the distinct vulnerabilities of the diverse climatic zones within Ghana and Burkina Faso. This tailored approach is essential for sustaining agricultural productivity and food security in the face of escalating climatic uncertainties, thereby supporting economic stability and community livelihoods in the region (Noureldeen et al., 2020). Our findings highlight the critical need for integrated water resource management and a redefinition of

agricultural practices, underpinned by a robust understanding of climate dynamics and their impacts on regional agricultural frameworks (Omotoso et al., 2023).

2.4. Conclusions

In conclusion, our research delved into the status of climate change in West Africa, with a particular emphasis on rainfall variability and drought occurrences. The utilization of NASA's satellite-derived meteorological data covering the period from 1981 to 2021 facilitated a thorough exploration of historical rainfall patterns and drought characteristics in Ghana and Burkina Faso. The integration of 36 satellite data points with 8 ground-based stations showed strong agreement across different timescales for both precipitation and mean temperature. Statistical measures such as R^2, RMSE, MAE, and bias highlighted consistent correlations daily, monthly, and yearly, with values supporting the accuracy and reliability of satellite data in representing ground conditions. This part underscores the complementary role of satellite data in climatic studies, especially valuable in regions like West Africa where ground data are sparse. By concentrating on these specific West African areas, our study contributes to a more localized and better comprehension of climate change impacts. This approach is particularly crucial in regions with constrained data resources, providing valuable insights for policymakers, researchers, and local communities who often face challenges in obtaining comprehensive and accurate meteorological information.

Both Ghana and Burkina Faso exhibited significant climatic changes from 1981 to 2021, with marked increases in mean daily rainfall and temperature. Trends determined by the Mann-Kendall test showed a significant upward trend in these elements, suggesting an alignment with global climate change patterns. Notably, the 2020s saw a 19.7% increase in rainfall for Ghana and a 25.9% increase for Burkina Faso.

Intriguingly, the last decade witnessed an increase in rainfall despite a marginal temperature rise, supporting recent research findings. The identification of rising temperatures during the dry season and a cooling effect in the wet season unveils potential risks and benefits for agriculture in the region. Positive correlations in the dry season alert us to the looming challenges of water scarcity and drought stress, signaling a call for resilient water management strategies. Conversely, negative correlations in the wet season indicate a potential cooling effect for crops, albeit with the associated risks of waterlogging and flooding. This nuanced understanding gleaned from our study offers actionable insights, emphasizing the imperative for sustainable agricultural practices and tailored water resource management strategies in West Africa.

Analysis of rainfall distribution from 1981 to 2021 indicated that higher rainfall percentiles (60th to 99th) correlated positively with total annual rainfall, suggesting that intense rainfall events are becoming more influential on annual totals. This aligns with global observations of increasing precipitation extremes under current climate trends. The performed data analysis revealed distinctive correlations in seasonal rainfall variability. The positive inclination towards increased rainfall in the dry season and the pronounced negative correlation during the wet season, possibly linked to intense rainfall events, present critical insights for future planning. The analysis of rainfall intensity and frequency distribution, notably the surge in extreme rainfall events over the past two decades, aligns seamlessly with broader global warming studies. The intricate relationships between different percentiles of rainfall events underscore the pivotal role of extremes in shaping annual rainfall totals. Regional variations, exemplified by the climatic zones in Ghana with more intense rainfall compared to Burkina Faso, emphasize the geographical shades influencing rainfall patterns. This understanding is not just informative but serves as a compass for localized decision-making and planning.

The drought evaluation using the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) across diverse time scales showed a slight positive trend in annual and

seasonal indices post-2001 emphasizes the importance of careful time scale selection, while the sensitivity variations between SPI and SPEI underscore the need for particular analysis in drought identification. The identified positive correlations between rainfall and temperature during the dry season and negative correlations during the wet season underscore the potential risks of drought stresses, particularly significant for rainfed agriculture. However, our study brings to light the limitations of relying solely on accumulated precipitation, advocating for a paradigm shift towards daily rainfall event intensity analysis. The results indicate a discernible shift towards less distributed rainfall, concentrated in more intense events, posing formidable challenges for agriculture in the studied area—a deviation from common drought indices depicting fewer extreme events in recent years. The heightened occurrence of extreme events necessitates a thoughtful consideration of potential consequences like flooding, soil erosion, and even drought, underscoring the paramount importance of analyzing rainfall intensity changes alongside commonly used drought indices. These findings present novel insights to the realm of climate research, advocating for a comprehensive and adaptive approach in crafting strategies that account for the evolving rainfall dynamics.

Furthermore, our study brings to light valuable lessons through temporal and spatial analyses that uncover distinct climatic zones influencing rainfall distribution, frequency, intensity, and drought occurrences in Burkina Faso and Ghana. Our outcomes underline the critical importance of considering both temporal and spatial scales in drought analysis, particularly in the context of considering climatic zone study in West Africa. Tailoring mitigation and adaptation strategies based on the unique characteristics of each climatic zone is imperative for enhancing climate resilience, especially in the vulnerable sector of rainfed agriculture. The dynamic nature of drought patterns, coupled with varied impacts across regions, highlights the necessity for a holistic approach to ensure sustainable and effective strategies for mitigating the recent climate change impacts in this vital agricultural context. These insights provide a foundation for informed decision-making and the development of targeted adaptation measures to address the specific challenges posed by climate variability. The lessons learned from these findings should guide informed decision-making, urging stakeholders to adopt adaptive measures that align with the distinctive climatic patterns in the region.

While this study provides valuable insights into the relationship between rainfall variability and meteorological droughts in West Africa, it is important to acknowledge its limitations. The analysis is confined to available satellite and ground-based meteorological data and does not include retrievals of soil moisture or other hydrological parameters that affect agricultural outputs. Additionally, the study focuses on a regional scale, which may mask localized variations in climate impacts. Future research could benefit from integrating more diverse data sources, including soil moisture and hydrological measurements, to provide a more comprehensive understanding of the implications for agriculture and water management.

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CHAPTER 3

3. Traditional In-Situ Water Harvesting Practices and Agricultural Sustainability in sub-Saharan Africa - A Meta Analysis

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Traditional In Situ Water Harvesting Practices and Agricultural Sustainability in Sub-Saharan Africa—A Meta-Analysis

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Abstract
Climate change severely impacts sub-Saharan Africa, which relies heavily on rain-fed agriculture for food production. Variable and insufficient rainfall exacerbates food insecurity across the region. Traditional in-situ water harvesting (IS_WH) practices enhance soil water-holding capacity, improve infiltration, and promote soil conservation. This meta-analysis of peer-reviewed literature examines IS_WH practices' effects on crop yield, soil moisture, runoff, and soil loss reduction across various rainfall conditions in sub-Saharan Africa. The analysis reveals that IS_WH practices significantly boost agricultural productivity, with a combined effect size showing a 71% increase in total crop yield. IS_WH practices also improve soil moisture retention by 59% and effectively reduce runoff by 53% and soil loss by 58.66%, demonstrating their robust water and soil conservation benefits. Despite their proven benefits, the adoption of IS_WH practices in sub-Saharan Africa is hindered by socio-economic and institutional barriers, *including limited technical knowledge, resource constraints, and inadequate extension services.* By addressing these barriers, there is *significant potential to scale up IS_WH practices*, enhancing agricultural productivity and sustainability across the region. Such efforts are crucial for mitigating the impacts of climate change, ensuring food security, and promoting sustainable development in sub-Saharan Africa.
Keywords: Crop productivity, In situ water harvesting, Runoff Soil moisture, sub-Saharan Africa, Sustainability and rainfed agriculture.

3.1. Introduction

Climate change poses a significant challenge to crop cultivation worldwide (Jagermeyr et al., 2021). In sub-Saharan Africa, climate change-induced yield reductions are exacerbating food insecurity, affecting 66.2% of the population with moderate to severe food insecurity (Bjornlund et al., 2022b). This region relies heavily on rain-fed agriculture, accounting for 97% of food production (Beyer et al., 2015), yet it faces increasingly variable and insufficient rainfall. Changing precipitation patterns and prolonged dry spells are becoming more common (Wainwright et al., 2022), leading to rapid declines in soil quality and moisture, and alarming reductions in yields (Akinsemolu et al., 2023). Water stress has emerged as the most pressing constraint on food production (Laskari et al., 2022).

High runoff occurs when soil cannot absorb water quickly enough, resulting in excess water flow, soil erosion, and moisture loss, which significantly contribute to land degradation and yield loss (Moragoda et al., 2022). Conversely, droughts due to prolonged low precipitation further decrease soil moisture content (Berg et al., 2018). Soil moisture is a critical factor affecting crop yield in both low and high-rainfall areas of sub-Saharan Africa (Bedeke, 2022).

For centuries, traditional in situ water harvesting (IS_WH) has been a significant water source for agriculture in sub-Saharan Africa (Piemontese et al., 2020). IS_WH practices, which include rainwater harvesting techniques that improve infiltration and enhance soil water-holding capacity (Mekuria et al., 2023), and increase water movement through soil surfaces, root systems, and groundwater (Saskia et al., 2016; Vohland et al., 2009)). These practices have shown promising results in reducing water stress and improving yields (Kugedera et al., 2023; Rockstrom et al., 2015). Moreover, traditional IS_WH practices are potential tools for integrated soil conservation and management, promoting healthy plant growth and sustainable production by ensuring adequate water supply and preventing soil erosion (Mekuria et al., 2023; Srivastav et al., 2021). Although IS_WH has attracted interest as an adaptation strategy to increase soil moisture and crop yields (Bouma et al., 2016; Lasage et al., 2015), its adaptation and intensification in sub-Saharan Africa have had limited success (Bouma et al., 2016; Drechsel, 2010; Kumar et al., 2020; Lamula, 2014; Manyanga et al., 2022).

Understanding the potential for scaling up IS_WH practices is crucial (Rockstrom et al., 2007). To date, no systematic assessment has evaluated the effects of IS_WH practices on soil moisture and their relationship to crop output in sub-Saharan Africa comprehensively. Although some global reviews on water harvesting exist, they do not cover sub-Saharan African countries in adequate depth and often categorize all systems under a single practice (Vohland et al., 2009). For instance, studies have indicated that the variability and context-specific nature of rainwater harvesting practices are often overlooked in broader reviews, which fail to provide a comprehensive regional analysis (Nord et al., 2022; Vohland et al., 2009).

This study presents a meta-analysis combining data from peer-reviewed literature on IS_WH practices, focusing on their effects on yield and soil moisture across different rainfall conditions. The meta-analysis aims to (1) analyze the responses of crop yield and soil moisture to IS_WH practices, considering regional rainfall variations, (2) investigate the effects of runoff and soil loss associated with IS_WH practices on soil moisture and yield, and (3) synthesize the adoption factors for successfully implementing IS_WH practices in the region.

3.2. Materials and Methods

3.2.1. Data Collection

We collected peer-reviewed studies published between 2000 and 2024 that explore the impact of traditional in situ water harvesting (IS_WH) practices on crop yield, soil moisture, soil loss, and runoff in sub-Saharan Africa. Our primary databases included Elsevier (ScienceDirect), Web of Science, and Google Scholar. Keywords were systematically combined using "AND" and "OR" to ensure extensive coverage. Key terms included "in-situ water harvesting," "crop yield," "fertilizer," " sub-Saharan Africa," and "rainfed agriculture." Additional specific keywords included "soil moisture", "runoff", "soil loss", "Soil/stone bunds," "Tied ridging," "Mulching," "Fanya Juu," "Grass strip," "furrow," "Terrace," "Infiltration pits," "Zaï pits," "Sub-soiling and ripping," "Hedgerows," "Conventional tillage," "Sorghum," and "Maize."

To be selected for meta-analysis, publications had to meet the following criteria:

- Only publications describing experiments conducted in the field with side-by-side comparisons of IS_WH and non-IS_WH practices were included; pot-level studies were excluded.
- Crop yield, soil moisture, soil loss, and runoff data under IS_WH and non-IS_WH practices were reported, and the primary data on crop yield, soil moisture, and runoff must be comparable.
- The mean, sample size, and a measure of dispersion (SE or SD) as numerical or graphical data were available, or the SD of data could be calculated from the reported data for IS_WH and non-IS_WH practices.

- Peer-reviewed articles published in English
- Experiments conducted in the sub-Saharan African countries.

If data were presented graphically, figures were digitized to extract the numerical values using the Get Data Graph Digitizer (ver. 2.22, Russian Federation).

3.2.2. PRISMA Statement

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The PRISMA statement was used to ensure the transparent and complete reporting of the systematic review (Ivaldi et al., 2024). A PRISMA flow diagram was included to illustrate the selection process of studies for inclusion, showing the number of records identified, screened, assessed for eligibility, and included in the review, along with reasons for exclusions at each stage. Following the inclusion criteria in total, 81 publications from 17 countries, including various pairs of observations for crop yield, soil moisture, soil loss, and runoff, satisfied our criteria for meta-analysis.

3.2.3. Database compilation

The database compilation process started with categorizing the final selected literature based on their relevance to facilitate detailed analysis and understanding of the impacts of IS_WH practices. The categorization focused on geographic distribution, specific IS_WH practices, crop types, fertilizer use, rainfall regions, and adoption rate. This approach ensures a comprehensive evaluation of the various factors influencing the effectiveness of IS_WH practices.

I. Geographical distribution

In this study, our primary focus lies on sub-Saharan African countries. The coverage is ensured by the inclusion of data from 17 countries in the database (Figure 19). Which comprise 61.1% of East Africa, 30.6% of West Africa, 2.8% of Central Africa, and 5.6% of Southern African countries. By incorporating data from these regions, we aim to capture diverse perspectives and experiences related to IS_WH practices across sub-Saharan Africa.

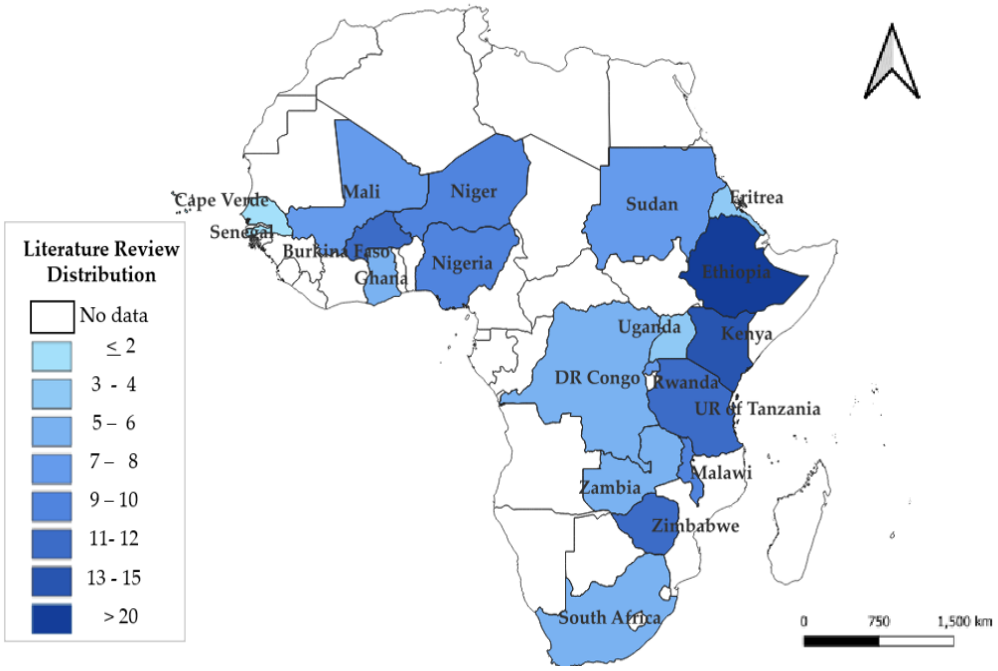

Figure 19. Geographic distribution of reviewed literature across Sub-Saharan African countries.

II. In Situ Water Harvesting (IS_WH) Practices

IS_WH practices sourced from existing literature were categorized to facilitate analysis in Table 6. The practices were grouped based on their functionality and application, providing a clearer understanding of their roles in water management and agricultural productivity enhancement.

Table 6. Categorization and distribution of in situ water harvesting (IS_WH) practices in the study.

IS_WH Practices	Brief Description	Distribution (%) in the database
Infiltration/Percolation/Planting Pits	Designed to store rainwater around the root zone and allow crops to use it during dry spells (e.g., Zaï Pits, Tassa) *(Bado et al., 2022; Chilagane et al., 2020)*.	19.6
Bunds/ Soil and stone/	Small embankments constructed across slopes to slow runoff and increase infiltration *(Kathuli et al., 2015)*.	17.6
Terraces	Flat platforms on slopes to prevent erosion and retain water (e.g., Fanya Juu) *(Saiz et al., 2016)*.	21.6
Ridges	Earthen ridges across slopes to slow runoff and reduce erosion *(Tadros et al., 2021)*.	23.5
Mulching	Covering soil with organic matter to reduce runoff and retain moisture *(Tadros et al., 2021)*.	17.6

To visually complement this data, Figure 21. illustrate the practical application of these IS_WH practices. Each image demonstrates how these methods are implemented in different regions, highlighting their effectiveness in soil moisture retention, runoff reduction, and overall contribution to sustainable agriculture. The visuals include examples of infiltration/percolation pits, stone bunds, terraces, ridges, and mulching, offering a clear depiction of their real-world use and benefits (Figure 20).

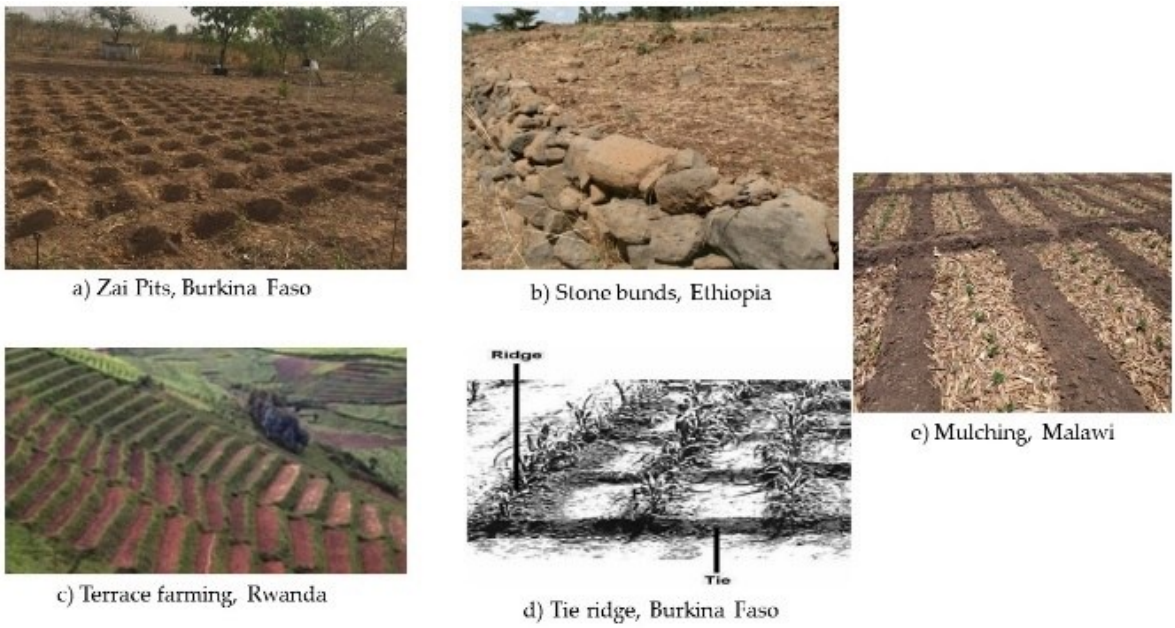

Figure 20. Traditional In-Situ Water Harvesting Practices source (Drake, 2022; Palé, 2010) and Author, taken 2022 (a)

III. Crop type and yield

The database focused on two predominant crops in the region: maize and sorghum. These crops were selected due to their significant role in sub-Saharan Africa. Maize, which supports over 300 million Africans as their primary staple food, represents 57.7% of the crops studied under in situ water harvesting (IS_WH). Sorghum, serving as a staple for about 500 million individuals, accounts for 25.9% of the crops studied under IS_WH, and the remaining 16.4% categorized as other crops. Yield impact was analyzed by evaluating the percentage change in crop yield associated with different IS_WH practices and fertilizer use.

IV. Fertilizer use

To isolate the impact of in situ water harvesting (IS_WH) practices, fertilizer use was categorized into two groups. The first group, "With Fertilizer," includes studies that reported the use of either organic or inorganic fertilizers. The second group, "Without Fertilizer," comprises studies that did not report any fertilizer use.

V. Rainfall distribution

The mean annual rainfall data from each study were categorized into arid (<300 mm), semi-arid (300-500 mm), dry sub-humid (500-800 mm), sub-humid (800-1000 mm), and humid (>1200 mm) regions.

VI. Adoption rate

Adoption factors were analyzed based on user-related, technology-related characteristics, and access to resources. Adoption rates, expressed as percentages, were calculated as the mean value of all countries where data were available. Factors influencing the adoption rates were categorized and analyzed to understand barriers and facilitators for IS_WH practices in sub-Saharan Africa, the study aimed to gain insights into the factors influencing the uptake of IS_WH practices in the region.

Data on soil moisture percentage, runoff, and soil loss were also collected due to their positive correlation with crop yield and in-situ water harvesting (IS_WH) practices. The measurements included soil moisture percentage, which refers to the proportion of water present in the soil relative to its total capacity; runoff, which denotes the movement of water across the land surface following precipitation; and soil loss, the reduction in soil loss because of erosion observed after implementing soil conservation measures. All these metrics are expressed as percentages compared to a baseline scenario without such practices. However, the soil loss analysis doesn't incorporate infiltration pits because of the data limitations.

3.2.4. Data analysis

Meta-analysis was conducted using the metaphor package v. 2.4-0 for R v. 2024.04.2 (Viechtbauer, 2024). The treatment effect (TE) in meta-analysis refers to the measure of the effect of an intervention compared to a control. The specific formula used to calculate TE depends on the type of data and the measure of effect being used. In our analysis, we used the following formulas for *TE* and its corresponding standard error (*SE*) (Borenstein et al., 2009)::

$$Mean\ Difference\ (MD) = \bar{x}_{intervention} - \bar{\bar{x}}_{control}$$

The standardized mean difference (SMD) was calculated for each study to measure the effect size using the formula (Borenstein et al., 2009):

$$SMD = \frac{\bar{x}_{intervention} - \bar{\bar{x}}_{control}}{SD_{pooled}}$$

Where $X_{\text{intervention}}$ and $X_{Control}$ are the mean yield changes for the intervention and control groups, respectively, and SD_{pooled} is the pooled standard deviation.

The standard error (*SE*) for the *SMD* is calculated using the formula:

$$SE = \frac{SD_{pooled}}{\sqrt{n}}$$

Where n is the sample size of the study

Meta-Analysis Model, A random effects model was used to account for variability between studies. The combined effect size and its 95% confidence interval (CI) were calculated using the following formulas (DerSimonian et al., 1986):

$$\hat{\theta} = \frac{\sum_{i=1}^{k} w_i \theta_i}{\sum_{i=1}^{k} w_i}$$

$$SE_{\hat{\theta}} = \sqrt{\frac{1}{\sum_{i=1}^{k} w_i}}$$

$$CI = \hat{\theta} \pm 1.96 \times SE_{\hat{\theta}}$$

Where is the combined effect size, w_i is the weight of the it study, θ_i is the effect size of the it study, and k is the number of studies.

Heterogeneity among the studies was assessed using the I^2 statistic and the τ^2 value: and Q-tests (Viechtbauer, 2024). A robust regression analysis was conducted to evaluate the relationship between rainfall and soil moisture retention. A funnel plot and trim-and-fill analysis were conducted to assess potential publication bias (Shi et al., 2019). Sensitivity analyses were performed to ensure the robustness of the results.

This meta-analysis was conducted by categorizing 81 studies and observations into different IS_WH practices, crop types, and rainfall categories to minimize heterogeneity. This approach helps to better understand the effectiveness of various in-situ water harvesting techniques by considering contextual factors such as implementation methods, climatic variations, and specific crop responses (Borenstein et al., 2009; Higgins et al., 2023; Rucker et al., 2008).

3.3. Results and Discussion

3.3.1. Study Selection

The study selection process adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009; Moher et al., 2009). The initial database search yielded 1,367 records, which were then subjected to a rigorous screening process. After the removal of duplicates, the remaining records were thoroughly screened based on titles and abstracts, resulting in the exclusion of studies that did not directly address the impact of in situ water harvesting (IS_WH) practices on agricultural outcomes in sub-Saharan Africa. Full-text articles were then reviewed for eligibility, with specific inclusion criteria focusing on field experiments, statistical data availability, and geographical relevance. Studies were excluded if they did not provide sufficient statistical data, were not peer-reviewed, or were not conducted within the specified region. Ultimately, 81 studies were included in the meta-analysis, providing a comprehensive assessment of IS_WH practices across diverse agroecological settings in sub-Saharan Africa. This rigorous selection process ensured that only the most relevant and high-quality studies were included in the synthesis, strengthening the validity and reliability of the findings.

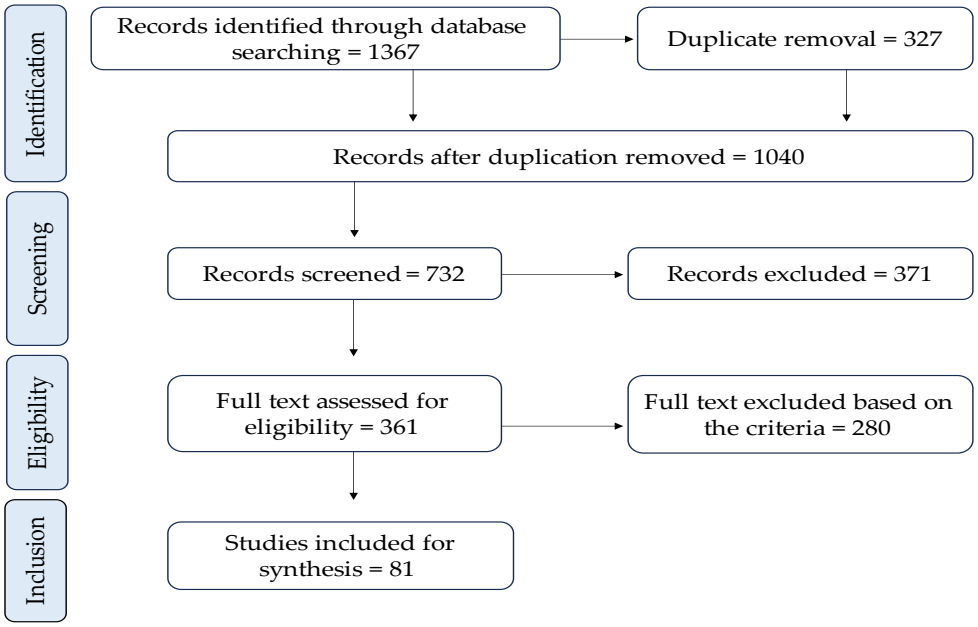

Figure 21. Records included for systematic and meta-analyses (PRISMA) flow diagram for the meta-analysis.

3.3.2. Study Characteristics

The detailed study characteristics provide a comprehensive understanding of the scope, diversity, and focus areas of the research analyzed in this review, highlighting the extensive examination of IS_WH practices across various agricultural contexts in sub-Saharan Africa. The table below summarizes these characteristics succinctly.

Table 7. Study characteristics

Characteristic	Description
Study Locations	17 sub-Saharan African countries (Figure 20)
IS_WH Practices	Soil/Stone Bunds, Tied Ridging, Mulching, Infiltration Pits, Others (Table 6)
Study Durations	1 Growing Season (32%), 2 Growing Seasons (56%), 3 or more Growing Seasons (12%)
Crops Studied	Maize, Sorghum, Other (Bean, Chickpea, Cowpea, Wheat, Teff, Millet, Barley, tomato, onion, potato, banana, coffee, watermelon, and pepper)
Outcomes Measured	Crop Yield (with and without fertilizer use), Soil Moisture, Soil Loss, Runoff, rainfall variability, and adoption factors for each IS_WH practice
Sources	Journal articles (76), book sections (3), and reports (2)

A detailed list of the studies and their specific characteristics is provided as a supplementary file to this manuscript. This supplementary file includes comprehensive information on the individual studies, further supporting the analysis and conclusions drawn in this review.

3.3.3. Impact on Crop Yield

The meta-analysis evaluates the impact of five types of In situ Soil and Water Harvesting (IS_WH) practices on yield changes, with data from 78 observations. Results reveal significant variations in yield enhancement associated with different IS_WH practices. The results, expressed as a percentage change in yield, indicate that all IS_WH practices significantly enhance yield. Specifically, infiltration pits lead to a 142% increase, mulching results in a 91% increase, soil/stone bunds yield a 69% increase, terraces provide a 48% increase and tied ridging results in a 74% increase. The combined effect size is 71%,

with a 95% confidence interval of [48%, 94%], demonstrating a significant positive impact on yield. The heterogeneity statistic *I*2 of 61% suggests moderate to substantial variability among the studies, indicating that the effectiveness of IS_WH practices can vary across different contexts and implementations. Suggesting factors such as crop type, climate, and soil influencing factors have to be considered in the outcomes. This indicates that while all IS_WH practices positively impact yield, the degree of effectiveness varies, emphasizing the need to consider specific contexts and tailored implementations for optimal results (Garg et al., 2022; Reddy, 2016; Tolossa et al., 2020). The forest plot (Figure 22) illustrates the variability in yield change (%) across diverse IS_WH practices.

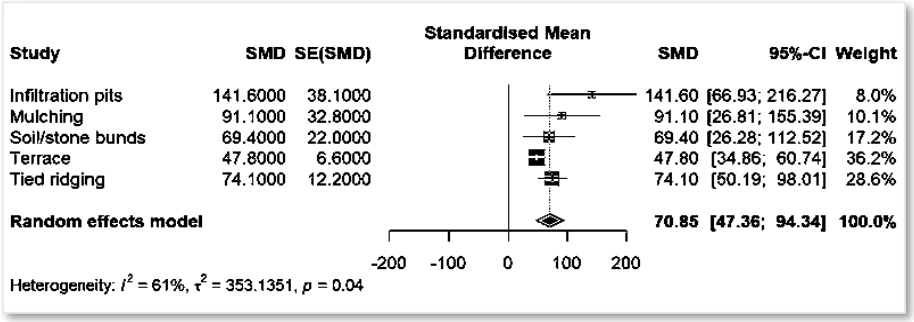

Figure 22. Impact of In-Situ Water Harvesting Practices on Yield Chang (5 IS_WH study practices). The forest plot shows the standardized mean differences (SMD) in yield change for various in-situ water harvesting (IS_WH) practices, with their corresponding 95% confidence intervals. The overall effect size (random effects model) is represented by the diamond at the bottom. Heterogeneity (I^2, τ^2, p) indicates variability and significance of the study.

Furthermore, the meta-analysis of 36 observations reveals a significant positive impact of IS_WH practices combined with fertilizer application on crop yields (Figure 23). The analysis demonstrates an overall yield increase of 142.17%, with individual increases of 109.3% for maize, 137.2% for sorghum, and 173.2% for other crops. This substantial improvement highlights the significant role of IS_WH practices in boosting crop productivity. Despite moderate heterogeneity among studies ((I^2 = 66%), the findings underscore the effectiveness of IS_WH practices and fertilizer application in significantly enhancing crop yield. This variability in yield can be primarily explained by the diverse crop types and different IS_WH practices implemented across the studies. For example, the yield increase for "Other crops" (which include a mix of cereals, vegetables, and fruits) shows a significantly higher SMD compared to maize and sorghum, due to the diverse physiological and growth characteristics of different crops. The observed heterogeneity can be attributed to the diverse crop types, varying IS_WH practices, and differences in geographical and climatic conditions across the studies.

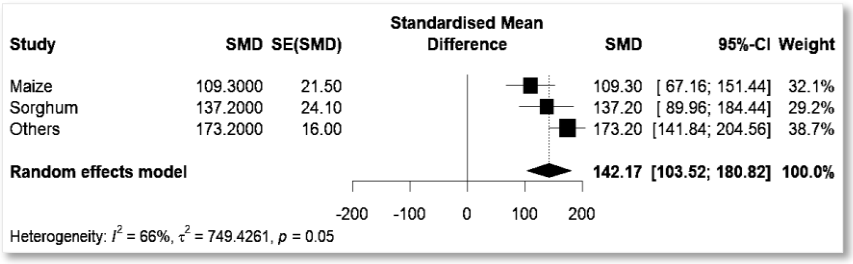

Figure 23. Impact of IS_WH practices combined with fertilizer on crop yield (3 crops under study). The forest plot depicts the standardized mean differences (SMD) in yield change due to the combined effect of IS_WH practices and fertilizer application, along with their 95% confidence intervals. The overall effect size (random effects model) is represented by the diamond at the bottom. Heterogeneity (I^2 τ^2 and, p) indicates the variability and significance of the study.

Additionally, the meta-analysis derived from 42 observations assesses the impact of IS_WH practices alone without fertilizer application on crop yields. The results indicate that the combined random effects model shows an overall standardized mean difference (SMD) of 76.4 with a 95% confidence interval (CI) of [60.90, 91.96], demonstrating a significant positive impact on crop yield due to IS_WH practices. Specifically, maize shows a 71.7% increase, sorghum a 68.2% increase, and other crops a significant 102.4% increase. The heterogeneity statistics (($I^2 = 21\%$) indicate low to moderate variability among the studies, suggesting that the effect sizes are relatively consistent across different crop types.

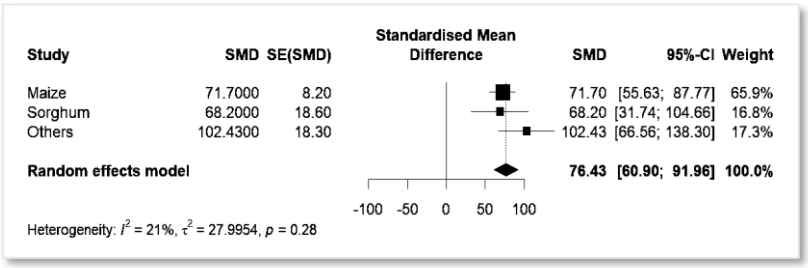

Figure 24. Impact of IS_WH practices on crop yield without fertilizer application (3 crops under study). The forest plot displays the standardized mean differences (SMD) in yield change for maize, sorghum, and other crops, along with their 95% confidence intervals. The overall effect size, calculated using a random effects model, is represented by the diamond at the bottom. The heterogeneity statistics (I^2, τ^2, $p < 0.01$) indicate low variability among the studies.

The heatmap in Figure 25 delineates the impact of various in-situ water harvesting (IS_WH) practices on crop yields across different rainfall categories, based on an analysis of 77 observations. Mulching exhibits the highest effectiveness in sub-humid regions, enhancing yields through moisture conservation and soil temperature regulation. Infiltration pits demonstrate significant yield benefits in semi-arid regions but reduce in effectiveness with increasing rainfall, highlighting their suitability for low-rainfall areas (Critchley, 2013). Tied ridging significantly improves yields in all rainfall categories, demonstrating adaptability across climates by enhancing water retention and reducing erosion. Terraces and soil/stone bunds better effectiveness in areas with above 800 mm rainfall indicates their adaptability to diverse climatic conditions and suitability for high-rainfall areas as supported by other studies (A. A. Alemayehu et al., 2020; Vancampenhout et al., 2006). Studies support the positive impact of IS_WH on crop yields (Bouma et al., 2016; Lal, 2010), highlighting the importance of selecting appropriate practices tailored to specific climatic conditions to optimize crop yields and enhance agricultural sustainability (Rockstrom et al., 2007).

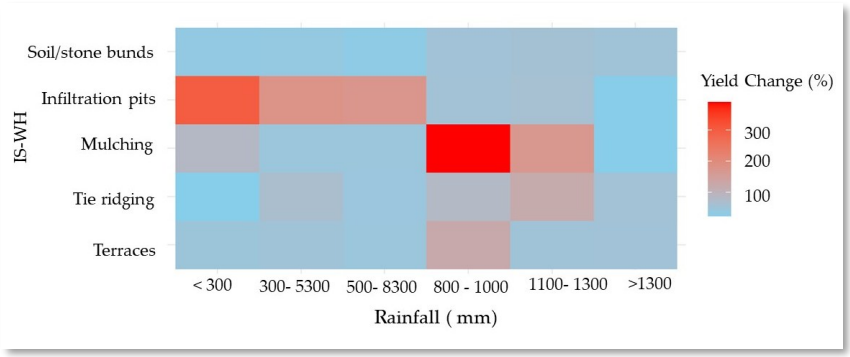

Figure 25. Yield Change (%) by IS_WH practice and rainfall category.
The color gradient in the heatmap represents yield change percentages, with blue indicating lower values and red indicating higher values.

The density plot (Figure 26) illustrates the distribution of various IS_WH practices across different annual rainfall categories, complementing the insights from the heatmap. Infiltration Pits show adaptability in 300-500 mm rainfall range, but they are also prevalent across all categories. Mulching is most effective in the 500-800 mm range, indicating its adaptability to moderate rainfall conditions. Soil/Stone Bunds and Terraces are primarily implemented in higher rainfall areas, with densities peaking around 1100-1300 mm and 1000 mm, respectively, highlighting their roles in erosion control and water management. Tied Ridging is evenly distributed, with noticeable peaks in both low (<300 mm) and moderate (500-800 mm) rainfall categories, emphasizing its use in soil moisture conservation in arid and semi-arid regions.

In addition to the yield data depicted in the heatmap, the density plot provides further insight into how the adaptability of these practices is influenced by rainfall distribution. Infiltration pits are ideal for semi-arid regions while mulching suits sub-humid areas. Soil/stone bunds excel in humid regions, and terraces are effective in sub-humid to humid areas. Tied ridging is versatile across all rainfall categories. The findings reveal that the frequency and preferred conditions for each IS_WH practice vary, indicating that their effectiveness and implementation are significantly affected by regional rainfall patterns.

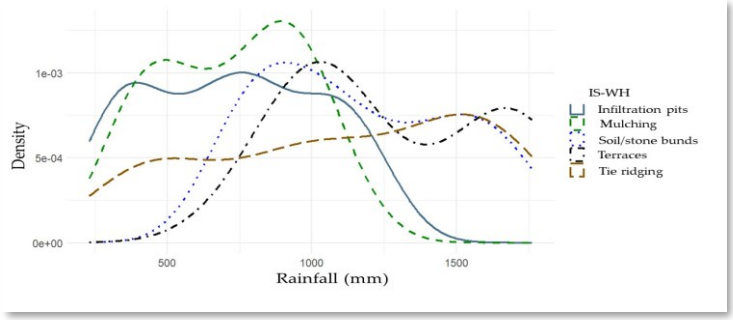

Figure 26. Density plot of IS_WH practices across different rainfall categories.
The plot shows how frequently each practice is utilized under varying rainfall conditions, highlighting the adaptability and optimal rainfall ranges for each IS_WH practice. The vertical dashed lines represent the boundaries of different rainfall categories, providing a clear visual comparison of the density of practices across these categories.

3.3.4. Impact on Soil Moisture Retention

The meta-analysis, encompassing 58 observations across 5 different in-situ water harvesting (IS_WH) practices, reveals significant findings regarding their impact on soil moisture retention (%). The forest plot shows that infiltration pits have the highest standardized mean difference (SMD) of 114.4% with a 95% confidence interval of [48.8, 182.02], indicating a substantial positive impact on soil moisture retention compared to other practices. Soil/stone bunds have an SMD of 76.4%, mulching 54.0%, tied ridging 48.9%, and terraces 40.5%. On average, the IS_WH practices studied resulted in a 58.9% increase in soil moisture retention, demonstrating their overall efficacy. Notably, the high effectiveness of infiltration pits is particularly relevant in arid and semi-arid environments, where their adoption is most dense. This correlation suggests that the superior soil moisture retention achieved with infiltration pits directly supports higher yield impacts in these challenging climates. Despite the variations among individual studies and practices, these findings offer a general indication of the positive impact of IS_WH practices on soil moisture retention, advocating for their adoption in sustainable agricultural strategies. The moderate heterogeneity observed can be attributed to differences in implementation techniques, geographical and climatic variations, study design, and measurement methodologies. These

results underscore the importance of categorizing IS_WH practices not only by type but also by contextual factors to better understand their effectiveness and optimize their application in diverse agricultural settings.

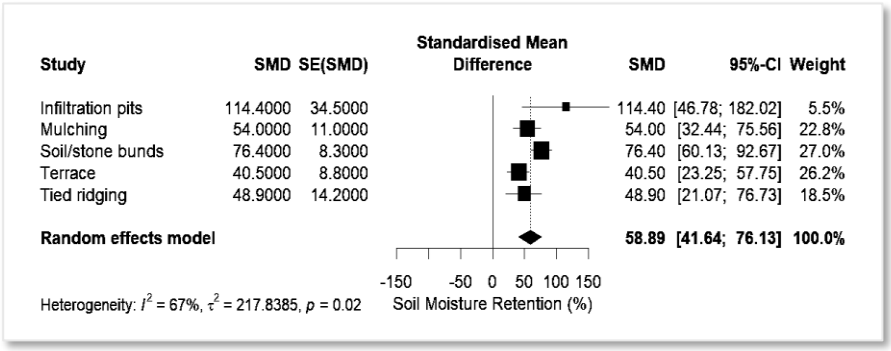

Figure 27. Impact of IS_WH Practices on Soil Moisture Retention.
The forest plot shows the standardized mean differences (SMD) in yield change for various in-situ water harvesting (IS_WH) practices, with their corresponding 95% confidence intervals. The overall effect size (random effects model) is represented by the diamond at the bottom. Heterogeneity (I^2, τ^2, p) variability among the study results and statistical significance.

Furthermore, the scatter plot with a robust regression line illustrates the relationship between rainfall (mm) and soil moisture retention (%) Figure 28. The robust regression analysis revealed a significant positive relationship between rainfall and soil moisture retention, with a coefficient of 0.0554 (SE = 0.0105, t = 5.2578, p < 0.001). This indicates that for each millimeter increase in rainfall, soil moisture retention increases by approximately 0.0554%. The residual standard error of 17.93 suggests moderate variability around the fitted regression line. Although the intercept was not statistically significant, the model overall demonstrates that increased rainfall substantially enhances soil moisture retention. The significant p-value (less than 0.001) confirms that this positive relationship is not due to random chance and suggests a real effect of rainfall on soil moisture retention. The robust regression plot further illustrates this relationship, emphasizing the importance of rainfall in sustaining soil moisture levels, crucial for improving agricultural productivity and resilience in varying climatic conditions. The findings emphasize the importance of implementing IS_WH practices in regions with varying rainfall patterns to optimize soil moisture levels, thereby supporting sustainable agricultural practices and mitigating the effects of drought and water scarcity.

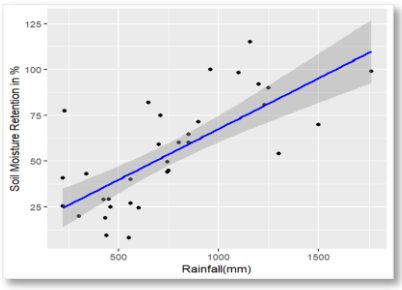

Figure 28. Scatter plot with robust regression line illustrating the relationship between rainfall (mm) and soil moisture retention (%).
The data points represent observations from 33 different studies. The blue line indicates the robust regression fit, and the grey-shaded area represents the 95% confidence interval around the regression line.

3.3.5. Impact on Runoff Reduction

The meta-analysis summarizes the impact of various in-situ water harvesting (IS_WH) practices on runoff reduction. The data includes four IS_WH practices: Mulching, Ridging, Soil/Stone Bunds, and Terrace. All four IS_WH practices show a significant positive effect on reducing runoff, with mean reductions ranging from 46.3% to 59.8%. Mulching has the highest mean reduction in runoff at 57.2%, followed by Terrace at 56.5%, Ridging at 53.6%, infiltration pits 52.1%, and Soil/Stone Bunds at 49.2%. The narrow confidence intervals in the random effects model suggest a high level of precision in the estimated overall effect. The heterogeneity metrics ($\tau^2 = 6.9168$, $I^2 = 0\%$, $p = 0.49$) indicate no significant heterogeneity among the studies, suggesting that the differences in the effect sizes are not statistically significant and are likely due to random sampling variability rather than inherent differences between the studies. The test of heterogeneity (Q-statistic) with a p-value further supports the conclusion of no significant heterogeneity. The lack of significant heterogeneity among the studies suggests that these practices are consistently effective across different conditions and implementations. This consistent effect underscores the robustness of IS_WH practices in water conservation efforts.

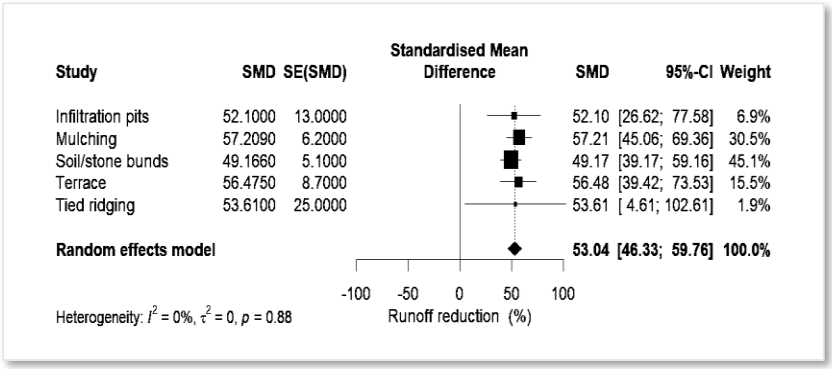

Figure 29. Impact of IS_WH Practices on Runoff Reduction.

The forest plot displays the treatment effects (TE) and standard errors (SE) for different in-situ water harvesting (IS_WH) practices on soil moisture retention. The 95% confidence intervals (CI) for each practice are shown. Heterogeneity statistics ($I^2 = 0\%$, $\tau^2 = 6.9168$, $p = 0.49$) indicate no significant variability between the studies, suggesting a consistent effect across different IS_WH practices.

3.3.6. Impact on Soil Loss Reduction

The meta-analysis of soil loss under various IS_WH practices reveals consistent effectiveness in reducing soil loss across different IS_WH practices from 29 study observations. The results indicate that Mulching leads to a mean reduction of soil loss of 68.67%, Ridging results in 54.97%, Soil/Stone Bunds yield 55.06%, and Terrace practices achieve 60.21%. The overall mean soil loss across all practices is approximately 58.6%, demonstrating a significant reduction due to these practices. The low heterogeneity metrics, including I-squared (0.0%) and tau-squared (0), suggest that the IS_WH practices have a consistent effect on reducing soil loss, with the variation in effect sizes being due to sampling error rather than differences between studies. The Q-statistic (0.57, p = 0.9042) further confirms no significant heterogeneity among the studies. Despite the overall consistency, additional studies could help refine the estimates for individual practices, particularly Mulching, to reduce uncertainty. These findings support the continued use and implementation of IS_WH practices in soil conservation strategies, given their demonstrated effectiveness in significantly reducing soil loss.

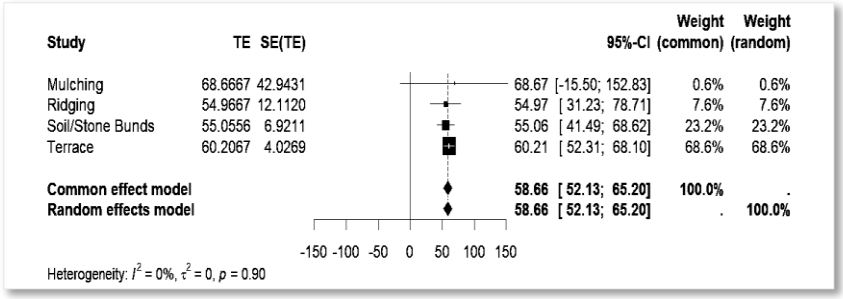

Figure 30. Impact of IS_WH Practices on Soil Loss.

The forest plot illustrates the treatment effects (TE) and standard errors (SE) for various in-situ water harvesting (IS_WH) practices on soil moisture retention. The practices analyzed include Mulching, Ridging, Soil/Stone Bunds, and Terrace. The plot presents both common effect and random effects models, highlighting the overall effect size at the bottom. Each IS_WH practice's 95% confidence intervals (CI) and combined effect sizes are displayed. Heterogeneity statistics (I^2 = 0%, τ^2 = 0, p = 0.90) indicate no significant variability among the studies, suggesting a uniform effect across the different IS_WH practices.

3.3.7. Regression Analysis

The robust regression analysis investigates the relationship between runoff reduction and rainfall amount under various IS_WH practices. The results indicate that with zero rainfall, the expected runoff reduction under IS_WH practices is approximately 59.80%. The t-value for the rainfall coefficient is -0.659, corresponding to a p-value that is not statistically significant ($p > 0.05$). This indicates that the amount of rainfall does not have a statistically significant impact on runoff reduction under the IS_WH practices studied.

Similarly, the robust regression analysis examining the relationship between soil loss and rainfall amount under IS_WH practices revealed no statistically significant association. The analysis estimated that with zero rainfall, the expected soil loss under IS_WH practices is approximately 50.67%. The regression coefficient for rainfall was 0.0064, indicating a very slight increase in soil loss with additional rainfall; however, this relationship was not statistically significant (t-value = 0.5552, $p > 0.05$). The wide confidence intervals and high residual standard error (17.82) suggest substantial variability and uncertainty in the estimates.

These findings imply that rainfall amount alone does not significantly influence soil loss or runoff reduction under IS_WH practices, suggesting that other factors play a more critical role in determining these outcomes. Consequently, it is essential to consider additional variables and more complex models to fully understand and optimize the effectiveness of IS_WH methods in reducing soil loss and runoff.

3.3.8. Publication Bias

Publication bias is a critical aspect to consider in meta-analyses as it can significantly influence the validity and reliability of the study's findings. In this manuscript, we analyze the impact of in-situ water harvesting (IS_WH) practices on crop yield, soil moisture retention, and runoff and soil loss reduction. To ensure the robustness and credibility of our results, it is essential to assess the presence of publication bias (Kepes et al., 2022). This can lead to overestimated effect sizes and misleading conclusions.

I. Yield Data

To assess potential publication bias, a Trim-and-Fill analysis was conducted (Shi et al., 2019). The results indicated that no studies were missing from the left side of the funnel plot (estimated number of missing studies = 0, SE = 2.50), suggesting a low risk of publication bias. The robustness of the model

results was confirmed by the Trim-and-Fill method, which did not adjust the overall effect size. In summary, the meta-analysis demonstrated a significant and robust positive effect of the interventions on crop yield, despite the high heterogeneity among studies. These findings highlight the efficacy of the studied interventions in enhancing agricultural productivity, providing a strong basis for their broader implementation to improve food security.

II. Runoff, Soil loss, and Soil Moisture Retention Data

The funnel plots for soil loss, runoff, and soil moisture retention provide a visual assessment of potential publication bias in the meta-analyses. The plots display a symmetrical distribution of observed outcomes around the central vertical line, which suggests a low risk of publication bias. Each plot shows that studies with larger standard errors are more dispersed, a common occurrence in meta-analyses due to increased variability in smaller studies. The application of the Trim-and-Fill method does not indicate a considerable number of missing studies, further supporting the robustness of the results. This symmetrical appearance and lack of additional imputed studies suggest that the meta-analyses' findings are reliable and not substantially influenced by publication bias.

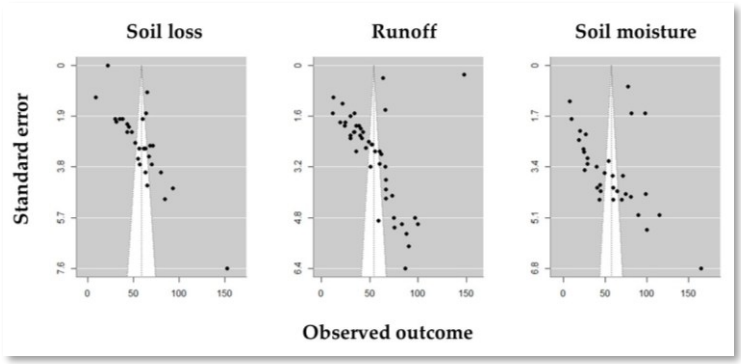

Figure 31. Funnel Plots for Soil Loss, Runoff, and Soil Moisture Retention.
The observed outcomes (x-axis) versus the standard errors (y-axis) for studies examining the effects of interventions on soil loss, runoff, and soil moisture retention. Each point represents a study, with larger studies (smaller standard errors) clustering towards the top. The dotted vertical line represents the combined effect size estimate, while the dashed lines form the pseudo 95% confidence limits. Asymmetry in the plots suggests potential publication bias.

3.3.9. Adoption factors

This study has demonstrated the significant impact of IS_WH practices on crop yield, soil moisture retention, and the reduction of soil loss and runoff in sub-Saharan Africa. However, a considerable body of literature also highlights a notable challenge, the uneven adoption of these practices across the region (Table 8). This issue is primarily determined by factors related to users, technology, and access. Classifying adoption factors into users, technology, and access provides a structured framework for understanding the complex dynamics influencing the uptake of IS_WH practices. By categorizing factors in this manner, researchers and policymakers can gain deeper insights into the multifaceted barriers and facilitators affecting adoption rates.

The analysis of 17 studies from 11 countries shows adoption decisions are heavily influenced by user-related characteristics such as social networks, farmers' education levels, and their ability to access extension services (Abdulai et al., 2013; Balehegn et al., 2019). Adoption rates are greatly impacted by technology-related characteristics such as labor effort, tool accessibility, and technical expertise (Hellen Aluku et al., 2021; Boillat et al., 2019b). Adoption rates are also highly influenced by access to basic resources including labour, capital, land, and inputs (Tilahun Amede et al., 2011; Kassie et al., 2011).

This demonstrates varying levels of adoption influenced by factors ranging from awareness to the availability of technical knowledge and resources. These results demonstrate the importance of addressing diverse factors to promote the widespread adoption of IS_WH practices for sustainable agricultural development in the region. Furthermore, the distribution percentages in Figure 32 highlight the need for targeted interventions to address specific barriers in each category.

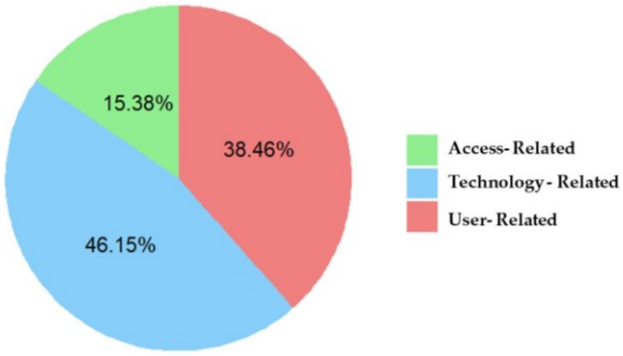

Figure 32. The distribution of factors influencing the adoption of traditional in-situ water harvesting practices in sub-Saharan Africa.

Furthermore, Table 8 summarizes these factors regarding relevant studies and provides a comprehensive overview of the elements influencing the adoption of IS_WH technologies in sub-Saharan Africa. Understanding and addressing these factors is crucial for devising effective strategies to promote the widespread adoption of IS_WH practices in sub-Saharan Africa, thereby enhancing agricultural productivity and sustainability in the region.

Table 8 Adoption rates and influencing factors of various in-situ water harvesting practices across different African countries.

IS_WH	Adoption rate (%)	Countries	User-Related,	Technology-Related,	Access-Related	Adoption rate (%)
Infiltration Pits	24.75 %	Ethiopia, Niger, Kenya, Malawi	Awareness of these practices among local communities, low access to training, and knowledge transfer opportunities for effective implementation and alignment of these practices with local traditions and cultural norms.	Labor intensive, and availability accessibility of the necessary tools, materials, and resources required for construction, the presence of successful case studies, the simplicity and feasibility of implementing these practices since it affected by varied factors like rainfall amount and intensity	The affordability of the resources and inputs needed for these practices, and proximity to suitable land for implementing these techniques. the presence of policies and incentives that encourage the adoption of these techniques.	(T. Amede et al., 2011; Wildemeersch et al., 2013)

Bunds (Stone and soil	42.75 %	Ghana, Ethiopia, Mali, Congo, Burkina-Faso, Nigeria	Limited technical skills, education, social networks and extension contacts, and farm soil conditions mainly determine, the extent to which bunds align with or conflict with traditional farming practices and local knowledge, the degree of community participation, and support for bund construction and maintenance.	Overambitious and myopic project planning, top-down approach, the accessibility of essential resources like stones, soil, and tools required for bund construction, low technical knowledge, and skills for proper bund design and construction for better suitability for the local ecological and topographical conditions and maintenance Requirements	Capital and labor constraints, land ownership and tenure systems, the ability to absence of government policies, incentives, and extension services aimed at promoting bund construction	(Balehegn et al., 2020; Birhanu, 2014; Heri-Kazi et al., 2020; Ogunniyi et al., 2023; Zougmor et al., 2005)
Terraces	58.72	Rwanda, Ethiopia Uganda, Tanzania , Kenya	Level of understanding and awareness among local communities about terrace construction, participation and engagement, the degree of community involvement, and support for terrace construction and maintenance.	The availability of technical knowledge and skills for designing and constructing effective terrace systems, suitability of terrace designs to the local topography and environmental conditions and Maintenance Requirements	Current productivity of the land or availability of other lands for farming, available resources and their competing uses, labor constraints, and past approaches for promoting the interventions	(H. Aluku et al., 2021; Bizoza, 2014; Kassie et al., 2011; Kisekka et al., 2018)
Ridges	52.4%	Ghana and Kenya	Farmers' education, social networks and extension contacts, and farm soil conditions determine. Farmers perceive the advantages of ridge systems	The presence of technical knowledge and skills required for proper ridge design and construction., the suitability of ridge designs to the local topography, climate, and soil	Capital and labor constraints, Farm size, access to credit, and material, the existence of government policies, incentives, and extension services aimed at	(Abdulai et al., 2014; Boillat et al., 2019a; Cofie, 2017)

				conditions, and the level of effort and resources needed to maintain ridge systems over time	promoting the adoption of ridge systems for sustainable agriculture	
Mulching	26.85	Uganda Kenya, Malawi	Awareness among farmers about mulching techniques and their benefits in agriculture, the extent to which mulching aligns with or conflicts with existing farming practices and traditions.	Access to the necessary resources and materials for mulching, including organic mulch materials or synthetic mulching films, and the suitability of mulching techniques to the local ecological and agricultural context. The effort and resources needed to maintain mulch cover over the growing season.	Capital and labor constraints	(Boillat et al., 2019a; Stanley, 2020)

3.4. Conclusion

The findings of this study highlight the significant benefits of In-Situ Soil and Water Harvesting (IS_WH) practices in enhancing agricultural productivity and sustainability. The marked yield improvements across various IS_WH techniques, including infiltration pits, mulching, soil/stone bunds, terraces, and tied ridging, align with previous research demonstrating the efficacy of soil and water conservation methods in diverse agro-ecological settings (Kassam et al., 2018; Rockström et al., 2003). The meta-analysis evaluates the impact of these IS_WH practices on yield changes, revealing significant variations in yield enhancement. Infiltration pits, for instance, lead to a substantial increase in yield, making them highly effective in water-limited environments (Nyakudya et al., 2014). Mulching is particularly beneficial in sub-humid regions for moisture conservation and soil temperature regulation (Demo et al., 2024). Soil/stone bunds are advantageous in areas with moderate to high rainfall, while terraces are suitable for steep terrains by preventing soil erosion and enhancing water infiltration. Tied ridging demonstrates versatility across various rainfall categories by enhancing water retention and reducing erosion (Ndung'u et al., 2023). Overall, the combined effect size indicates a significant positive impact on yield, though the variability among studies underscores the importance of tailoring IS_WH practices to specific local conditions such as soil type, crop type, and climate for optimal results (Branca et al., 2013; Thierfelder et al., 2010).

Beyond yield improvements, IS_WH practices significantly enhance soil moisture retention, which is critical for crop growth, especially in arid and semi-arid environments. Infiltration pits, for example, have the highest effectiveness in increasing soil moisture retention, directly supporting higher yield impacts in challenging climates (Nyakudya et al., 2014). Mulching, soil/stone bunds, tied ridging, and

terraces also contribute significantly to soil moisture retention, advocating for their broader adoption to improve soil water availability. These findings suggest that IS_WH practices can effectively mitigate drought impacts and enhance agricultural productivity across diverse environments in sub Saharan Africa.

Moreover, IS_WH practices play a crucial role in reducing runoff and soil loss, essential for maintaining soil health and agricultural productivity. The study indicates that mulching and terraces are particularly effective in mitigating soil erosion and conserving water. Soil/stone bunds and ridging also show substantial reductions in runoff and soil loss, highlighting their robustness in water conservation efforts. The consistent effectiveness of these practices across different conditions further supports their reliability and uniform impact.

The adaptation of IS_WH practices to specific contexts can optimize their effectiveness and ensure sustainable agricultural outcomes. Despite these proven benefits, the uneven adoption of IS_WH practices in sub-Saharan Africa remains a significant challenge. Factors influencing adoption rates include socioeconomic conditions, technical knowledge, access to resources, and institutional support. Social networks, education levels, and access to extension services play critical roles in the decision-making process of farmers (Maertens et al., 2023; Mowo, 2010). Additionally, the availability of necessary tools and materials, as well as technical expertise, are crucial for successful implementation. Addressing these barriers requires a multi-faceted approach involving policy support, capacity building, and community engagement. Government policies and incentives that promote sustainable farming practices, along with targeted extension services, can significantly enhance the adoption of IS_WH techniques. Moreover, fostering local knowledge and participatory approaches can help align these practices with traditional farming systems and cultural norms, thereby facilitating broader acceptance and implementation.

In conclusion, this study demonstrates the significant impact of IS_WH practices on crop yield, soil moisture retention, and the reduction of soil loss and runoff in sub-Saharan Africa. The meta-analysis results indicate substantial yield improvements, with a combined effect size of 71% (95% CI: [48%, 94%]), including specific increases such as 142% for infiltration pits, 91% for mulching, 69% for soil/stone bunds, 48% for terraces, and 74% for tied ridging. Additionally, IS_WH practices enhance soil moisture retention, with infiltration pits showing an SMD of 114.4%, and significantly reduce runoff and soil loss, with mulching reducing runoff by 57.2% and terraces reducing soil loss by 60.21%. The variability in effectiveness across different geographical regions and environmental conditions suggests that the benefits of IS_WH practices are context-dependent. High heterogeneity statistics underscore the importance of tailoring these practices to local conditions such as soil type, crop type, and climate to optimize their effectiveness and ensure sustainable agricultural outcomes. By addressing adoption barriers through policy support, capacity building, and community engagement, IS_WH practices can play a vital role in enhancing agricultural productivity and resilience in the region. These findings provide a strong basis for their broader implementation to improve food security and agricultural sustainability in sub-Saharan Africa.

Supplementary Materials: The full reference list used for the meta-analysis and the database can be shared as requested.

Data Availability Statement: Data will be made available on request.

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Conflicts of Interest: The authors declare no conflicts of interest.

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CHAPTER 4

4. Remote Sensing and Field Data Analysis to Evaluate the Impact of Stone Bunds on Rainfed Agriculture in West Africa

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Remote Sensing and Field Data Analysis to Evaluate the Impact of Stone Bunds on Rainfed Agriculture in West Africa

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Abstract

This study evaluates the effectiveness of stone bunds in enhancing soil moisture, vegetation health, and crop yields in Ghana's semi-arid Upper East Region, an important area for agricultural productivity in West Africa. In this region, agricultural practices are heavily impacted by erratic rainfall and poor soil moisture retention, threatening food security. Despite the known benefits of traditional soil conservation practices like stone bunds, their effectiveness in this context has not been fully quantified. Field and remote sensing data were used to evaluate the influence of stone bunds on soil moisture dynamics, vegetation growth, and crop yield. Experimental plots with and without stone bunds were monitored for climate, soil water infiltration, and soil moisture and analyzed using the NDVI from Sentinel-2 satellite imagery over two growing seasons under sorghum production (2022–2023). The results indicated that stone bunds enhanced soil moisture retention and increased infiltration rates. The NDVI analysis consistently revealed higher vegetation health and growth in the plots with stone bunds, particularly during critical growth periods. The intermediate results of the conducted experiment indicated that stone bunds increased sorghum yields by over 35% compared to the control plots. The substantial agronomic benefits of stone bunds as a soil and water conservation strategy were evident, improving soil water infiltration, water retention, vegetation health, and crop yields. These findings suggest that the adoption of stone bunds could improve agricultural productivity and resilience to climate variability. However, *further research is recommended to assess the long-term impacts and large-scale effects of stone bunds, particularly to address data limitations and understand the potential for broader adoption in semi-arid regions.* Exploring the integration of stone bunds with other sustainable farming practices could also optimize rainfed agricultural outcomes on a larger scale.

Keywords: Stone bunds; Water harvesting; Soil moisture; Semi-arid regions; NDVI dynamics; Soil and Water Conservation; Crop yield Improvement

4.1. Introduction

Ghana's agriculture sector relies heavily on rainfall, with approximately 70% of the land depending on it for crop water requirements (Amponsem, 2015). This sector employs about 52% of the workforce, contributes 54% to the gross domestic production, and provides over 90% of the country's food needs, thereby exerting significant pressure on natural resources (FAO, 2024). In this challenging context, the agricultural sector faces soil degradation, desertification, and drought, making Soil and Water Conservation (SWC) measures essential for sustainable production (Breman, 1992; Darkoh, 1989; Quinton, 2012; Warren et al., 2001; Yirdaw et al., 2017). In particular, crop farmers in Ghana's northern

region encounter significant challenges due to the unpredictability and intensity of rainfall (Dang et al., 2019).

Water scarcity is a critical issue in arid and semi-arid regions, where maintaining optimal soil moisture levels is essential for agricultural productivity (Tefera et al., 2024). Over centuries, agricultural practices and water erosion have significantly degraded soil fertility and altered the hydraulic properties of soil (Hossini et al., 2022; Li et al., 2022; Tefera et al., 2014). These challenges are exacerbated by a warming climate, posing sig-nificant obstacles to sustainable crop production (Indoria et al., 2020) . Recent studies, such as (Taye et al., 2015; Taye et al., 2024) underscores the vital role of surface soil moisture in regulating ecological and hydrological processes. Effective soil moisture management is crucial for enhancing crop and livestock productivity in water-limited environments. The hydraulic properties of soil are fundamental in determining both soil and environmental quality and the soil's capacity to support ecosystem functions (Indoria et al., 2020). Moreover, soil and water conservation measures, such as stone bunds, pits, half-moons, and contour stones, have proven effective in mitigating water stress and erosion (Tefera et al., 2024; Zougmoré et al., 2014). Integrating these conser-vation practices with sound agronomic techniques can significantly improve agricultural yields and water productivity.

Monitoring soil moisture is crucial for assessing the impact of water harvesting techniques in rainfed agriculture, providing valuable insights into soil water capacity and moisture distribution. However, field-based monitoring presents significant finan-cial and logistical challenges due to the vast agricultural landscapes, leading to common data scarcity. To address this issue, integrating remote sensing data, particularly the Normalized Difference Vegetation Index (NDVI), offers a promising solution (Kumar et al., 2022; Rekha et al., 2018; Surendran et al., 2024). NDVI provides a comprehensive perspective on vegetation health and vigour, serving as a proxy for soil moisture effects on vegetation in rainfed agricultural systems (Wang, 2009; Zhang et al., 2018). Studies integrating NDVI with on-field soil moisture measurements have successfully identified crop water stress periods and enhanced agricultural water management understanding (Ding et al., 2022; Felegari et al., 2022; Ihuoma et al., 2021). Combining NDVI data with ground-based observations allows researchers to extend their findings to larger areas, offering a holistic view of water harvesting techniques like stone bunds across varied landscapes. This interdisciplinary approach holds immense potential for informing water management strategies, optimizing crop yields, and promoting sustainable agri-cultural practices in regions characterized by rainfall variability and limited data access (Chanev et al., 2023).

Stone bunds are widely recognized for their effectiveness in mitigating surface runoff and managing soil erosion. They are the predominant techniques adopted by farmers across West Africa due to their ability to promote sedimentation, soil infiltration, and increase moisture retention (Naazie et al., 2023; Singh, 2023). The effectiveness of stone bunds depends on several factors, including climatic conditions, design, soil characteristics, and crop selection (Taye et al., 2015; Zougmoré et al., 2014). The adop-tion of these structures has significantly improved crop yields, annual income, and the livelihoods of smallholder farmers (Meresa et al., 2023). Research by (Alemayehu et al., 2020), (Barry et al., 2008),(Wolka et al., 2011) and (Wolka et al., 2018) demonstrates substantial yield increases in areas utilizing stone bunds, with some studies reporting yield increases ranging from two to three times compared to control areas (Wolka et al., 2011).

Previous research in West Africa has predominantly focused on yield, soil fertility and erosion (Abi et al., 2018; Nyssen et al., 2007; Sultan et al., 2018; Zougmoré et al., 2014). However, there is a notable gap in addressing the impact of stone bunds on enhancing soil moisture. Additionally, most of these studies are limited to small-scale, localized field analyses, with a scarcity of research specifically examining the effectiveness of stone bunds in Ghana. This study aims to address these gaps and provide through integrated field data and remote sensing analysis valuable insights into the effects of stone bunds on soil moisture retention and agricultural productivity in Ghana.

The specific objectives are the following: 1) Examine the influence of stone bunds on soil moisture dynamics, 2) Evaluate the effect of stone bunds on vegetation growth using NDVI data on a large spatial scale and 3) Analyze the relationship between stone bunds, environmental factors, and agri-cultural productivity

4.2. Materials and methods.

4.2.1. Study area

The experiment was conducted in Nangodi (Soliga) Nabdam district, located in the Upper East Region of Ghana, at coordinates 10°51′10.44″N, 0°40′12.72″W, with an elevation of 198.6 m (Figure 33). This area is part of Ghana's savanna zone and experiences a semi-arid climate characterized by distinct wet and dry seasons. Rainfall in this region is typically lower compared to the southern part of Ghana, with the rainy season extending from May to October, averaging 1039 mm annually between 1981 and 2023 according to NASA (2024). Stone bunds, widely used for soil and water conservation, are prevalent in the region. A survey with local experts and farmers revealed that the stone bunds in the experimental plots ranged from 20 to 30 years old and have been consistently maintained according to local farmers' practices.

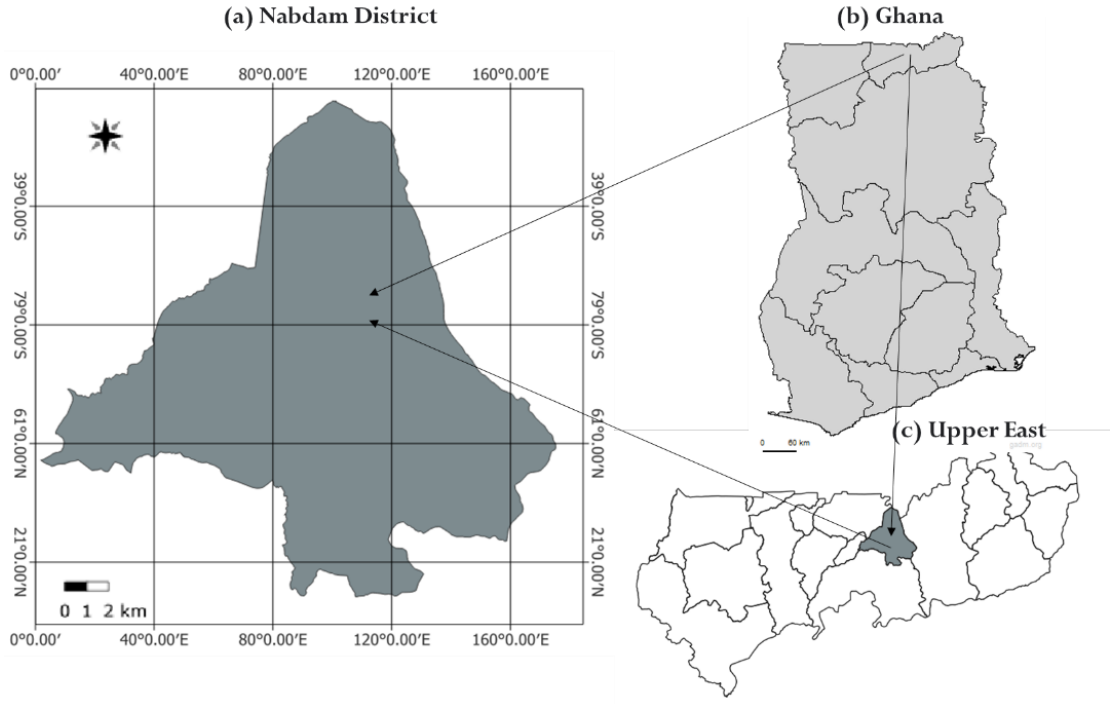

Figure 33. Location of the experimental site in the Upper East Region, Nabdam District, specifically in Nangodi (Soliga), Ghana.

4.2.2. Data Collection and Analysis

In the top 10 cm layer, the soil texture is predominantly loam, with high levels of organic matter and active biological processes. As the depth increases, the soil transitions to clay loam at 10–20 cm and 20–30 cm and to clay at 30–40 cm. This gradation is ac-companied by a decrease in organic matter, total nitrogen, and phosphorus levels, while the C/N ratio increases (Table 9). The topsoil's bulk density was observed as 1.37 g/cm³, which corresponds to the typical range for loam soils (USDA, 1999). Based on the observed soil properties, the soils in the study area are classified as Alfisols, specifically Ustalfs, ac-cording to [37]. These soils are characteristic of semi-arid regions, with high base saturation and

fertility. The loam texture in the top layers and the transition to clay loam and clay at deeper depths further support this classification.

Table 9. Soil texture and chemical characteristics across different depths (April 2022).

Soil depth	Soil texture	pH (H_2O)	Organic matter ($g.Kg^{-1}$)	Total N ($g.Kg^{-1}$)	C/N($g.Kg^{-1}$)	P_2O_5 ($mg.Kg^{-1}$)	K_2O ($mg.Kg^{-1}$)
0-10	Loam	6.3	26	1.3	12	9	150
20-30	Clay Loam	6.3	21	0.9	13	5	89
20-30	Clay Loam	6.2	9	0.6	8	5	14
30-40	Clay	6.2	9	0.4	13	4	28

4.2.3. Experimental plots

Two experimental plots were established for evaluating the soil moisture dynamic and crop productivity: a treatment plot with stone bunds and a control plot without stone bunds serving as a comparative baseline. Each plot was equipped with two WaterScout SMEC 300 Soil Moisture sensors, installed centrally to monitor moisture levels at 10 cm and 20 cm depths. Soil moisture data were recorded at 15 min intervals throughout the study period. Additionally, a WatchDog 2800 Series Weather Station was installed on-site to record weather parameters at the same intervals. Figure 34 provides a graphical overview of the stone bunds, including their dimensions and the placement of moisture sensors (MSP) within the study area.

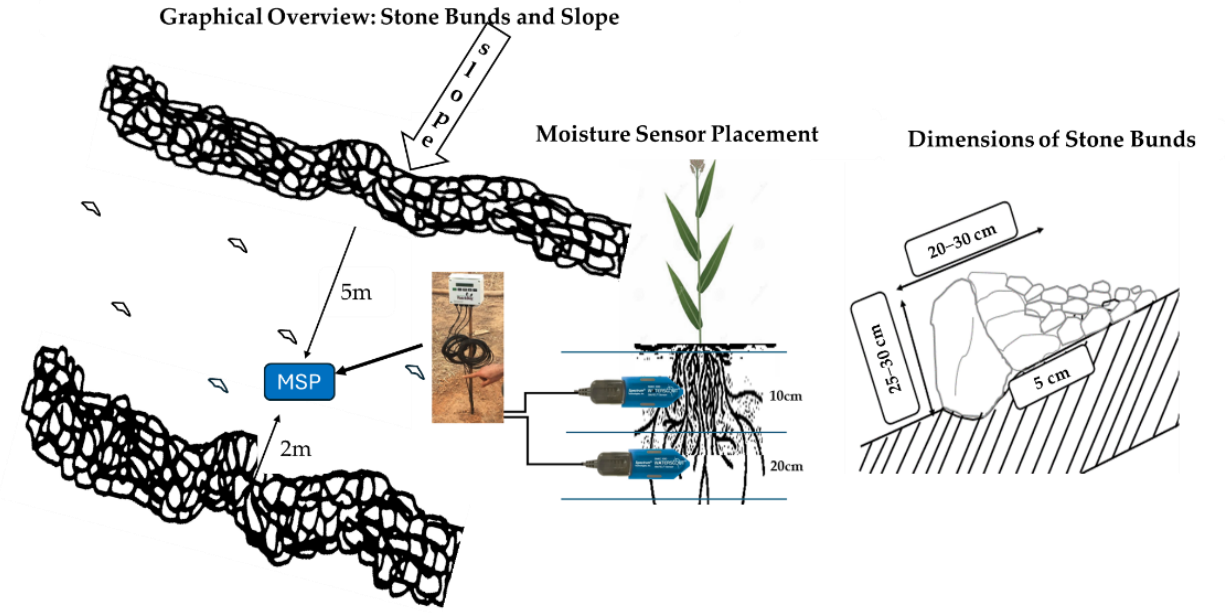

Figure 34. Graphical overview of stone bunds: dimensions, moisture sensor placement (MSP), installed in the study area.

Weather data, including rainfall (R), temperature (T), relative humidity, wind speed, wind gusts, and solar radiation, were collected for both the 2022 and 2023 growing seasons to understand the environmental conditions affecting crop growth. Cumulative rainfall during the study period was recorded at 1002 mm in 2022 and 871 mm in 2023. Average temperatures were monitored and showed an increase from 27.2 °C in 2022 to 27.8 °C in 2023. Relative humidity levels were also tracked, rising slightly from 80% to 82% over the two years. Wind conditions were measured, revealing a decrease in wind gusts from 7.1 km/h in 2022 to 6.5 km/h in 2023, with the average wind speed dropping from 2.8 km/h to 2.2 km/h. Solar radiation data were captured, showing a slight increase in 2023, with values

rising from 230 W/m2 in 2022 to 235 W/m2 in 2023. Figure 35 illustrates the monthly rainfall and mean temperature variations during the 2022 and 2023 growing seasons.

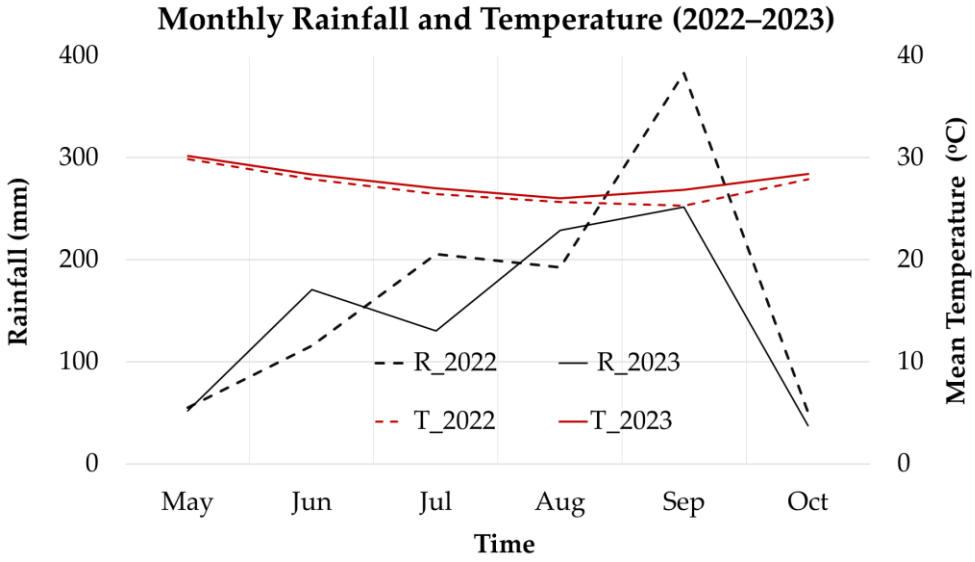

Figure 35. Rainfall and temperature variability, 2022 and 2023 rainy season in the study area (Nabdam)

The experiment focused on sorghum, widely favored by local farmers and recognized as the third most cultivated cereal in Ghana. The chosen variety, Kapaala white, endorsed by the regional research center, matures within 100 to 120 days. Sorghum cultivation in the area depends heavily on rainfall, with significant yield gaps observed. Actual yields have been reported to be 96.5% below the potential yield of 2.0 Mt.ha^{-1} [38]. Planting typically begins in the first week of June, with flowering occurring in late August and harvesting concluding in early October, according to the agricultural calendar. Traditional compost fertilizer was uniformly applied across all study plots. Data collection spanned the years 2022 and 2023, with yield measurements taken from each plot, each covering an area of 6 m × 6 m and replicated three times.

4.2.4. Soil hydraulic properties

Fifteen single-ring infiltration tests were conducted to estimate the saturated soil hydraulic conductivity (Ks) using the Beerkan Estimation of Soil Transfer parameters through Infiltration Experiments (BEST) algorithm (van Genuchten, 1980). Eleven of these tests were performed in three stone bund plots located on a slope ranging from 6 to 10 degrees, with the steepest gradient observed in the upper bund. Four experiments were conducted in both the upper- and mid-bund plots, while three tests were carried out in the lower bund. Additionally, four tests were conducted in a control plot with a uniform 6-degree slope.

The BEST procedure enables the estimation of both the soil water retention curve (SWRC) and the hydraulic conductivity curve with minimal experimental data. Key inputs include particle-size distribution (PSD), dry soil bulk density, cumulative three-dimensional (3D) infiltration, and initial and final soil water content. The BEST method is based on the (van Genuchten, 1980) model for the SWRC. It utilizes the (Brooks, 1964) model for hydraulic conductivity, as expressed by the following equations:

$$K(Q) = K_s \left({}^{\theta - \theta_r}/_{\theta_s - \theta_r} \right)^{\eta}$$

$$\eta = \frac{2}{m * n} + 3 + P$$

where K_s is the saturated soil hydraulic conductivity; θ is the volumetric soil water content; θ_s is the saturated soil volumetric water content; θ_r is the residual volumetric soil water content; n, m, and η are shape parameters; and P is a tortuosity parameter.

The determination of hydraulic parameters is performed in two stages. In the first stage, the SWRC shape parameters n, m, and η are obtained from the PSD curve. An analytical function is fitted to the PSD data (after excluding gravel fraction) and is given by the following equation:

$$F_D = \left[1 + \left(\frac{D_g}{D}\right)^{N_g}\right]^{-M_g}$$

where F_D is the cumulative particle mass fraction associated with particle diameter D, D_g is a characteristic particle diameter, and N_g and M_g are shape parameters related by $M_g = 1 - 1/N_g$. The parameters n and m are linked to N_g and M_g by a relationship that involves soil porosity. The details of this calculation are provided by Brooks (1964).

The remaining parameters are obtained from the infiltration experiment. Each test involved inserting a 15 cm diameter ring into the soil to a depth of at least 1 cm to prevent water loss from the soil surface. Infiltration tests were conducted under ponded conditions, where 150 mL of water was repeatedly added to the ring, and the time required for infiltration was recorded until a steady infiltration rate was achieved. Undisturbed soil samples were taken before and after the tests to measure dry bulk density and initial and final soil water content. Infiltration rates (f, mm/min) and cumulative infiltration (F, mm) were calculated based on the measured infiltration times and water volumes. The cumulative infiltration data were then used to derive Ks using the BEST slope algorithm.

4.2.5. NDVI analysis

For For the large-scale analysis, the NDVI data were acquired from Sentinel-2 satellite imagery, covering the Nabdam District from 1 January 2022 to 1 January 2024. The Sentinel-2 satellites, part of the European Union's Copernicus program (https://dataspace.copernicus.eu/, accessed on 8 September 2024), provide high-resolution imagery with a spatial resolution of up to 10 m and a revisit time of 5 days. This high frequency and fine resolution make Sentinel-2 data suitable for the long-term spatiotemporal analysis of vegetation dynamics, even in regions with relatively small and fragmented agricultural fields.

Twelve fields were selected to compare the effects of stone bunds on crop growth under rainfed conditions. Figure 36 illustrates a sample field polygon with stone bunds used for the NDVI data extraction in the study area (Nabdam, Ghana). These fields were identified through local surveys and were managed using the same crop type and agricultural practices. The geographic coordinates of these sites were registered, and additional information was collected from local partners. The control plots, without stone bunds, ranged in size from 2100 m^2 to 15,329 m^2, collectively covering an area of 33,820 m^2. The treatment plots, with stone bunds, ranged from 2200 m^2 to 20,876 m^2, spanning a total area of 38,576 m^2. The control plots were covered by 338 pixels, and the treatment plots were covered by approximately 386 pixels. Figure 36 illustrates the aerial view of the study plot with stone bunds, showing the field boundaries. The geographic coordinates are provided for spatial reference.

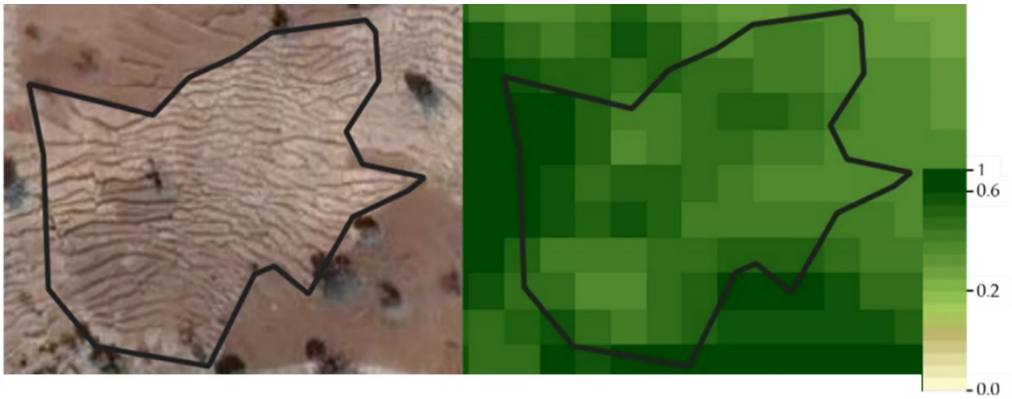

Figure 36. Sample stone bund polygon for NDVI data extraction in the study area (Nabdam, Ghana): Google Earth (a), actual image (b), and Sentinel 2 retrieved NDVI pixels for the 4rth of September 2023 (c).

The NDVI data were obtained from the Copernicus Database portal (https://dataspace.copernicus.eu/, accessed on 8 September 2024). The Sentinel-2 Level-2A data were first filtered for cloud coverage, applying a threshold of 80%. Then, pixel-level cloud detection algorithms, specifically the Sentinel-2 Cloud Masking (s2cloudless) algorithm, were applied to mask out the pixels affected by clouds, shadows, and haze to further improve the data quality. Subsequently, the NDVI values for the filtered images corresponding to the selected acquisition dates were retrieved. The mean NDVI values for each field were retrieved from the cloud-free pixels on each acquisition date. The NDVI values for the selected fields were then downloaded and used directly for analysis. To improve the reliability of the analysis, NDVI values below 0.2 were excluded to eliminate non-vegetated areas. Finally, the daily NDVI values were obtained by linear interpolation between the available cloud-free images to create a continuous time series over the study period, ensuring that key vegetation growth stages were captured. In our methodology for analyzing the NDVI distributions, we categorized the NDVI data according to established threshold values. This classification approach is essential for interpreting the NDVI data effectively, allowing for us to distinguish between var-ying levels of vegetation vigor. The NDVI index ranges typically from −1 to +1, with higher values indicating healthier and more vigorous vegetation. To facilitate our analysis, we defined specific threshold values to categorize the NDVI data (Table 10) according to literature sources (Angulo-Jaramillo et al., 2019; Aranguren et al., 2020; Dalezios et al., 2001; Lee et al., 2022). By categorizing the NDVI values according to these thresholds, we can quantify and compare the vegetative cover in areas with stone bunds versus control areas, assessing the effectiveness of such land management practices in promoting vegetation health. This classification is valuable for mapping and monitoring changes in vegetation over time, providing a quantifiable measure of environmental impact.

Table 10. Vegetation classes and NDVI value.

NDVI Category	NDVI Range	Description
Low	0.2< NDVI < 0.3	Sparse or stressed vegetation
Mid	0.3 ≤ NDVI < 0.5	Moderate vegetation coverage
High	NDVI ≥ 0.5	Dense and healthy vegetation

4.2.6. Statistical analysis

To assess the effectiveness of stone bunds in enhancing soil moisture retention at different soil depths compared to control plots, we employed descriptive statistics, Pearson/Spearman correlation analysis with rainfall, and temporal trend analysis. Additionally, the percentage change in VWC at each soil depth between stone bunds and control plots was calculated using the following formula:

$$\%\Delta v_v = \left(\frac{V_{sb} - V_c}{V_C}\right) \times 100$$

where $\%\Delta v_v$ is the percent difference in VWC at each depth between the stone bunds (V_{sb}) and control (V_c) areas, providing a measure of the effectiveness of the stone bunds.

For non-normally distributed data, the non-parametric Wilcoxon rank sum test, also known as the Mann–Whitney U test, was used to compare two independent samples and determine if they come from the same distribution. It is particularly useful for comparing medians between two groups, i.e., stone bunds and control. The Wilcoxon rank sum test is defined as the following:

$$W = R_s - \frac{n_s(n_s + 1)}{2}$$

where R_s is the sum of the ranks and n_s is the number of observations in the stone bund sample. This test provides a *p*-value, and a *p*-value less than 0.05 typically indicates a statistically significant difference between the moisture content in the stone bund and control plots, leading to the rejection of the null hypothesis. The Wilcoxon rank sum test was performed using R, version 2024.04.2, a programming language and statistical software.

For the crop data, a two-way ANOVA (analysis of variance) was conducted to assess the effects of treatment (control vs. stone bunds) and year (2022 vs. 2023) on crop yield, including their interaction. The model included fixed effects for treatment and year and random effects for replication within each year. Significance was determined at $p < 0.05$. The data were structured with treatment and year as the main factors and crop yield as the response variable. The statistical model used was the following:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where Y_{ijk} represents the yield for the kth replication in the ith treatment and j^{th} year, μ is the overall mean yield, α_i is the effect of the ith treatment, β_j is the effect of the jth year, $(\alpha\beta)_{ij}$ is the interaction effect between treatment and year, and ϵ_{ijk} is the random error. The ANOVA was performed using the aov function in R, and the significance of the main effects and interaction was determined at the 0.05 significance level. The statistical analysis was conducted using RStudio version 2024.04.2 Build 764 (Posit Software, PBC), with R version 4.2.2 for documentation.

For the NDVI, the statistical analysis was performed using regression analysis to elucidate the relationship between the NDVI values and related variables, such as rainfall and soil moisture. Regression models were fitted to the dataset to quantitatively assess the impact of these factors on the NDVI. The significance of the coefficients was evaluated using statistical tests, including the t-statistic and *p*-value. Measures of model performance, such as R-squared and adjusted R-squared, were employed to gauge the explanatory power of the regression models, while the F-statistic provided insights into their overall significance.

The equations for simple and multiple linear regression are as follows:

For simple linear regression,

$$Y = \beta_0 + \beta_1 \quad X_1 + \varepsilon$$

For multiple linear regression,

$$Y = \beta_0 + \beta_1 \quad X_1 + \beta_2 \quad X_2 + \cdots + \beta_p \quad X_p\, \varepsilon$$

where X_1, X_2, ..., X_p represent independent variables; β_1, β_2, ..., β_p are the coefficients associated with each independent variable; and ε represents the error term.

The methodology also included a residual analysis to validate the regression models and ensure the absence of systematic errors. Residual plots and tests for normality were conducted to assess the appropriateness of the regression assumptions and the accuracy of model predictions. Finally, smoothing techniques, such as moving averages, were employed to enhance the quality and reliability of the NDVI time-series data by mitigating noise and interpolating missing data points.

4.3. Results

4.3.1. Soil moisture dynamics

The dataset analyzed in Figure 37, which includes in situ soil moisture and rainfall measurements taken at 15 min intervals, provides evidence of the effectiveness of stone bunds in regulating soil moisture, particularly under variable rainfall conditions. This analysis focuses on volumetric water content (VWC%) comparisons between stone bund and control plots, highlighting distinct moisture dynamics influenced by rainfall. The correlation coefficients between rainfall and soil moisture levels are 0.51 for the stone bund plots and 0.42 for the control plots. Figure 37a,b clearly show that stone bunds consistently maintain higher soil moisture levels, especially during periods of increased rainfall. Table 11 presents the statistics of soil moisture content in the stone bund and control areas. The stone bund areas sustained higher average VWC levels compared to the control areas, with notable increases at both 10 cm and 20 cm depths, quantitatively supporting the superior moisture retention capabilities of stone bunds. Specifically, the stone bund plots retained 21.33% more moisture than the control plots at 10 cm depth and 8.94% more at 20 cm depth over the entire study period. During the growing season of 2022, stone bunds retained 17.44% more moisture at 10 cm and 10.51% more at 20 cm. In 2023, these values increased to 22.99% and 23.70%, respectively.

Table 11. Statistics of rainfall (in mm/15 minutes) and soil moisture content (VWC, in %) at 10 cm and 20 cm depths in stone bunds and control areas across three categories during the 2022 and 2023 rainy seasons, as well as for all the study period. SD stands for Standard Deviation.

		VWC at 10 cm		VWC at 10 cm	
		Stone bunds	Control	Stone bunds	Control
All study period	Maximum	50.3	42.3	54.6	49.3
	Mean	18.2	15	25.1	23.04
	SD	7.9	6.8	8.1	7.44
May-Oct 2022	Maximum	50.3	42.3	54.6	49.3
	Mean	22.02	18.75	31.23	28.26
	SD	6.43	5.9	9.7	8
May-Oct 2023	Maximum	45.5	39.7	47.2	39.8
	Mean	24.23	19.7	27.82	22.49
	SD	7.49	6.6	6.2	6.2

Despite a lower maximum rainfall of 22.9 mm in 2022, stone bunds helped achieve a soil moisture peak of 54.6 mm at 20 cm depth. Conversely, in 2023, a higher rainfall in-tensity of 26.4 mm resulted in a slightly lower moisture peak of 47.2 mm. Statistical validation using non-parametric tests, appropriate due to the non-normal distribution of the data, corroborates the hypothesis that stone bunds significantly improve soil moisture retention. The Wilcoxon rank sum test results at both 10 cm (W statistic: 225,254, p-value: $1.979 \times 10{-}4$) and 20 cm (W statistic: 244,776, p-value: $1.053 \times 10{-}9$) depths indicate that the differences in VWC between the stone bund and control areas are statistically significant. Figure 37 a,b illustrate the temporal variations in soil moisture for both depths along with the corresponding rainfall events..

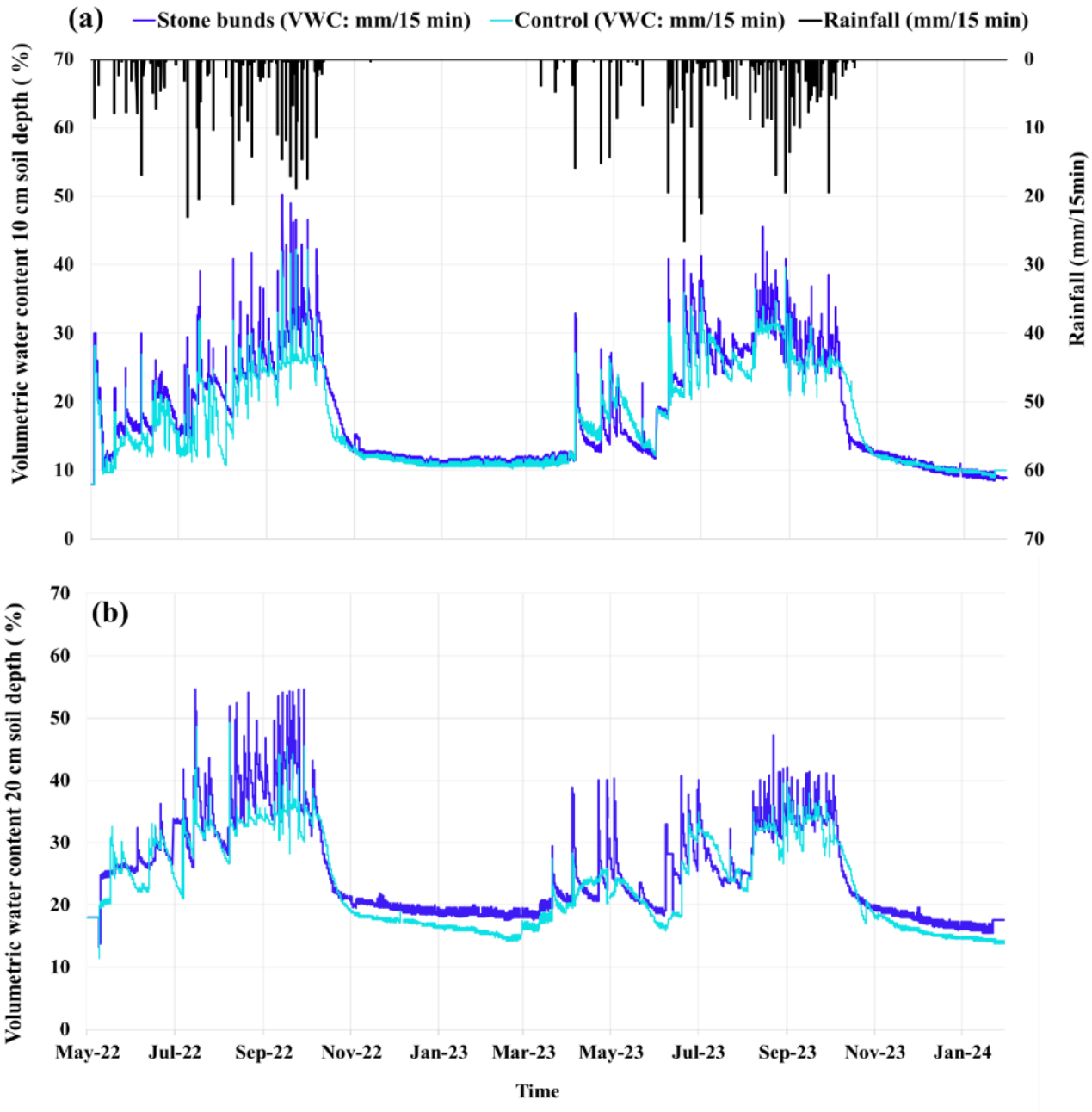

Figure 37. Observed time series of the rainfall and the soil water contents in the stone bunds and control areas at (a) 10 cm of soil depth; (b) 20 cm of soil depth. Data interval is 15 minutes.

4.3.2. Infiltration rates and hydraulic conductivity

The mean instantaneous infiltration rate for the control plot was 6.2 mm/min compared to a higher rate of 8.7 mm/min for the stone bund plot. Additionally, the median infiltration rates were 4.8 mm/min for the control and 6.5 mm/min for the stone bunds, further demonstrating the enhanced water infiltration efficiency achieved with stone bunds. The mean cumulative infiltration was 95.2 mm for the control plot and 139.4 mm for the stone bund plots as shown in Figure 38. These results indicate that stone bunds could enhance soil permeability and water infiltration capacity compared to the control.

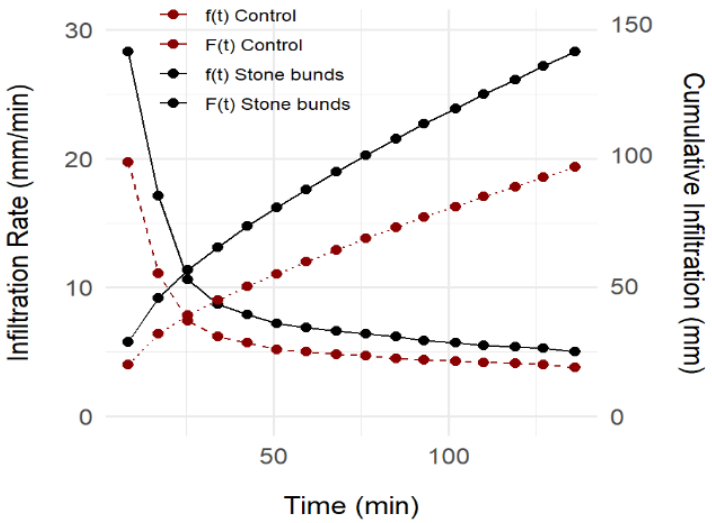

Figure 38. Cumulative infiltration (F(t)) and infiltration rate (f(t)) were measured in April 2022. The black lines (f(t)) represent the infiltration rates, whereas the brown lines (F(t)) illustrate the cumulative infiltration accumulated over time.

The mean soil's saturated hydraulic conductivities (Ks) were 1.732 mm/min and 1.185 mm/min in the stone bund and in the control, respectively. Table 12 provides de-tailed Ks values for the upper-, mid-, and lower-bund plots and the control plot. The three bunds showed higher mean Ks values compared to the control. Higher mean Ks values were found in the upper- and mid-stone bunds that had the highest slopes.

Table 12. Statistics for the saturated soil hydraulic conductivity (Ks) determined in different plot locations during April 2022.

Plot	Infiltration Tests	K_s Min (mm/min)	K_s Max (mm/min)	K_s Mean (mm/min)	Standard Dev (mm/min)
Upper Bund	4	0.992	3.232	1.654	0.917
Mid Bund	4	0.802	2.853	2.032	0.858
Lower Bund	3	0.858	2.047	1.435	0.486
Control	4	0.834	1.832	1.185	0.399

A temporal analysis of rainfall recorded at 15 min intervals in conjunction with the saturated hydraulic conductivity (Ks) offers valuable insights into the likelihood of sur-face runoff occurrence. This analysis assumes a uniform rainfall rate within the 15 min data acquisition intervals. During the rainy seasons of 2022 and 2023, eleven 15 min rainfall observations in the control plot exceeded the average Ks value, indicating the potential for surface runoff. In contrast, only one rainfall event in the plots with stone bunds surpassed the mean Ks value. The observed peaks in soil moisture within the stone bund plots suggest a higher rate of infiltration, providing a more accurate reflection of the rainfall recorded at these intervals. This variation illustrates that soil moisture responses are better correlated with rainfall events, especially since rainfall is not uniformly distributed over the 15 min intervals. The control plot, lacking these pronounced peaks, struggles to absorb the intensity of rainfall, leading to increased runoff.

4.3.3. NDVI analysis and vegetation response to stone bunds

The NDVI analysis over the growing seasons of 2022 and 2023 reveals that stone bunds consistently result in higher NDVI values compared to the control plots, indicating better vegetation health and growth. During the peak growth from mid-August to mid-September, the NDVI values in the stone bund fields reached 0.61, while the control fields recorded lower values of 0.52 in 2022 and 0.48 in

2023. Figure 39 illustrates the dynamics of the mean daily NDVI values from multiple plots under different management practices (with and without stone bunds) across the 2022–2023 growing seasons. The analysis shows that, in 2022, the stone bund fields exhibited higher NDVI values from sowing to mid-season (approximately up to day of year 230), attributed to favorable conditions, like higher rainfall and better soil moisture. From DOY 150 to DOY 200, the plots with stone bunds of 2023 were higher than the 2023 control plots and similar to the 2022 control plots. After DOY 200, in 2023, the plot with stone bunds maintained higher NDVI levels than the control plots of 2022, despite the lower rainfall, and reached similar values to the stone bund plot of 2022 near mid-season. The decline in NDVI values towards the end of the season corresponds to the physiological maturation and harvesting phases of the crops. Figure 39 illustrates the temporal dynamics of the mean daily normalized difference vegetation index (NDVI) values for two consecutive years across different agricultural stages.

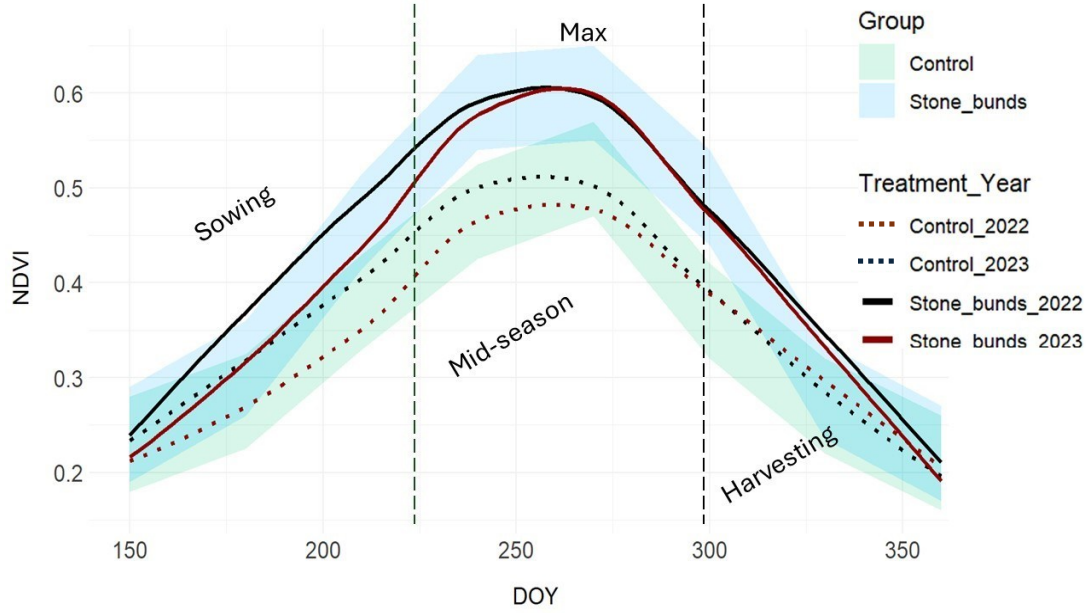

Figure 39. Temporal dynamics of mean daily normalized difference vegetation index (NDVI) values for two consecutive years across different agricultural stages, marked by days of the year (DOY). The shaded regions denote the confidence intervals, providing an estimate of variability around the mean.

A pixel-based spatiotemporal analysis of the NDVI distributions, as illustrated in Figure 40, during the rainy periods (May to October) reveals significant differences of vegetation vigor between the areas with and without stone bunds. The stone bund areas exhibited a higher percentage of high NDVI (24%) compared to the control areas (9.2%).

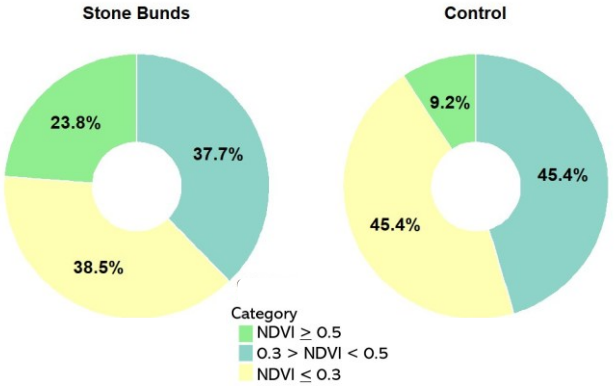

Figure 40. NDVI pixels distribution over the two seasons (2022 - 2023).

Statistical analysis reveals significant effects of both treatment (presence or absence of stone bunds) and location on the NDVI values, as shown in Table 13. The presence of stone bunds significantly increased the NDVI ($p < 0.001$), indicating their positive impact on vegetation vigor. The location also showed a significant effect on the NDVI ($p < 0.001$), suggesting spatial variability in vegetation response across different sites. Notably, the absence of a significant interaction effect between treatment and location suggests that the beneficial effects of stone bunds are consistent across various locations.

Table 13. ANOVA results for treatment and location effects on NDVI.

	Df	Sum Sq	Mean Sq	F-value	Pr (>F)	Significance
Treatment	1	0.232	0.2322	17.262	3.79E-05	***
Location	5	0.318	0.0636	4.729	0.000309	***
Rainfall	1	2.39	2.3901	177.678	< 2e-16	***
Treatment : Location	5	0.033	0.0066	0.492	0.782596	No
Treatment : Rainfall	1	0.062	0.0618	4.596	0.032492	*
Residuals	26	0.22	0.01			
*Significance. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*						

Further analysis of the interaction between rainfall and the NDVI reveals significant impacts, particularly in regions with stone bunds. In these areas, the correlation coefficient between rainfall and the NDVI is 0.68, indicating a robust positive relationship, compared to a moderate positive correlation of 0.57 in areas without stone bunds. Regression analysis further elucidates this relationship. In the presence of stone bunds, the multiple R is 0.69, with an R^2 of 0.48, implying that 48% of the NDVI variation can be attributed to rainfall. This association is statistically significant, supported by an F-statistic and a *p*-value. Conversely, in the absence of stone bunds, the multiple R is 0.67, and the R^2 indicates that 44% of the NDVI variation is explained by rainfall, supported by an F-statistic of 331.2 and a *p*-value of 8.53644×10^{-55}.

4.3.4. Crop yield response

A statistical analysis was conducted to examine the effects of treatment type (control vs. stone bunds) and year (2022 vs. 2023) on crop yield, including their interaction. The analysis revealed a statistically significant main effect of treatment on yield, $F(1,10) = 479.39$, $p < 0.001$, indicating that the use of stone bunds significantly increased crop yields compared to the control treatment. Specifically, the mean yields were higher by 38.1% in 2022 and 32.05% in 2023 compared to the control. Additionally, there was a significant main effect of year on yield, $F(1,5) = 13.69$, $p = 0.014$, suggesting that crop yields differed significantly between the two years, potentially due to varying environmental conditions or other temporal factors. Figure 41 illustrates the mean yield of sorghum under stone bunds compared to the control plot over the two years. The mean yields were higher in 2022 than in 2023 for both treatments. Despite lower overall rainfall in 2023, the timing, distribution, and amount of rainfall likely contributed to the yield re-duction. The interaction between treatment and year was not significant, $F(1,10) = 0.001$, $p = 0.975$, indicating that the increase in yield due to the stone bunds treatment was consistent across both years.

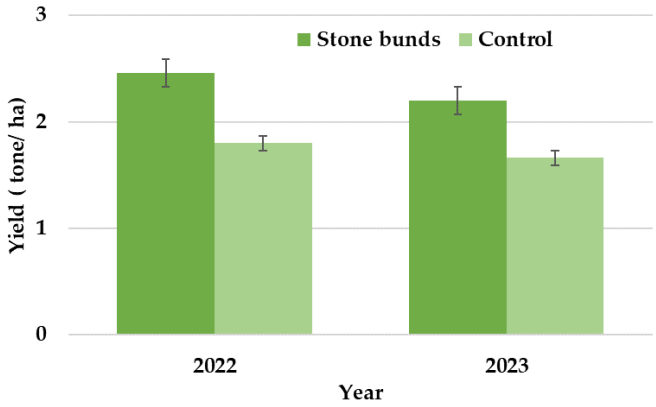

Figure 41. Mean yield of sorghum (Kapaala White) under stone bunds and control plot over the two years.

4.4. Discussion

The decrease in rainfall in 2023, from 1002 mm in 2022 to 871 mm, led to lower soil moisture levels, impacting crop growth and water availability. Abdisa, Mamo Diga, and Regassa Tolessa Abdisa et al. (2022) and Tolosa et al. (2023) found that over 75% of the variability in sorghum yields in Ethiopia is attributable to fluctuations in rainfall and temperature. The infiltration tests showed the benefits of using stone bunds for improving soil characteristics for more productive rainfed agriculture. The higher mean infiltration rate observed in the stone bunds compared to control plots indicates an improved infiltration capacity. The slightly higher saturated hydraulic conductivity (Ks) evaluated for the stone bunds indicates soil conditions that facilitate water movement through the soil profile, underscoring the potential of stone bunds to enhance water retention and reduce surface. The temporal analysis of Ks in relation to the 15 min rainfall during the rainy seasons suggests that stone bunds can mitigate the risks of in-filtration excess consequent to heavy rainfall events (Horton, 1941). The observed soil moisture dynamics further demonstrate the effectiveness of stone bunds in enhancing rainfed agricultural resilience. The stone bunds consistently maintained higher soil moisture levels with respect to the control plot, especially during periods of increased rainfall, mirroring the findings from Singh et al. (2021) and (Alemayehu et al., 2020). The higher mean VWC observed in the stone bund plots over the study period reflects significant improvements in moisture retention. Additionally, the greater VWC at deeper soil layers in these plots can be attributed to the enhanced infiltration and water retention capacity associated with stone bunds. The exceptionally low p-values, well below the conventional threshold of 0.05, confirm that stone bunds enhance soil moisture retention more effectively at both observed soil depths, underscoring their potential as a valuable strategy for sustainable agricultural practices in water-limited environments. These findings highlight the positive impact of stone bunds in optimizing soil moisture during reduced rainfall periods Kirkby et al. (1982), which is essential for sustainable agriculture in challenging environmental conditions.

The effectiveness of stone bunds in managing soil moisture is evident from our intermediate data. In 2022, despite a lower maximum rainfall, stone bunds achieved the highest soil moisture peak at a 20 cm depth. Conversely, in 2023, a higher rainfall in-tensity of 26.4 mm resulted in a lower moisture peak. This highlights the importance of considering slope and rainfall intensity when optimizing stone bunds to capture and retain more moisture. Adapting the design of stone bunds to the local conditions is essential for maximizing their benefits. Proper maintenance and strategic design of stone bunds are crucial for optimizing soil moisture retention and minimizing erosion, particularly in regions with variable rainfall patterns (Alemayehu et al., 2020; Klik et al., 2018). The effectiveness of stone bunds is significantly enhanced by tailoring their height and ensuring their structural integrity to accommodate

different rainfall intensities (Gebrernichael et al., 2005; Nyssen et al., 2007; Taye et al., 2015).This approach not only prevents waterlogging during intense rainfall events but also ensures adequate moisture availability during drier periods. Regular monitoring and community involvement in maintaining these structures are essential for sustaining their benefits, making agricultural systems more resilient and productive in the face of climatic challenges.

The NDVI analysis conducted during the growing seasons of 2022 and 2023 reveals that stone bunds consistently yield higher NDVI values than control plots. High NDVI values are typically associated with improved crop health and biomass, directly correlating with increased yields (Bannari et al., 1995; Wiegand et al., 1991). The enhanced vegetation cover in areas with stone bunds indicates that these structures create optimal growth conditions for sorghum, particularly during the growth season when the crop's water demands are highest, supporting findings from Liu et al. (2015) and Mando et al. (2006). However, increased vegetation vigour does not always translate to higher yields, as rainfall during non-critical growth stages can enhance NDVI without significantly benefiting grain filling (Akinseye et al., 2020; Katerji et al., 2014; Wakjira et al., 2021).

In this study, the improved vegetation health likely contributed to increased sorghum yields, emphasizing the effectiveness of stone bunds as a soil and water conservation strategy in rainfed agricultural systems. Specifically, the average yields were consistently higher in the stone bund plots compared to the control plots, aligning with prior research that highlights the positive impact of stone bunds on agricultural productivity (Alemayehu et al., 2020; Zougmoré et al., 2014). Interestingly, the mean yields were higher in 2022 than in 2023 for both treatments, likely due to reduced rainfall in 2023 creating less favourable conditions for sorghum growth and yield. Nonetheless, the plots with stone bunds in 2023 still outperformed the control plots from 2022, which had received more rainfall, indicating that stone bunds increase the resilience of this rainfed agriculture to drought periods.

This finding is particularly significant because better moisture management is critical for maintaining crop health and increasing yields, especially given the increasingly erratic weather conditions affecting rainfed agricultural systems. Rainfed agriculture is highly susceptible to changes in rainfall patterns and intensity, leading to significant agricultural losses due to both drought and excessive rainfall disrupting crop growth cycles (Liaqat et al., 2024). The changing climate further complicates water management, with intense rainfall events causing rapid runoff and decreased water availability for crop (Adimassu et al., 2023). Additionally, regions like the Upper East Region of Ghana have recently experienced a shift toward less frequent but more intense rainfall events (Quaye-Ballard et al., 2020). This shift poses significant threats to rainfed agriculture, as increased rainfall intensity leads to heightened runoff and soil erosion, while less distributed rainfall results in insufficient water for crops during critical growing periods. Tolosa et al. (2023) underscored the importance of rainfall distribution, showing strong correlations between sorghum yields and the number of rainy days throughout the growing season.

The consistency of results in soil hydraulic conductivity, infiltration rates, soil moisture dynamics, NDVI, and yield across this field study suggests that stone bunds are a beneficial agricultural practice capable of enhancing rainfed agriculture and crop yields despite annual variations. Our results are in line with other studies in different African drylands, which have demonstrated that stone bunds can significantly enhance sorghum yields by improving soil fertility and moisture availability (Amede et al., 2014; Nyssen et al., 2009) or by enhancing soil water retention and reducing runoff (Vohland et al., 2009). These results are particularly important for developing sustainable agricultural strategies that can withstand yearly fluctuations, ensuring more predictable and stable improvements in crop productivity. However, as this analysis is based on only two years of data and limited locations, further research over a more extended period is recommended to confirm these findings and ensure their generalizability across different environmental conditions and periods. Overall, the results demonstrate

the significant agronomic benefits of implementing stone bunds in crop production, leading to higher yields compared to traditional methods.

4.5. Conclusion

Combining in situ soil moisture measurements, remote sensing data (NDVI), and yield data, this study provides a thorough assessment of the effectiveness of stone bunds in semi-arid regions of Ghana's Upper East Region. By improving surface infiltration and soil moisture and increasing crop yields, stone bunds effectively address the challenges posed by climate variability and changing rainfall patterns. These findings highlight the significance of integrating stone bunds into agricultural practices to promote sustainable and resilient crop production.

The consistent positive effects observed across multiple metrics and years affirm stone bunds as a valuable tool for enhancing agricultural productivity, food security, and the sustainability of rainfed agriculture. These results advocate for more sustainable farming practices and improved food security in semi-arid regions. For policymakers and practitioners, the findings underscore the need to promote stone bunds as part of integrated soil and water management strategies. Implementing training programs and providing support for farmers in the construction and maintenance of stone bunds can facilitate widespread adoption and maximize their impact on agricultural productivity.

While this study provides evidence of the benefits of stone bunds, future research should explore their long-term impacts and integration with other sustainable farming practices. Conducting longitudinal studies over multiple growing seasons and extended periods is recommended to validate these findings and assess their applicability across diverse environmental conditions and timelines.

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CHAPTER 5

5. Integrating Remote Sensing, Machine Learning, and In-Situ Data for Enhanced Soil Moisture Prediction in Semi-Arid Regions.



Abstract

This study integrates high-resolution remote sensing (RS) data, in-situ measurements, and advanced machine learning, specifically a Long Short-Term Memory (LSTM) model, to predict soil moisture dynamics in semi-arid regions. By leveraging predictors such as Actual Evapotranspiration (AETI), Normalized Difference Vegetation Index (NDVI), temperature, precipitation, and solar radiation, the model delivers enhanced spatial and temporal soil moisture estimates. Combining satellite data, including SMAP (1 km resolution), with local ground-based observations, this approach addresses the challenges of data scarcity in fragmented agricultural landscapes. The results demonstrate that the model surpasses existing datasets in accuracy and error metrics, particularly in heterogeneous environments, underscoring the value of integrating high-resolution predictors with localized data for improved soil moisture monitoring. Notably, the study validates the effectiveness of stone bunds in enhancing soil moisture retention across varying topographic and environmental conditions. The model detected significant increases in soil moisture due to stone bunds, with the most pronounced effects observed on steep slopes and in areas with low to moderate Topographic Wetness Index (TWI) values, where water retention is most critical. This research demonstrates the importance of integrating diverse data sources and machine learning techniques to overcome soil moisture monitoring challenges in data-scarce regions. *By bridging the gap between satellite-derived retrievals and ground-level applications, this approach offers a scalable solution to enhance agricultural sustainability and resilience in semi-arid regions*, where effective soil moisture management is essential for food security and climate adaptation.

Keywords: Soil Moisture, Remote Sensing, Machine learning, LSTM model, Stone Bunds, West Africa

5.1. Introduction

Soil moisture is a critical component of the Earth's hydrological cycle, significantly influencing various environmental and agricultural processes (Dobriyal et al., 2012; McColl et al., 2017). An accurate, representation of the spatiotemporal dynamics of soil moisture is essential for a wide range of applications, from local field studies to continental-scale assessments. These applications include short-term weather forecasting (Schubert et al., 2002), drought monitoring (Bolten et al., 2009; Sheffield et al., 2004), modeling catchment hydrologic responses (Western et al., 2002), and understanding

ecological processes and spatial patterns (Kannenberg et al., 2024; Robinson et al., 2008). In regions reliant on rain-fed agriculture, such as semi-arid West Africa, understanding soil moisture dynamics is crucial for sustaining agricultural productivity, monitoring drought, and managing water resources effectively (Loucks et al., 2017; Sinore et al., 2024). However, erratic rainfall patterns and limited soil moisture data complicate agricultural planning, impacting local economies and leaving farmers and policymakers with insufficient information to make informed decisions (Ritchie, 2022), leading to missed opportunities to mitigate environmental impacts (Togneri et al., 2022). Continuous soil moisture monitoring is essential to mitigate environmental impacts, enhance crop resilience during dry periods, and support sustainable agricultural productivity and food security (Vadez et al., 2024).

Estimating soil moisture accurately across diverse landscapes remains a challenge due to its spatial variability, driven by heterogeneities in soil properties, topography, and vegetation cover (Sungmin et al., 2021). Surface soil moisture estimates can be derived from *in-situ* measurements, remote sensing, or modeling approaches (Batjes, 2016; Moran et al., 2004; Romano, 2014; Western et al., 2002); however, the applicability and accuracy of some methods often depend on the scale of application. While *in-situ* networks provide high precision, their sparse distribution limits their effectiveness for large-scale applications (Togneri et al., 2022). Achieving high-resolution soil moisture data for precision interventions like irrigation and water conservation often requires significant resources, necessitating a balance between detail and practicality (Vergopolan et al., 2021).

Remote sensing (RS) satellite data offers advantages for large-scale soil moisture estimation, providing broad spatial coverage. However, these datasets frequently have coarse spatial resolution and data gaps, limiting their utility in regions with small, fragmented agricultural systems. For example, NASA's Soil Moisture Active Passive (SMAP) mission provides wide coverage but lacks the spatial resolution needed for fine-scale analysis (Peng et al., 2021; Skulovich et al., 2023). Although physically based models can generate continuous soil moisture data globally, their accuracy is affected by complex, non-linear interactions among variables like soil heterogeneity and vegetation cover, which introduce additional uncertainty (Sungmin et al., 2021). High-density ground-based measurements could address these gaps but are often impractical due to logistical and cost constraints (Dobriyal et al., 2012). This absence of comprehensive, high-resolution soil moisture data especially impacts data-scarce regions like West Africa, limiting timely and effective agricultural interventions (Vadez et al., 2024).

Recent literature increasingly emphasizes the need for improved fine-scale soil moisture estimates to better represent hydrological and ecological processes (Peng et al., 2017; Vergopolan et al., 2022). Machine learning (ML) techniques have shown significant promise in enhancing soil moisture estimation, effectively generating gridded soil moisture data with increased spatial and temporal coverage, even at sub-daily intervals (Hengl et al., 2017; Sungmin et al., 2021; Teshome et al., 2024). ML models excel at downscaling coarse-resolution data and capturing fine-scale variations, making them ideal for evaluating small-scale differences. Additionally, they integrate diverse data sources such as satellite observations, meteorological inputs, and local climate data into cohesive datasets, advancing soil moisture analysis (Abowarda et al., 2021; Ali et al., 2015).

While recent advancements provide a strong foundation for soil moisture estimation, progress in evaluating the landscape-scale impact of soil conservation practices, such as stone bunds, remains limited. Stone bunds, widely used in northern Ghana, are constructed along slopes to reduce runoff and enhance soil moisture retention (Alemayehu et al., 2006; Meresa et al., 2023; Naazie et al., 2023; Singh, 2023; Tefera, Awada, et al., 2024). Traditionally, their effectiveness has been evaluated through localized field tests or experimental plots (Nyssen et al., 2007; Tefera, Awada, et al., 2024). Although these studies have demonstrated success at a small scale, scaling up these assessments to the landscape

level is challenging due to logistical and resource constraints, thereby limiting a comprehensive understanding of these conservation practices' broader impact. To effectively evaluate the landscape-scale effects of stone bunds on soil moisture and better inform water resource management, it is essential to develop models that capture soil moisture dynamics across diverse landscapes and climatic conditions. This requires high-quality soil moisture data products that integrate high-resolution satellite data and ML techniques to capture fine-scale variability. By enhancing and validating these models with robust ground (observed) data, researchers can more accurately assess the impact of stone bunds on moisture retention. Such refined models will support the broader adoption of effective soil conservation strategies, promoting sustainable water and land management in semi-arid regions (Brocca et al., 2017; Huang et al., 2024; Sungmin et al., 2021; Tavakol et al., 2021; Tefera, Seddaiu, et al., 2024).

This study introduces a comprehensive methodology for soil moisture estimation by integrating satellite RS data, in-situ measurements, and ML techniques. This integrative approach addresses critical gaps in soil moisture assessment and enhances our understanding of its variability, offering valuable insights for effective water resource management in the semi-arid regions of Ghana. The primary objective is to develop a data-driven ML model capable of downscaling existing RS-based soil moisture products to achieve finer spatial resolutions. Specifically, this research seeks to:

- Leverage machine learning to integrate multiple data sources, including high-resolution Sentinel 2-derived Normalized Difference Vegetation Index (NDVI), in-situ meteorological variables, RS-derived actual evapotranspiration and interception (AETI), and SMAP soil moisture products.
- Provide spatial insights into surface soil moisture variability by capturing its complex dynamics across diverse environmental and climatic conditions, ranging from localized in-situ measurements to broader regional scales.
- Characterize spatiotemporal soil moisture patterns in data-scarce, fragmented rainfed agricultural landscapes, particularly in regions implementing various land conservation practices.

5.2. Methods and Methodology

5.2.1. Study area

This study focuses on a site within the Nandom District in Ghana's Upper West Region, covering approximately 391 square kilometers between latitudes 10°40'–11°00' N and longitudes 2°25'–2°45' W. Situated in the Guinea Savannah ecological zone, the landscape is predominantly flat with gentle undulations and scattered vegetation. Soils are primarily sandy loam, offering varying capacities for moisture retention and infiltration.

The district has a semi-arid climate with a single rainy season from May to October, and a dry season from November to April. Annual rainfall averages between 800 and 1,100 mm, and temperatures range from 25°C to 35°C, conditions that pose challenges for soil moisture retention and drought resilience. Two categories of fields, those with stone bunds (S) and those without were identified through field surveys and Google Earth imagery. Coordinates for each field were recorded during surveys, enabling precise spatial mapping of sites with and without stone bunds (N). (Figure 42).

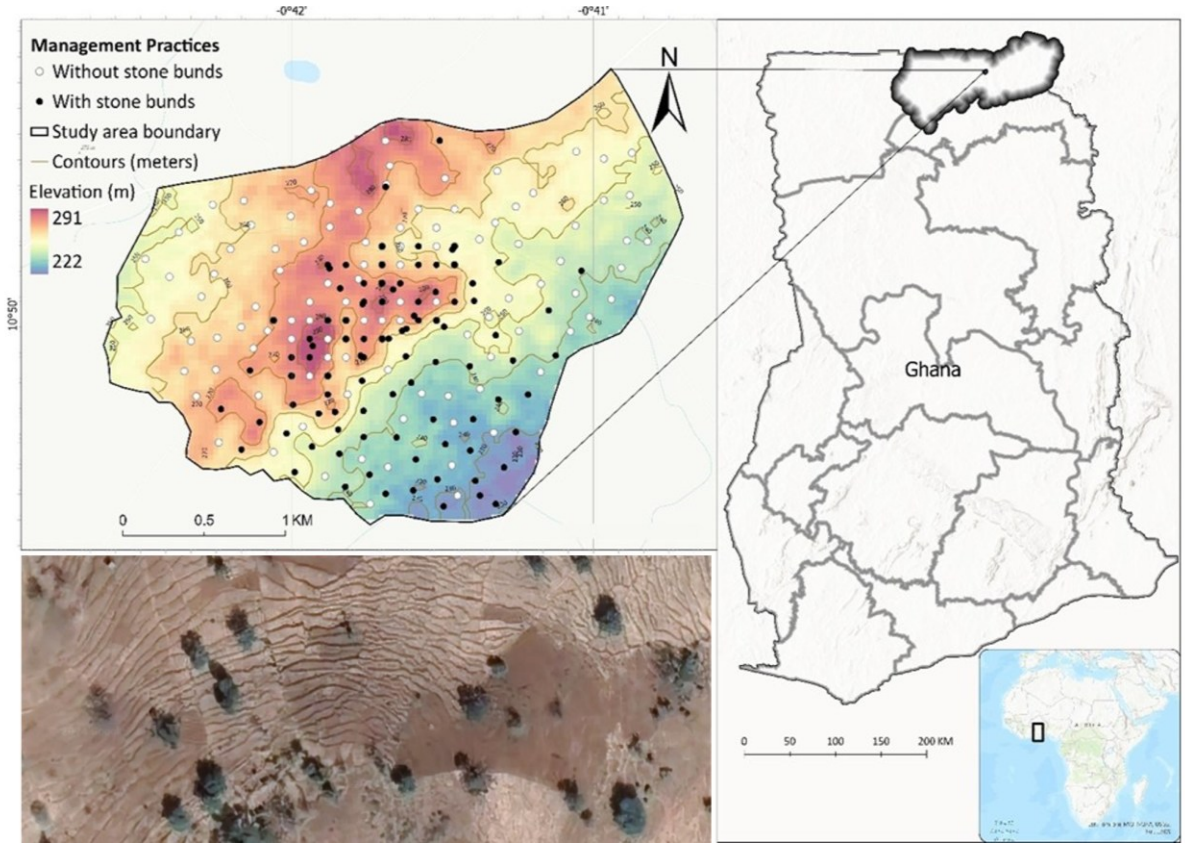

Figure 42. Study area within Nandom District, Upper West Region, Ghana. The map shows the location of fields with and without stone bunds. The google earth image shows one of the selected plots with stone bunds retrieved from earth.google.com.

To capture the diverse topography of the study area, this research utilized the Advanced Land Observing Satellite (ALOS) global digital surface model dataset (Dataset | ALOS@EORC), which provides a 30-meter spatial resolution (Table 14). The study area, characterized by elevations ranging from 220 to 290 meters, benefited from the Digital Elevation Model (DEM) to extract critical topographic features, such as slope and elevation. From this, the Topographic Wetness Index (TWI) was derived, considering slope and upstream contributing areas, to identify regions with high moisture-retention potential. The distribution of stone bunds is influenced by elevation, slope, and TWI. Stone bunds are more commonly found in areas with steep slopes, being 75.6% more frequent than in non-stone bund areas. They are also found in higher elevations, which is 5.7% higher than in N. In contrast, N are more prevalent in areas with high TWI (57%) compared to S. These patterns suggest that stone bunds are strategically placed in regions where moisture control and soil conservation are crucial, particularly in areas with less favorable natural moisture retention (Sørensen et al., 2006; Tagil et al., 2008).

Table 14. Distribution of stone bunds across slope, elevation and TWI categories in the study area

	Category	Stone Bunds (S)	Without Stone Bunds (N)
Slope	Steep (>10%)	16	9
	Moderate (5-10%)	13	19
	Mild (0-5%)	71	94

	High (>270 m)	37	35
Elevation	Moderate (231-270 m)	57	56
	Low (<=230 m)	6	31
	High (>4)	15	35
TWI	Moderate (3-4	56	38
	Low (<=2)	29	49
Total number of sites		100	122

5.2.2. Data Collection

I. Ground-Based Data - In Situ measurements

In situ soil moisture measurements and meteorological data were collected at a depth of 10 cm from two sources. Between 2019 and 2022, data were recorded by the International Soil Moisture Network (ISMN) (https://ismn.earth). From 2022 to 2024, soil moisture data were gathered at the EWA-BELT experimental site, which comprised two plots: a treatment plot with stone bunds and a control plot without bunds, used for comparative analysis. Each plot was equipped with two WaterScout SMEC 300 soil moisture sensors positioned centrally to monitor soil moisture at a 10 cm depth. Measurements were taken every 15 minutes and averaged to produce daily values, providing robust validation data for soil moisture analysis.

Meteorological data at the EWA-BELT site were monitored by a WatchDog 2800 Series Weather Station, which recorded parameters at 15-minute intervals to complement soil moisture data. Field surveys and lab analysis identified the topsoil (10 cm) in the study area as predominantly loam, with a pH of 6.3, 26 g/kg organic matter, and 1.3 g/kg total nitrogen (Tefera, Awada, et al., 2024). This soil data was instrumental in assessing water retention capabilities under the influence of stone bunds

II. Remote Sensing retrieved data

To achieve comprehensive and accurate soil moisture estimation, this study utilized multiple satellite-based datasets covering the period from 2019 to 2024. The Soil Moisture Active Passive (SMAP) mission provided soil moisture estimates at 1 km and 9 km spatial resolutions, sourced through the https://nsidc.org/data/smap. Specifically, the SMAP L3 dataset, with 1 km resolution, offered daily global soil moisture data ideal for large-area monitoring, though downscaling was necessary to align with the field-level resolution of the study area. Downscaling to a daily temporal resolution was achieved using a Random Forest regression model, which incorporated local meteorological variables like temperature (T), precipitation (P), and calculated reference evapotranspiration.

For vegetation analysis, high-resolution NDVI data at a 10-meter spatial resolution were obtained from the Sentinel-2 satellite via the Copernicus Open Access Hub. The data were accessed via the Sentinel-2 | Copernicus Data Space Ecosystem. To ensure data quality, cloud-free NDVI images were filtered using an 80% cloud coverage threshold and further refined with the s2cloudless pixel-level cloud detection algorithm. A linear interpolation technique between cloud-free dates generated daily NDVI values, capturing key vegetation growth stages throughout the study period.

For evapotranspiration dynamics, decadal Actual Evapotranspiration and Interception ($AETI_d$) data were sourced from the https://data.apps.fao.org/wapor platform (FAO, 2020), providing a 100-meter

resolution at a decadal temporal scale. The $AETI_d$ data, derived from the ETLook model (Bastiaanssen et al., 2012), was downscaled to daily estimates (AETI) using the FAO 56 Penman-Monteith equation for daily reference evapotranspiration (ET_o) (Allen, 1998):

$$ET_O = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_{s-} e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

Where, Δ is the slope of the vapor pressure curve, R_n is the net radiation at the crop surface, G is the soil heat flux density, γ is the psychrometric constant, T is the mean daily air temperature at 2 meters height, u_2 is the wind speed at 2 meters height, es is the saturation vapor pressure and e_a is the actual vapor pressure.

Then the decadal AETI ($AETI_{10d}$) is downscaled into daily values ($AETI_i$). This downscaling approach preserved AETI data's high spatial resolution while providing daily estimates necessary for field-scale analysis of soil moisture and evapotranspiration dynamics. The $AETI_i$ was obtained as follows:

$$AETI_i = ET_{o,i} \left(\frac{AETI_{d10d}}{ET_{o,10d}} \right)$$

Where the subscript *i* denotes the daily values while d represents 10-day values.

5.2.3. Machine Learning Model Development

I. Model Selection and Data preprocessing

To predict fine-scale soil moisture across the study area, two ML models were employed: a Random Forest (RF) regression for downscaling SMAP soil moisture, NDVI, and AETI data. RF has been widely validated in environmental modeling and downscaling tasks, often outperforming simpler methods in accuracy and robustness (Hutengs et al., 2016; Pang et al., 2017). The RF model is chosen because soil moisture and AETI dynamics are influenced by non-linear interactions among T, P, NDVI, and topography. RF excels at modeling these complexities compared to spline interpolation or linear regression (Breiman, 2001). Furthermore, a Long Short-Term Memory (LSTM) neural network was used to further improve soil moisture predictions and capture long-term dependencies. Developed by (Hochreiter et al., 1997), LSTMs are a specialized form of Recurrent Neural Networks (RNNs) designed to retain information over long sequences. Unlike traditional RNNs, LSTMs address the vanishing gradient problem (Géron, 2019) by incorporating a unique cell structure with gates for memory retention and updates. These mechanisms make LSTMs particularly well-suited for time-series data, enabling them to capture both short-term variations and long-term trends in soil moisture dynamics.

The LSTM model utilized a set of meteorological and environmental predictors, including precipitation P, T, AETI, Rs, NDVI, and downscaled SMAP soil moisture. The dataset, loaded with time-indexed observations, was standardized using min-max normalization to ensure all features were scaled within [0, 1]. This process mitigates the effect of differing scales and enhances model convergence during training. If X=(P, T, AETI, Rs, NDVI, SMAP) denote the feature set, and if Y= $\theta_{observed}$ represent the target variable. The scaling was applied as follows:

$$X' = \frac{(X - X_{min})}{(X_{max} - X_{min})}$$

where X' denotes the scaled features, X_{min} and X_{max} are the minimum and maximum values of each feature across the training set (70% of the dataset spanning from 2019-12-01 to 2023-01-01),

respectively. The scaler was then applied to the test set (30% of the dataset from 2023-01-02 to 2024-07-31).

II. LSTM Model Architecture and Hyperparameter Optimization

The LSTM network, with its specialized gates, is designed to retain both short-term and long-term dependencies in sequential data. The architecture includes the following core components:

Hidden State Update (h_t): At each time step t, the hidden state h_t is updated based on the current input x_t, the hidden state from the previous time step h_{t-1}, and a learned bias b_h. The hidden state is calculated as follows:

$$h_{t=\sigma(w_h.[h_t-1,x_t]+b_h)}$$

Where σ is the sigmoid activation function, $w_h$represents the weight matrix, h_{t-1} is the hidden state from the previous time step, x_t is the current input, and b_h is the bias term.

Cell State *(c_t):* Retains long-term dependencies across time steps and is updated using the following formula:

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t$$

Where f_t the forget gate determines the retention of the previous cell state c_{t-1}, i_ts the input gate controlling the integration of new information, and $\tilde{c}_t$represents the candidate cell state.

Output Gate *(o_t)*: Determines the final hidden state for each time step:

$$h_t = o_t * tanh\ (c_t)$$

To capture temporal dependencies in soil moisture, sequences of past observations were created. The sequence length, or number of time steps, was treated as a tunable hyperparameter. This setup allows the model to learn both short-term and seasonal dependencies in the data. Using a sliding window approach, each sequence X_t= [X_{t-k}, X_{t-1}] captures historical data up to time t to predict soil moisture at t+1. This approach enhances the model's ability to recognize temporal patterns in soil moisture dynamics.

To optimize model performance, key hyperparameters, such as the number of LSTM units, sequence length, 'activation functions, dropout rate, and learning rate were tuned. Random search was conducted with Keras Tuner, and early stopping with a patience of epochs was applied to prevent overfitting. Batch normalization was also applied to improve generalization. The LSTM model workflow, including data preprocessing, feature engineering, model architecture, and evaluation steps, is summarized in Figure 43.

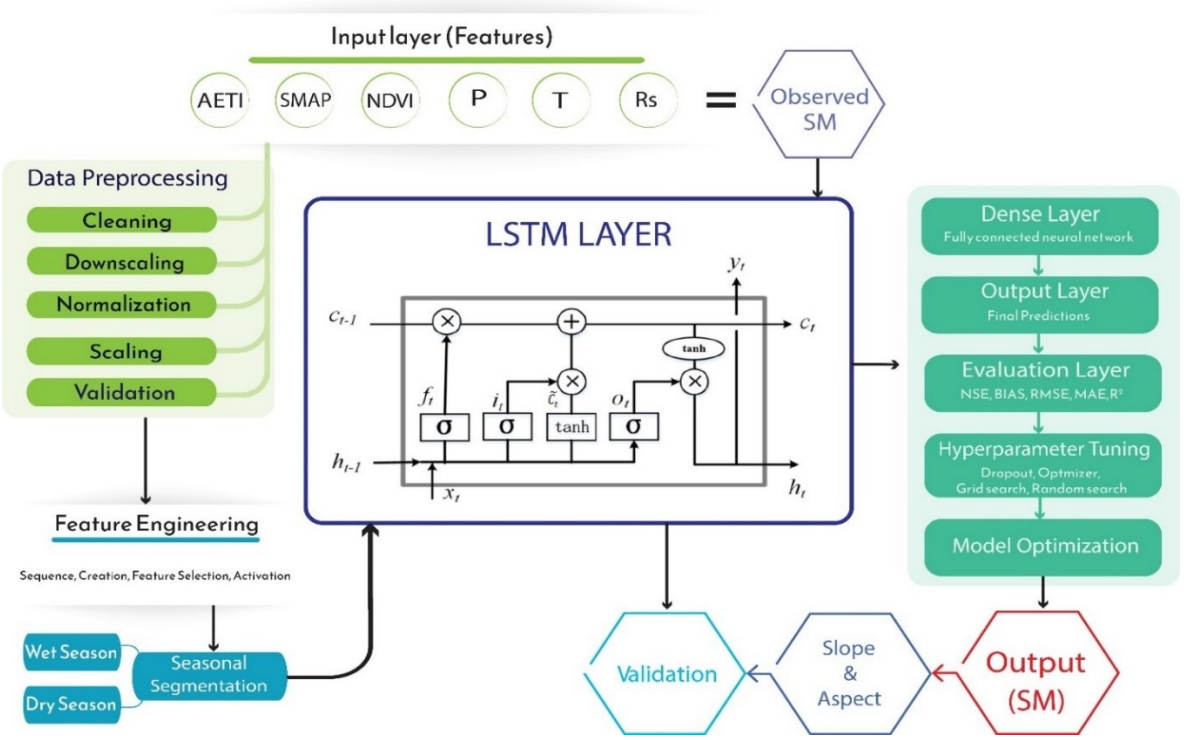

Figure 43. Overview of the soil moisture prediction model using an LSTM neural network. The diagram illustrates the data preprocessing, feature engineering, LSTM architecture, and model evaluation steps, integrating environmental variables for soil moisture estimation.

5.2.4. Model Application and Evaluation

The algorithm was applied for the period 2019-12-10 to 2024-07-31 over a total of 222 sites. 100 of these sites have stone bunds while 122 do not. Temporal evaluation was done by comparing the daily time series of predicted soil moisture across both treated and untreated sites while spatial analysis was conducted using seasonal soil moisture totals. A paired t-test was applied to evaluate whether the differences in soil moisture retention between these two groups are statistically significant. The trained LSTM model was saved in HDF5 format (Soil_moisture1_lstm_model.h5) for reuse, providing a ready-to-use tool for researchers interested in soil moisture prediction across similar objectives.

The model's performance on the test set was evaluated using various metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS). These metrics assess the accuracy and bias of the predictions compared to the observed soil moisture values, providing a comprehensive evaluation of the model's predictive power on daily bases.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\hat{\theta}_i - \theta_i}{\theta_i}\right] \text{ x } 100\%$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left[\hat{\theta}_i - \theta_i\right]$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{\theta}_i - \theta_i)^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\theta_i - \hat{\theta_i})^2}{\sum_{i=1}^{n}(\theta_i - \bar{\theta})^2}$$

Where $\hat{\theta_i}$ is the predicted soil moisture value; θ_i is the observed soil moisture value; n is the number of observations and $\bar{\theta_i}$ is the mean of the observed soil moisture values.

5.3. Results

5.3.1. Data Evaluation and Refinement

I. Dataset Selection and Downscaling

The selection and evaluation of soil moisture (SM) datasets showed the SMAP 1 km dataset surpassed all others in accuracy and reliability for SM estimation. This dataset demonstrated superior Nash-Sutcliffe Efficiency (NSE), the least Root Mean Square Error (RMSE), and minimal bias, suggesting that it was the most reliable source for estimating soil moisture. In comparison,, the SMAP 9 km and NASA Power datasets exhibited higher correlation coefficients with the observed data but performed poorly in terms of NSE (with negative values) and had higher biases. Table 15 provides a comprehensive comparison of the SM estimation performance across these datasets.

Table 15. Comparison of soil moisture estimation performance across different datasets

Metrics	SMAP(1km)	SMAP(9km)	NASA Power
Correlation coefficient (r)	0.802	0.901	0.894
Coefficient of Determination (R^2)	0.643	0.812	0.799
Nash-Sutcliffe Efficiency (NSE)	0.588	-4.396	-4.093
Root Mean Square Error (RMSE)	0.056	0.202	0.197
Mean Absolute Error (MAE)	0.036	0.121	0.116
Bias	0.002	0.12	0.115
Mean	0.127	0.245	0.24
Median	0.091	0.12	0.12
Standard Deviation (σ)	0.090	0.237	0.233

After selecting the most reliable dataset, downscaling was performed using the Random Forest (RF) model on NDVI, SMAP, and AETI data. The downscaling produced excellent results, with R^2 values of 0.91 for NDVI, 0.99 for SMAP, and 0.89 for AETI. The low RMSE and MAE values (SMAP: 0.013, NDVI: 0.05, AETI: RMSE: 0.20, MAE: 0.141) confirmed that daily values were accurately reproduced, highlighting the effectiveness of the downscaling process.

II. Predictor Matrix and its Importance for Soil Moisture Estimation

SMAP, NDVI, AETI, and the measured soil moisture (SM) were found to be strongly correlated, as shown in Figure 44. The correlation coefficients for SMAP, NDVI, and AETI were 0.85, 0.86, and 0.65, respectively, indicating their critical function in estimating soil moisture. In contrast to temperature (T) and solar radiation (Rs), which had negative correlations with SM (-0.56 and -0.21, respectively), precipitation had a somewhat positive correlation with SM (0.34). These associations highlight the significance of incorporating important variables such as SMAP, NDVI, and AETI into SM models, as well as taking into account how T, P, and Rs affect SM dynamics.

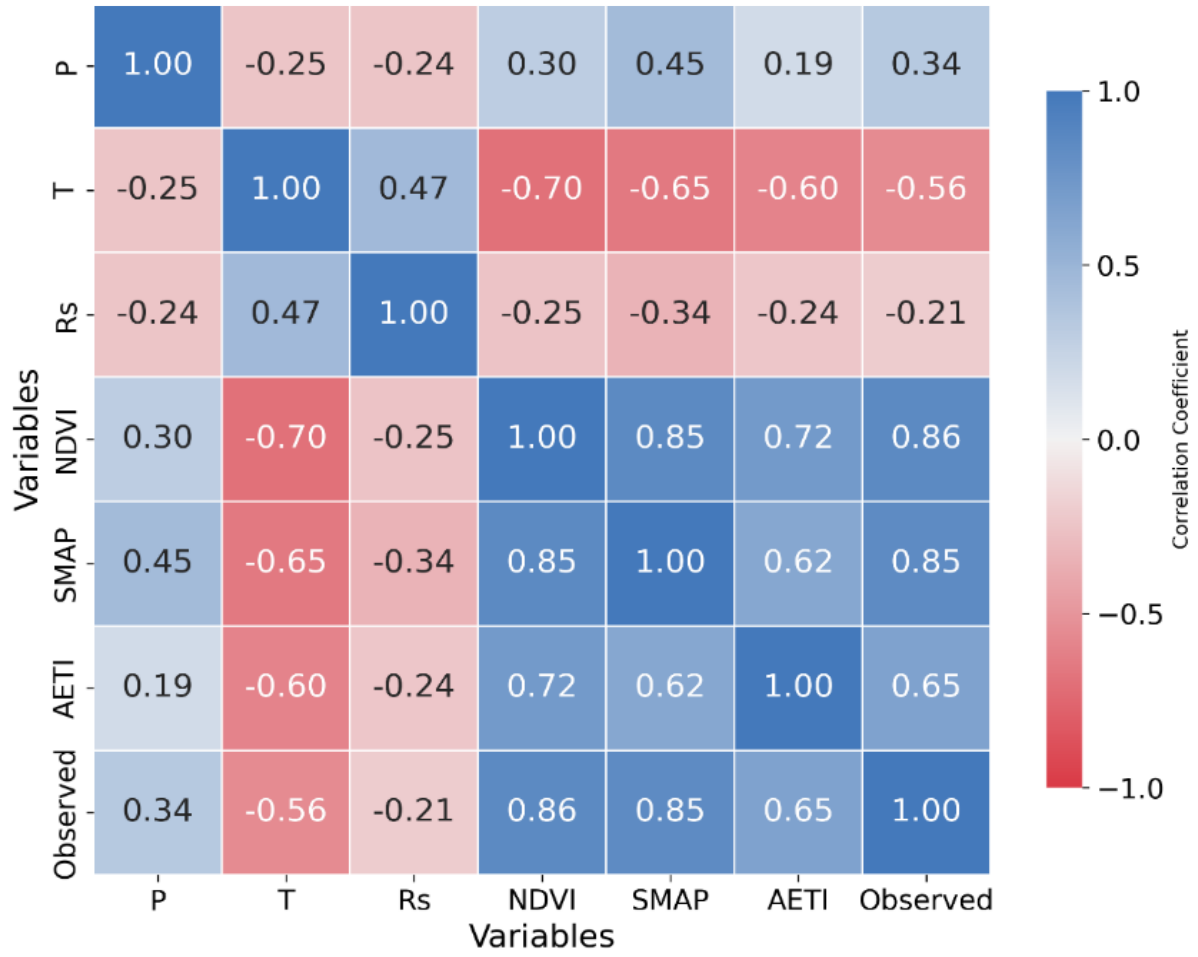

Figure 44. Correlation matrix showing the relationships between key meteorological and RS variables (P, T, Rs, NDVI, SMAP, and AETI) to the observed soil moisture. The color gradient reflects the correlation strength, where red represents negative (minimum of -1) and blue represents positive (maximum of +1).

5.3.2. Evaluation of Soil Moisture Prediction Model

I. Model Performance Evaluation

The performance of the predictive SM model was evaluated using metrics such as RMSE, MAE, MAPE, R^2, NSE, and bias. The model achieved a MAPE of 33.53%, indicating enhanced precision, with an RMSE of 0.093 and MAE of 0.066, reflecting minimal errors. Its high R^2 value of 0.854 and positive NSE demonstrate its strong ability to capture SM variability, while a near-zero bias of -0.007 indicates negligible systematic error, affirming its dependability for fine-scale measurements. Compared to SMAP data, the model consistently outperformed across all metrics. It reduced RMSE by 33.43% (0.093 vs. 0.141), MAE by 33.63%, and bias by 86.07% (-0.007 vs. -0.052). The model's R^2 (0.854) was significantly higher than SMAP's (0.672), and it achieved a positive NSE, unlike SMAP. Scatter plots comparing observed SM with model predictions showed the model closely aligned with the 1:1 line, indicating accurate estimates (Figure 45). In contrast, SMAP data exhibited greater dispersion and higher variability, underscoring the model's superior performance in capturing SM dynamics. Feature significance analysis revealed that AETI and NDVI had the greatest influence on SM predictions, with MSE increases of 0.0286 and 0.0274 during feature permutation. SMAP

contributed less (0.0023 MSE gain) due to its coarser resolution, while meteorological variables like T, Rs, and P had smaller impacts, with MSE increases ranging from 0.0015 to 0.0044.

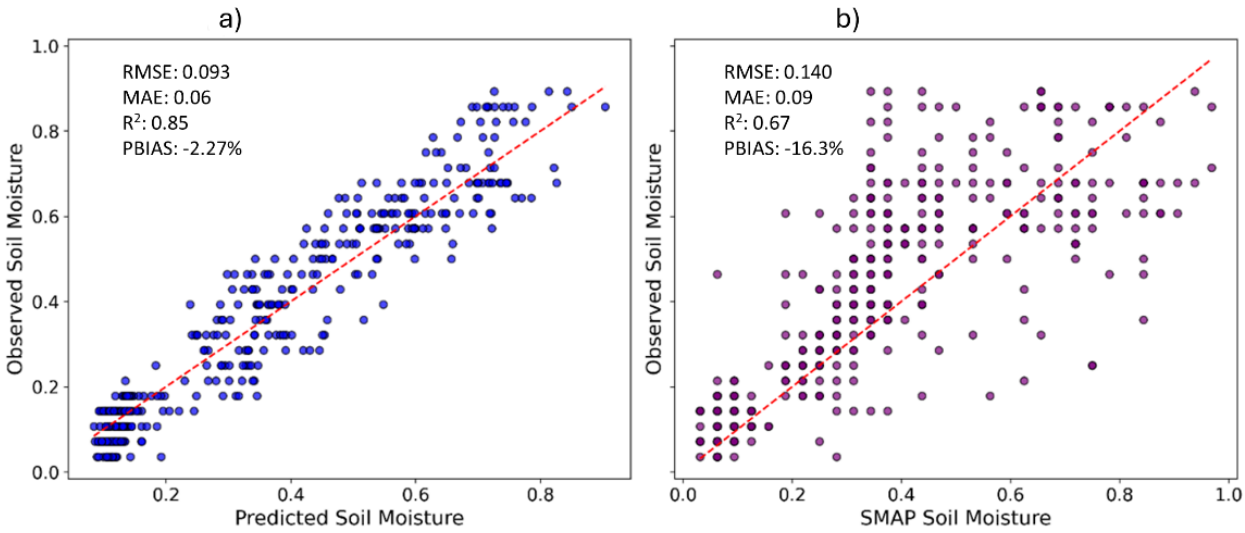

Figure 45.(a) Comparison between observed soil moisture and model predictions, and (b) comparison between observed soil moisture and SMAP data. The dashed red line in both plots represents the 1:1 line.

II. Spatiotemporal Evaluation of Model Performance

The predictive SM model consistently outperformed SMAP in forecasting SM across all seasons, demonstrating superior accuracy and reliability. The model demonstrated an improvement of almost 28% in R^2 during the dry season, with RMSE and MAE error reductions of 41% and 40%, respectively (Table 16). The model outperformed SMAP during the wet season, improving R^2 by nearly 107% and reducing RMSE and MAE by 31% and 30%, respectively. The model demonstrated a 27% increase in R^2 during the course of the season, as well as 33% and 28% decreases in RMSE and MAE, respectively. The model closely matches observed soil moisture, with minor discrepancies (0% to 3.5%) and aligned standard deviations, indicating strong accuracy.

Table 16. Comparison of Model Performance with SMAP in Predicting SM across Seasons (Test Set)

Metric	**Dry Season**		**Wet Season**		**Whole Season**	
	Predicted	SMAP	Predicted	SMAP	Predicted	SMAP
R^2	0.898	0.701	0.681	0.328	0.854	0.672
RMSE	0.054	0.092	0.127	0.185	0.094	0.141
MAE	0.041	0.068	0.097	0.139	0.066	0.092
Mean	0.185	0.134	0.467	0.431	0.31	0.266
SD	0.154	0.158	0.186	0.221	0.22	0.239

Temporal dynamics of SM from January 2023 to July 2024 (Figure 46) further illustrated the model's superior performance. The model effectively captured daily and seasonal variations, accurately reflecting wet season peaks and dry season troughs. In contrast, SMAP data smoothed transitions, underestimating peak moisture levels in the wet season and failing to capture abrupt changes during the dry season. The model demonstrated a robust ability to reflect fine-scale temporal variability in SM dynamics, outperforming SMAP in all evaluated metrics.

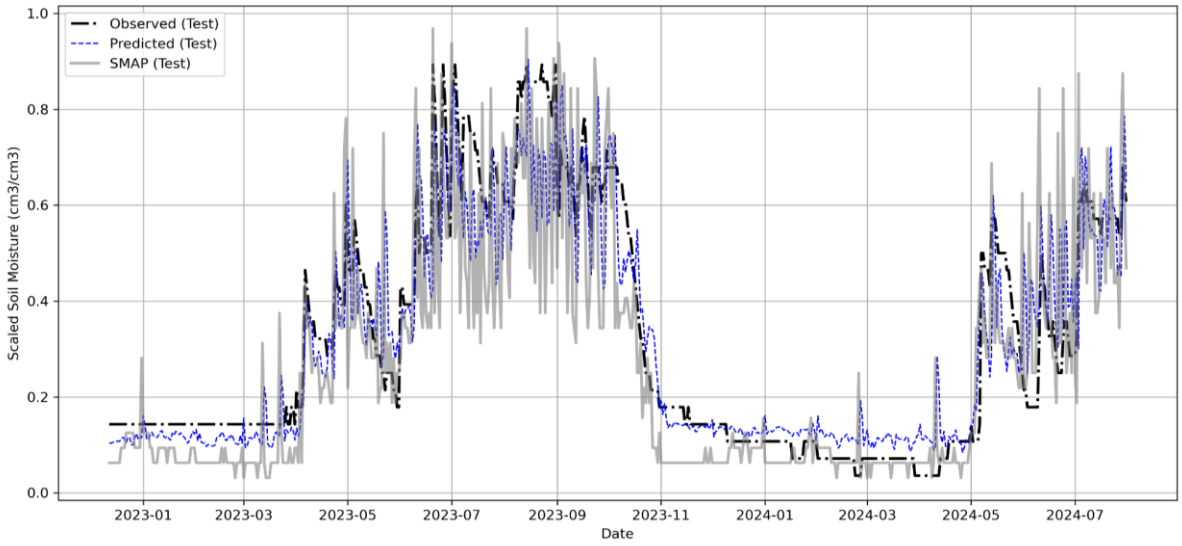

Figure 46. Daily temporal dynamics of observed, predicted, and SMAP-derived soil moisture over the period from January 2023 to July 2024.

The model-predicted spatial distribution of SM between 2020 and 2023 exhibited significant variability, highlighting clear patterns across the study area (Figure 47). While SMAP data predominantly recorded SM levels within a narrow range of 0.21–0.25 cm^3/cm^3, indicating moderate conditions, the model predictions revealed a broader range, from ≤0.20 to ≥0.31 cm^3/cm^3. This demonstrated the model's superior ability to capture localized variations in soil moisture. For instance, in 2020, the model provided a distinct differentiation between regions with low and high soil moisture, particularly in topographically sensitive areas with steep slopes and higher altitudes. These regions, primarily located in the center and northern parts of the study area, displayed enhanced SM retention. In contrast, SMAP data showed a more uniform distribution, limiting its ability to identify such variations. Similar trends were observed in 2021, 2022, and 2023, where the model consistently outperformed SMAP in capturing localized moisture patterns, offering improved resolution and insight into the spatial dynamics of SM across diverse landscapes.

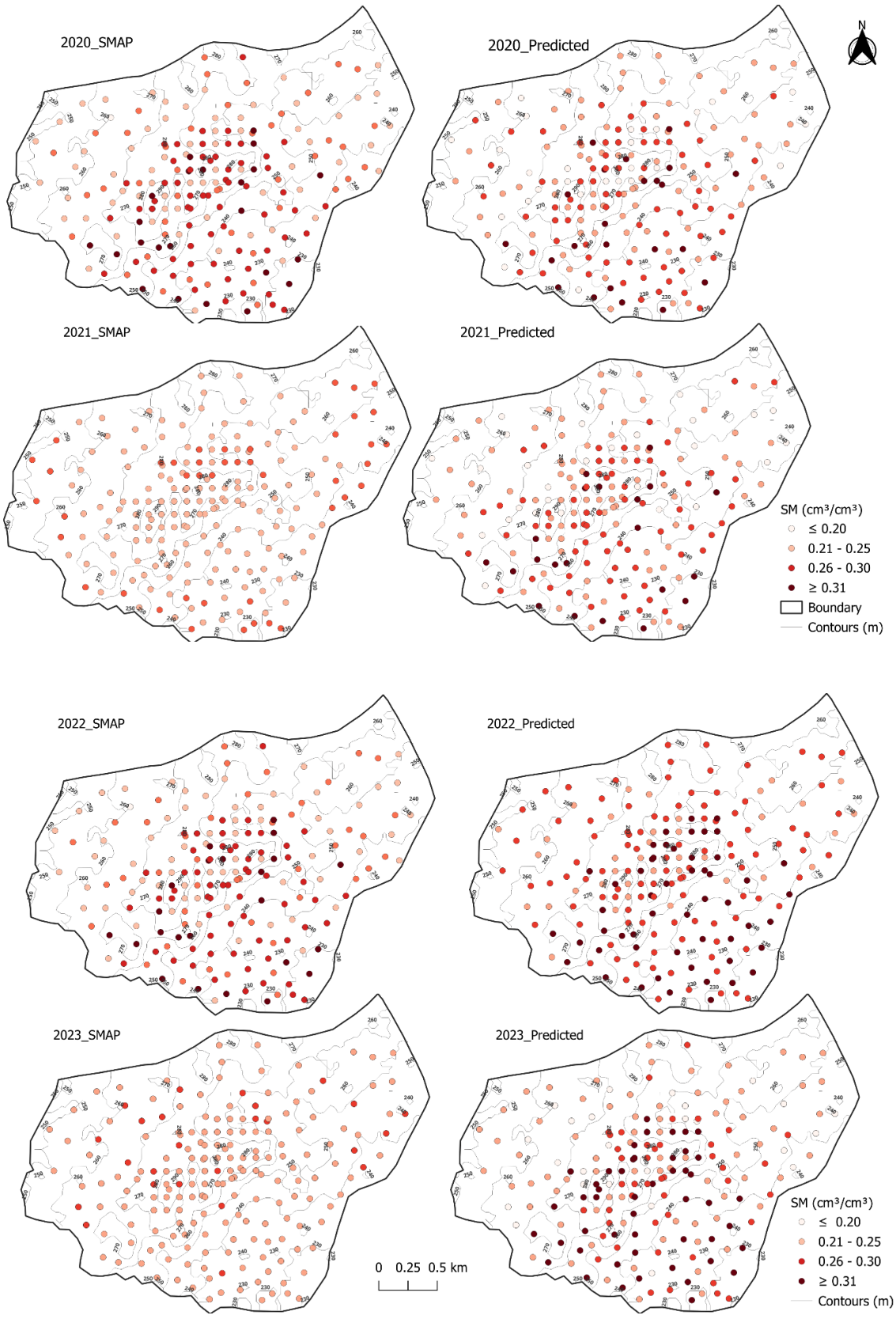

Figure 47. Spatial Distribution of Predicted soil moisture and SMAP Satellite-Derived soil moisture for 2020 to 2023.

5.3.3. Model Performance in Capturing Soil Moisture Variability

The daily average SM dynamics and precipitation Patterns are shown in Figure 48. From 2019 to 2024, statistical analysis consistently demonstrated significant differences in SM levels between areas with stone bunds (S) and those without (N). SM was consistently higher in regions with stone bunds, supported by t-statistics ranging from -2.367 to -3.227 and p-values between 0.0024 and 0.0026, all below the 0.05 threshold of significance. For example, in 2019, the average SM was 0.188 in non-stone bund areas and 0.197 in stone bund areas, with a t-statistic of -3.199 and a p-value of 0.0026 indicating a significant difference. Similarly, in 2020, average SM was 0.224 in non-stone bund areas and 0.237 in stone bund areas, with a t-statistic of -3.045 and a p-value of 0.0024. This trend persisted across the years, with SM consistently higher in stone bund areas. The percentage increase in SM due to stone bunds ranged from 4.09% to 6.0% across 222 sites. Seasonally, regions with stone bunds exhibited a 5.3% increase in SM during the wet season and a 4.0% increase in the dry season, emphasizing their role in enhancing SM retention throughout the year.

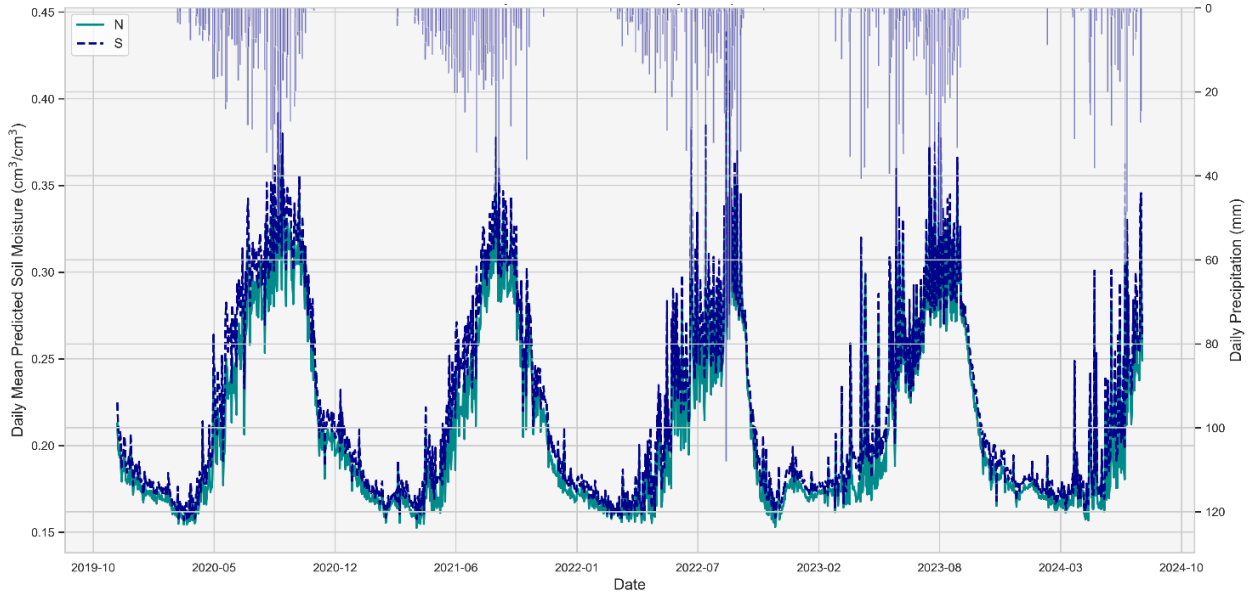

Figure 48. Daily average SM Dynamics and precipitation Patterns: Comparison Between Sites With (S) and Without Stone Bunds (N)

Figure 49 illustrates the spatial annual SM distribution at sites with and without stone bunds from 2020 to 2023. The model's predicted SM levels are clearly depicted in these maps, showcasing the significant differences in moisture retention between the two land management techniques. In Figure 49a, darker tones represent higher moisture content, which is typically observed at sites with stone bunds (S). This pattern is particularly noticeable during wetter years. The data indicates consistent increases in SM levels across all years, with total mean changes ranging from 7.55% to 11.28% at all sites. At the same time, the maximum SM levels at stone bund sites improved by 5.43% to 10.66%, while the minimum SM levels showed percentage increases from 4.35% to 9.68%.

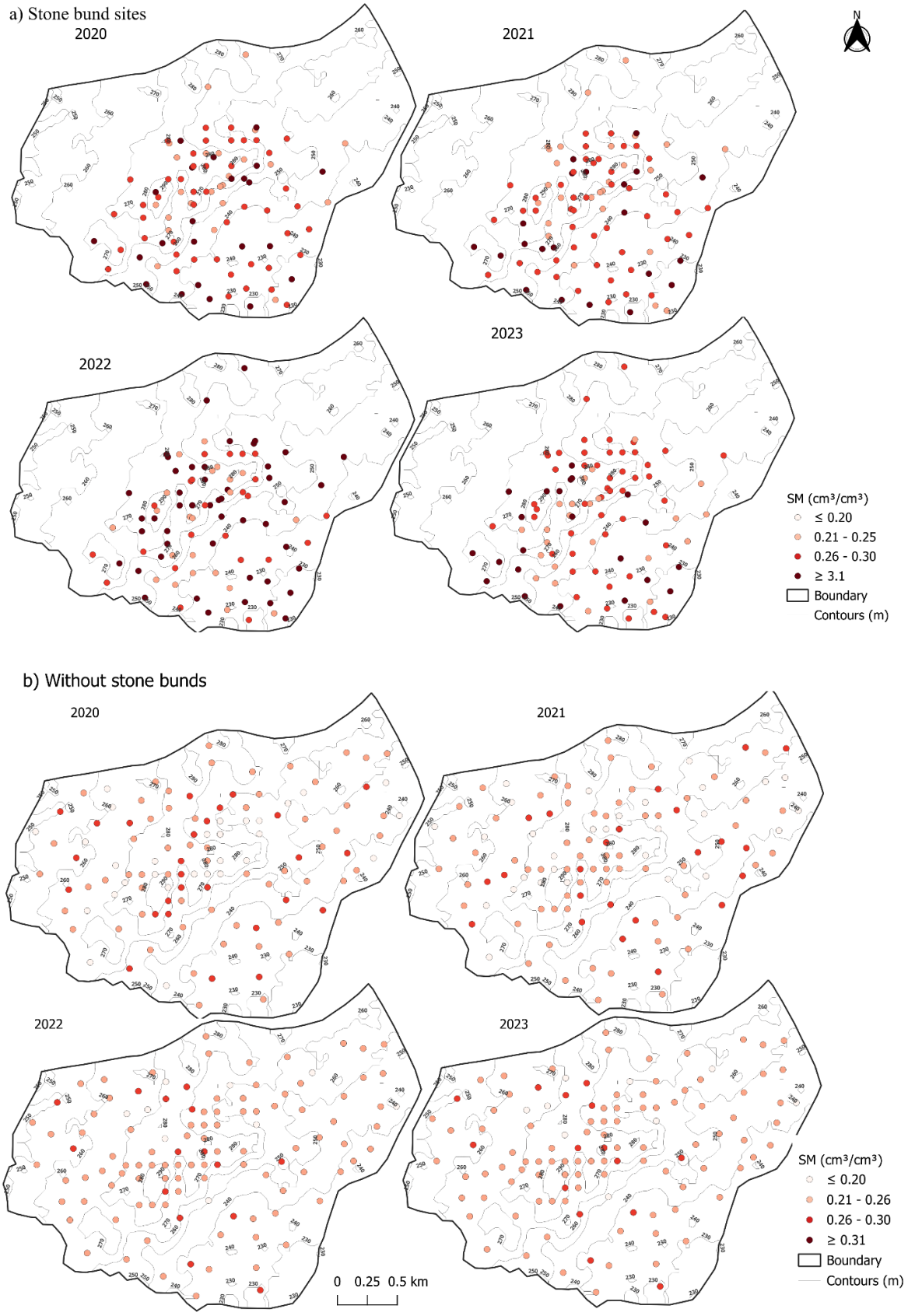

Figure 49. Spatial annual soil moisture in sites with (a) and without (b) stone bunds (2020-2023).

5.3.4. The Relationship between Predicted Soil Moisture and Topographic Variables

The normalized SM in stone bund and non-stone bund sites over various slope and TWI categories are displayed in the box plots in Figure 50. Particularly in the Mild and Steep slope categories, where notable variations are observed, stone bund areas continuously show greater moisture retention in the slope comparison. Stone Bund regions retain higher moisture across all TWI classes but more in Low, and Moderate according to the TWI comparison. In every category, the data showed a considerable difference between the two groups. In the comparison of slopes, there was a highly significant difference in the "Mild" class (p-value = $2.37e^{-12}$), a moderately significant difference in the "Moderate" class (p-value = 0.033), and an extremely significant difference in the "Steep" class (p-value = 0.00088). Likewise, in the TWI comparison, all three classes ("Low," "Moderate," and "High") showed notable disparities, with the "Low" (p-value = $2.43e^{-06}$) and "Moderate" (p-value = $9.01e^{-11}$) TWI classes showing the biggest differences. The highest moisture values are typically seen in places with Moderate TWI, indicating their exceptional capacity for moisture retention. These findings further support the beneficial role of stone bunds in enhancing SM retention across various topographic conditions.

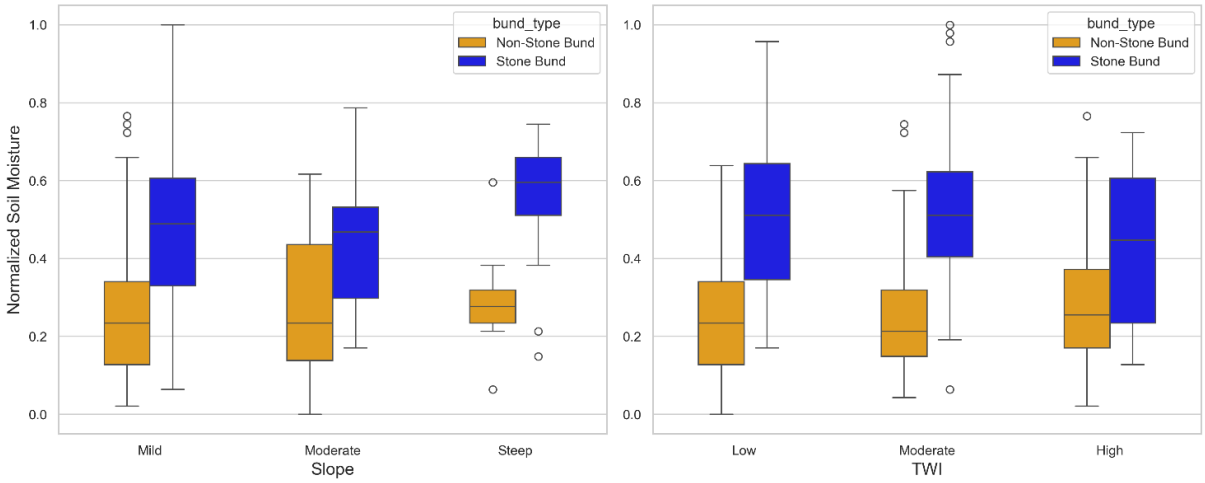

Figure 50. Relationship between predicted soil moisture and the topographic variables (slope and TWI) for stone bund and without stone bunds sites

5.4. Discussion

The results of this study emphasize the value of integrating higher-resolution remote sensing (RS) data, in-situ data, and advanced machine learning (ML), in improving soil moisture (SM) predictions in semi-arid regions. By combining robust evaluation metrics with spatial and time-series analyses, the predictive model offers a more reliable representation of SM dynamics than the SMAP dataset. This evaluation underscores the importance of spatial resolution and in-situ data integration for capturing fine-scale SM variability in heterogeneous landscapes. Notably, SMAP data at a 1 km resolution outperformed both SMAP at 9 km and NASA POWER datasets in terms of accuracy, error metrics, and consistency, reaffirming the critical demand for high-resolution data in SM monitoring (Schneider et al., 2013). Additionally, the integration of in-situ data with remote sensing variables, such as NDVI, SMAP, and AETI, using Random Forest (RF) modeling, demonstrated significant potential for generating reliable daily estimates in data-limited regions (Zhang et al., 2024). This approach aligns with recent studies that emphasize the importance of combining satellite-derived data with localized ground-truth information to enhance both spatiotemporal resolution, thereby improving SM predictions

in data-scarce environments (Guan et al., 2023; Khaki et al., 2020; Peng et al., 2017; Tahmouresi et al., 2024; Vergopolan et al., 2022).

The integration of multiple predictors, including AETI, NDVI, temperature (T), precipitation (P), and solar radiation (Rs), enhances the SM prediction model's effectiveness in capturing the complex interactions influencing SM dynamics. Among these, remotely sensed AETI plays a vital role in SM estimation by reflecting evapotranspiration, directly linking SM with vegetation and atmospheric conditions (Awada et al., 2024). This is especially vital in semi-arid agricultural regions, where evapotranspiration is an integral part of the water cycle. Similarly, NDVI, which represents vegetation health and cover, provides key insights into moisture uptake and demonstrates a strong correlation with SM variability (Awada et al., 2022). The sensitivity of the model to AETI and NDVI highlights their role as primary drivers of SM dynamics. Including T, P, and Rs further refines the model by accounting for additional hydrological processes that influence SM variability, such as precipitation events and solar-induced evaporation (Piedallu et al., 2019; Wang et al., 2023).

The resolution differences among datasets significantly influence model performance. While SMAP at 1 km resolution effectively captures broader spatial patterns, higher-resolution datasets such as AETI and NDVI provide finer details that better represent localized variations, enhancing the model's ability to account for spatial heterogeneity. AETI, despite its lower spatial resolution compared to NDVI, plays a critical role in SM estimation by representing evapotranspiration, a key process linking SM with vegetation dynamics and atmospheric conditions (Awada et al., 2024; Peng et al., 2021). The inclusion of in-situ data as the target variable ensures that the model's predictions are not only spatially accurate but also temporally reliable, thereby strengthening its applicability in agro-hydrological studies. These findings align with recent research that underscores the importance of integrating multi-source predictors with high-resolution in-situ observations to achieve robust and reliable SM estimations (Lopez et al., 2023; Musuuza et al., 2023; O et al., 2021).

The evaluation metrics used to assess the SM prediction model, such as RMSE, R^2, MAE, NSE, and Bias, offer a comprehensive view of its performance. Low RMSE and MAE values indicate the model's effectiveness in minimizing prediction errors, while high R^2 and positive NSE values highlight its success in capturing the observed SM variability and trends. These findings are consistent with research emphasizing the importance of using multiple metrics to fully assess model performance, as each metric offers insights into different aspects of accuracy and reliability (Datta et al., 2023; Li et al., 2022; Willmott et al., 2011). The near-zero Bias value suggests that the model minimizes systematic errors, confirming its reliability for practical SM applications. The model outperforms SMAP data, particularly in terms of error reduction and stronger correlations with observed values, underscoring the potential of combining high-resolution environmental datasets with ML for more accurate SM estimation (Karamouz et al., 2022; Zhong et al., 2024). By integrating the broad spatial coverage of satellite data with the localized accuracy of in-situ measurements, the model provides high-resolution SM estimates, a significant advancement in SM monitoring. This integration is crucial for overcoming the limitations of satellite data, which often struggles to capture fine-scale heterogeneity, and the challenge of sparse in-situ data for large-scale applications (Peng et al., 2021; Tahmouresi et al., 2024).

When scaling to larger spatial areas, The model's effectiveness to capture SM variability was validated through its strong performance relative to the 1 km SMAP dataset. By incorporating higher-resolution predictors, the model not only improved accuracy but also revealed spatial patterns of SM across broader regions. This capability is particularly significant for assessing land management practices,

such as stone bunds, in conserving SM across diverse landscapes. The functionality of stone bunds in improving SM retention has been widely studied, particularly through in-situ monitoring, where small-scale observations demonstrate their potential for enhancing water retention on steep slopes. However, most studies have focused on these localized settings, and their applicability to larger-scale areas remains limited (Klik et al., 2018; Tefera, et al., 2024; Vancampenhout et al., 2006). However, The model's competence in accurately detect and quantify the impact of stone bunds enhances its application, especially when addressing diverse topographies and scale. This modeling approach offers a more precise and spatially comprehensive assessment of stone bunds' effectiveness, providing valuable insights for sustainable land management and soil conservation practices.

Furthermore, The benefits of stone bunds in improving SM retention varied with varying topographic conditions, with the greatest improvements observed in areas with steep slopes and low to moderate TWI values. In steep slope areas, the stone bunds significantly enhanced SM retention, as these regions typically face higher runoff, and the bunds' water retention capabilities were particularly beneficial in these conditions. The model showed a noticeable improvement in SM retention in these areas, surpassing a 27% increase compared to regions without stone bunds. On the other hand, in moderate slopes and high TWI regions, the presence of stone bunds showed a more moderate improvement, reflecting the fact that the effectiveness of the bunds was slightly less pronounced, though still notable (Raduła et al., 2018). These findings highlight the need for targeted land management strategies where the design and placement of stone bunds are optimized for varying slope gradients (Bayisa et al., 2024; Masha et al., 2023).

The importance of the SM prediction model in areas with data scarcity and fragmented land use, such as in smallholder or rainfed agricultural systems, cannot be overstated. In regions with limited ground-based data, the integration of high-resolution satellite data provides a robust solution for understanding SM dynamics (Tavakol et al., 2021; Wang et al., 2024). Looking ahead, the model's versatility can support water management strategies, offering detailed insights into spatial variability that are essential for optimizing water use. Its ability to detect subtle SM differences across diverse landscapes is especially valuable for assessing interventions like water harvesting and land conservation techniques, crucial for water conservation in fragmented terrains.

5.5. Conclusions

This study demonstrates the advantages of combining detailed remote sensing, in-situ measurements, and machine learning to improve SM predictions in semi-arid regions. By integrating satellite data with ground observations, the research provides a scalable solution for addressing SM variability in fragmented agricultural landscapes. The use of more detailed resolution predictors like AETI and NDVI enhanced SM estimates, capturing critical spatial and temporal variations in heterogeneous environments. The model also highlighted the role of land conservation measures, such as stone bunds, in improving SM retention. These findings underscore the importance of tailored conservation practices for sustainable water use and land management. Future work should focus on incorporating even higher-resolution data and integrating the model into broader water management strategies to support climate resilience and food security in water-scarce regions.

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List of papers published during the PhD (1-11-2021 / 31-09-2024)

Published

i. *Meron Lakew Tefer∗, Alberto Carletti, Laura Alteac, Margherita Rizzu, Quirico Migheli, and Giovanna Seddaiu. (2024) " Land degradation and the upper hand of sustainable agricultural intensification in sub-Saharan Africa - A systematic review", Journal of Agriculture and Rural Development in the Tropics and Subtropics , DOI: 10.17170/KOBRA-202403129757.*

ii. *Meron lakew Tefera∗ , Giovanna Seddaiu and Alberto Carletti. (2024) "Traditional In Situ Water Harvesting Practices and Agricultural Sustainability in sub-Saharan Africa" Sustainability. DOI: 10.3390/su16156427*

iii. *Meron Lakew Tefera, Hassan Awada∗, Mario pirastru, James Mantent Kombiok, Joseph Adjebeng-Danqua6, Ramson Adombilla, Peter Asungre, George Mahama, Alberto Carletti, and Giovanna Seddaiu "Remote Sensing and Field Data Analysis to Assess the Impact of Stone Bunds on Rainfed Agriculture in West Africa" land. DOI: 10.3390/land13101654*

iv. *Meron Lakew Tefera∗, Giovanna Seddaiu, Alberto Carletti1 and Hassan Awada, "Rainfall Variability and Drought in West Africa: Challenges and Implications for Rainfed Agriculture" Theoretical and Applied Climatology. 10.1007/s00704-024-05251-8*

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v. *Tefera, Meron lakew and Zeleke, Ethiopia B. and Pirastru, Mario and Melesse, Assefa M. and Seddaiu, Giovanna and Awada, Hassan, Integrating Remote Sensing, Machine Learning, and In-Situ Data for Enhanced Soil Moisture Prediction in Semi-Arid Regions. Available at SSRN: https://ssrn.com/abstract=5050320 or http://dx.doi.org/10.2139/ssrn.5050320 Abstract accepted for AGU conference and under review to be submitted for publication , International Journal of Applied Earth Observation and Geoinformation*