FACULTY OF HUMANITIES AND SOCIAL SCIENCES
DEPARTMENT OF GEOGRAPHY

West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL)
Doctorate Research Programme in Climate Change and Disaster Risks Management

Ecosystem-Based Adaptation (EbA) Strategies in the Agricultural Sector for Reducing Climate Change Risks in the Savanna Region, Northern-Togo

Thesis Submitted in partial fulfillment of the requirements for the degree of DOCTOR of PHILOSOPHY (Ph.D.) of the University of Lomé (Togo Republic) in Climate Change and Disaster Risks Management

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November 2023

DEDICATION

I dedicate this Ph.D. research work

To

The Living God Almighty, who has seen, guided, and strengthened me throughout my life and through my academic course of study to this level, all glory to him.

To

Rosaline Houngbedji, my late mother, sadly did not live to see the fruits of the seedlings she planted. May the All-Powerful God accept her into His Paradise.

To

My Husband Kokouvi Dodji BATADJAGA who always inspired me to aim higher.

To

My Father Kodjo KISSI, My Sister Esther KISSI

My children: Aaron, Raphael, and Karen

And to all my family

Thank you for supporting me and praying for me during this Ph.D. program.

May the Lord bless you.

ACKNOWLEDGEMENTS

I am truly grateful to the Almighty God for my life, for His guidance, blessings, love, and care, and for giving me wisdom, knowledge, and understanding during this Ph.D. study.

I would like to thank the WASCAL program and the German Federal Ministry for Education and Research (BMBF) which funded this study.

I am indebted to Professor KOKOU Kouami for all the efforts he has made to make this doctoral program possible at the University of Lomé, of which I am one of the beneficiaries.

My heartfelt gratitude goes to the management and staff of the Climate Change and Disaster Risk Management (CCDRM) program, especially Professor AGBOKA Komi (Director, WASCAL- CCDRM, Lomé), Dr. BEGEDOU Prosper (Deputy director, WASCAL- CCDRM, Lomé), Dr. IDRISSOU (Scientific coordinator, WASCAL- CCDRM, Lomé), Mrs. Sefako SEGBE, Kuevi FOLLY, and Koudjo KPENE, and the University of Lomé, Togo for allowing me to conduct this work in a good environment.

My special thanks go to my supervisor Dr. Abbey Georges for accepting to supervise this thesis despite his tight schedule, for his patience, unceasing and tireless efforts, guidance, and mentorship, for his encouragement, constructive comments, remarks, suggestions, and support during the writing process of this thesis.

I am most grateful to Dr. Grace B. Villamor for the great supervision and her support during this work. Dr. Villamor was always available to help me. She shared with me her experience and knowledge to take me through the understanding of scientific approaches for the quality of this study.

My thanks also go to Professor AMEKUDZI Kofitse Leonard, professor ADJONOU Kossi, and Professor EGBENDEWE Aklesso for their careful reading and all their comments, suggestions, observations, and scientific rigor, which helped to improve the content of this work.

I would like to express my sincere thanks to Dr Somiyabalo PILABINA and Dammintéte LAMBONI who supported me in data collection and for all their constructive suggestions

I acknowledge the support of colleagues of this fourth batch of WASCAL-Togo especially Nadege DOSSOUMOU and for all that have contributed to the achievement of this work.

My gratitude also goes to the Ministry of Agriculture for providing me with the necessary documentation and to all my colleagues of the Ministry of Agriculture especially Labishi Selome DAHAN, Lagno Djiedjom ASSOUGNON, Justine AKAKPO for their assistance and constant encouragement.

I extend my thanks to all my family, and friends, for their diverse support, prayers, and constant encouragement, and to those, I did not mention, please accept my sincere gratitude.

ABSTRACT

The Savanna region of Northern Togo is facing degradation of its main agroecosystems due to the decrease in their ecosystem services exacerbated by the increase frequency and intensity of extreme climatic events, such as droughts and floods which affect farming communities' livelihoods and well-being. From the literature, Ecosystem-based Adaptation (EbA) strategy is seen as an effective strategy and its adoption needs to catch up among farmers. The study aims to: (i) examine farmer's perception of climate change risks in the agroecosystems, (ii) analyze the effectiveness and co-benefits of existing EbA strategies adopted by farmers and (iii) assess the key drivers in farmers' planning decision to sustain their livelihood in the context of climate change. Climate data (rainfall and temperature from 1961-2021) from Togo Meteorological service, and primary data through participatory workshops, focus group discussions and household survey (425 farmers) were collected to achieve the objectives of the study. Three-stage analysis were conducted in this regard. Firstly, the rainfall anomaly index, and a standardized climate change risk perception index (SCCRPI) were used to analyze climate variability and assess climate change risk perception. Secondly an EbA framework was used to assess the effectiveness and co-benefits of common practices used by farmers in the study area. Three dimensions comprised such EbA framework which are: (i) provision of ecosystem services, (ii)improvement of adaptation benefits, and (iii) improvement of livelihood and food security. Weighted average index was computed to assess farmers' perception of the three dimensions of EbA practices and key drivers of their assessment using a multiple regression analysis. The third stage of the analysis used the theory of Planned Behavior which aims to examine the decision-making process leading to the adoption of EbA practices by farmers. A structural equation modeling (SEM) and discriminant analysis were applied to model farmers' adoption behavior and decisions. The results showed that climate conditions in the study area, such as increased frequency and the span of dry spells, and erratic rainfall when coupled with socioeconomic and ecological drivers, increase climate impacts on target agroecosystems in the study area. From the various practices surveyed, five practices (agroforestry, crop rotation, grass hedge/stone bunds, in-filed water drainage channel, and intercropping) strike out as most effective in improving agroecosystem resilience, enhancing adaptation benefits, and increasing livelihood and food security. The study also showed that farmers' planning decision to adopt any number of EbA practices is significantly dependent on their perception of control over the use and the benefits drawn from such EbA practices, as well as their vulnerability and exposure to climate hazards. Therefore, those factors were seen to improve farmers' adoption decision of EbA practices.

Keywords: Climate Change Risks; Agroecosystems, Farmers, Ecosystem-based Adaptation (EbA), Savanna region

RESUME

La région des Savanes du Togo est confrontée à la dégradation des agroécosystèmes et de leurs services en raison de l'augmentation de la fréquence et de l'intensité des événements extrêmes, tels que les sécheresses et inondations, qui affectent les moyens de subsistance et le bien-être des agriculteurs. La stratégie d'adaptation fondée sur les écosystèmes (AfE) est une stratégie efficace pour faire face aux impacts du changement climatique et garantir les services écosystémiques. Cependant, l'adoption doit être rattrapée par les agriculteurs dans de nombreuses parties du monde, en particulier dans la région des Savanes. Cette étude a permis de faire l'analyse des indicateurs de la variabilité climatique, des facteurs de risque climatique, la perception du risque climatique par les agriculteurs, l'identification des principales pratiques d'adaptation basées sur les écosystèmes mises en œuvre par les communautés agricoles, l'évaluation de l'efficacité perçue et les co-bénéfices par les agriculteurs et la modélisation des décisions d'adoption des pratiques d'AfE par les agriculteurs. Des données climatiques observées – précipitations et températures de 1961 à 2021, des données d'enquête auprès de 425 ménages agricole ont été utilisés pour atteindre les objectifs de cette étude. L'indice d'anomalie pluviométrique, un indice standardisé de perception des risques liés au changement climatique (SCCRPI), l'analyse en composantes principales et l'analyse en grappes K-means ont été utilisés pour analyser la variabilité climatique, les facteurs de risques liés au changement climatique et le niveau de perception des risques liés au changement climatique par les agriculteurs. L'étude a utilisé un cadre de pratiques d'adaptation basées sur l'écosystème pour évaluer l'efficacité et les co-bénéfices pour l'adaptation au changement climatique. L'indice moyen pondéré, l'indice d'importance relative, l'analyse des correspondances et l'analyse de régression multiple ont été utilisés pour analyser l'évaluation par les agriculteurs des pratiques d'EbA et des facteurs influents. L'étude a également appliqué le cadre de la théorie du comportement planifié (Theory of planned behavior), ainsi que la modélisation par équation structurelle et l'analyse discriminante pour modéliser les décisions d'adoption des pratiques d'AfE par les agriculteurs. Les résultats ont montré que les conditions climatiques dans la zone d'étude, avec l'augmentation des périodes de sécheresse, des précipitations irrégulières et des précipitations extrêmes, lorsqu'elles sont associées à des facteurs de vulnérabilité socio-écologique, augmentent les impacts sur les agroécosystèmes et la production agricole, et contribuent aux risques climatiques sur l'agroécosystème dans la zone d'étude. Cinq pratiques (agroforesterie, rotation des cultures, haies d'herbes/cordon pierreux, canaux de drainage de l'eau, et cultures intercalaires) ont été principalement mises en œuvre par les agriculteurs ; celles-ci sont perçues comme efficaces pour améliorer la résilience des divers agroécosystèmes, renforcer les avantages de l'adaptation et améliorer les stratégies de subsistance. Les résultats ont également montré que la décision des agriculteurs d'adopter peu ou plus de pratiques d'adaptation fondées sur les écosystèmes est statistiquement significative basée sur leur perception du contrôle qu'ils ont sur l'utilisation des pratiques AfE, leur intention d'adopter les pratiques, leur perception des avantages liés aux pratiques AfE, la perception de leur vulnérabilité et de leur exposition aux aléas climatiques. Par conséquent, l'étude recommande la prise en compte des facteurs socio-psychologiques et cognitives pour améliorer l'adoption des pratiques AfE par les agriculteurs. Ces pratiques pourraient permettre d'améliorer la productivité agricole et les moyens de subsistance des agriculteurs.

Mots-clés : Risques climatique, Agroécosystèmes, Agriculteurs, Adaptation fondée sur les écosystèmes (AfE), Région des Savanes.

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LIST OF ABBREVIATIONS

ARCAB:	Action Research for Community Adaptation in Bangladesh
ATT:	Attitude
BI:	Behavioral Intention
BEH:	Behavior
CAADP	Comprehensive Africa Agricultural Development Program
CBA:	Community-based Adaptation
CBD	Convention on Biological Diversity
CBNRM:	Community-based natural resource management
CC:	Climate Change
CCKP	Climate Change Knowledge Portal
CCRN	Community Conservation Research Network
CCRPI:	Climate Change Risk Perception Index
CCRPS:	Climate Change Risk Perception Score
CFI:	Comparative Fit Index
CMP:	Conservation measures partnership
CSA:	Climate-Smart Agriculture
DEWHA:	Department of Environment, Water, Heritage and the Arts
DGMN:	Direction Générale de la Météorologie Nationale
DGSCN:	Direction Générale de la Statistique et de la Comptabilité
DIT	Diffusion Innovations Theory
EBA	Ecosystem-based Adaptation
ES:	Ecosystem Services
FAO	Organisation pour l'alimentation et l'agriculture
FC:	Facilitating Conditions
FEBA	Friends of Ecosystem-based Adaptation (FEBA)
FGD:	Focus group discussions
GDP:	Gross domestic product
GHG:	Greenhouse Gas
IDT:	Innovation Diffusion Theory
IFAD:	International Fund for Agricultural Development
IFI	Incremental Fit Index IMF
INSEED	Institut National de la Statistique et des Etudes ..
INT	Intention
IPBES	Intergovernmental Platform on Biodiversity and Ecosystem
IPCC:	Intergovernmental Panel on Climate Change
ISFM	Integrated Soil Fertility Management
IUCN:	International Union for Conservation of Nature
KCA:	K-mean Cluster Analysis
KMO:	Kaiser-Meyer-Olkin
MAEH:	Ministère de l’Agriculture, de l’Elevage et de l’Hydraulique
MERF:	Ministère de l’Environnement et des Ressources Forestière
NBS:	Nature-based Solutions
NDD:	Number of dry days
NGO:	Non-Governmental Organisation
NRD:	Number of rainy days
ORSTOM:	Office de la Recherche Scientifique et Technique Outre-Mer
PAM :	Programme Alimentaire Mondial
PBC :	Perceived Behavioral Control

PCA:	Principal Component Analysis
PEU:	Perceived Ease of Use
PCIT:	Perceived Characteristics of Innovating Theory
PU:	Perceived usefulness
RAI:	Rainfall Anomaly Index
RII:	Relative Importance Index
SE:	Self-Efficacy
SES:	Social-Ecological System
SEM:	Structural Equation Modelling
SLM:	Sustainable Land Management
SN:	Subjective Norms
SRMR:	Standardized Root Mean Square Residual
RMSEA:	Root Mean Square Error of Approximation
TAM:	Technology Acceptance Model
TFR:	Total Fertility Rate
TLI:	Turcker-lewis Index.
TPB:	Theory of Planned Behavior
TRA:	The theory of Reasoned Action
UNCCD:	United Nations Convention to Combat Desertification
UNEP	United Nations Environment Program
UNFCCC:	United Nations Framework Convention on Climate Change
UNISDR:	United Nations Office for Disaster Risk Reduction
VIF:	Variance Inflation Factor
WAI:	Weighted Average Index

CHAPTER 1: GENERAL INTRODUCTION

1.1. Background of the Study

Climate change is one of the major challenges facing the whole world nowadays. All countries around the world are victims of climate-related events particularly developing countries more than ever before with implications for food security, poverty, and ecosystem degradation. The likelihood of those events is increasing as a result of climate change impacting rural communities in developing countries with consequences for loss and damage due to their high dependency on ecosystems, biodiversity, and land-based activities such as agriculture, for their livelihoods and well-being (Zommers et al., 2016; Fedele, 2017). Rural people have adjusted their lives to regular and predictable changes in seasons, rainfall, and other climatic factors. Even a slight difference in climate variables can cause significant disruptions to ecosystems, biodiversity, and people's livelihoods (GIZ and CMP, 2020).

West Africa is one of the world's most vulnerable regions to climate variability and change. Increasing temperatures and shifting rainfall patterns are already affecting agriculture livelihoods, and food security (USAID, 2018). EMDAT and DesInventar database show that disasters in West African countries are dominated by weather-related hazards such as floods, and droughts (Osuteye et al., 2017; CRED, 2019). From 2000 to 2020, 250 climate-related events (floods and drought) occurred in West Africa with huge losses and damages to agriculture productive assets and disruption of agroecosystem functioning (EM-DAT, 2020). High variability in rainfall patterns has led to an increase in the frequency of floods and droughts in West Africa in the last two decades exacerbating the vulnerability of rural communities already under pressure from multiple stresses such as environmental, economic, and social changes, infectious diseases, combined with the lack of sustainable adaptation (Asare-Kyei et al, 2017). It is expected for West Africa that the magnitude of these weather events will rise (Sylla et al, 2015) and their association with non-climate stressors will likely place more strain on populations living in vulnerable areas and those with minimal financial means and economic alternatives (IPCC, 2014).

According to IPCC (2014), an amplification of weather events (floods and droughts) in intertropical regions will have an impact on ecosystems and consequently on human security.

When ecosystems are increasingly degraded or fragmented, they provide fewer resources to sustain livelihoods for people (Fedele, 2017). Thus, the protection and conservation of natural resources are important not only for the health of ecosystems but also for human well-being. The UNFCCC has recognized the role that sustainable management of natural resources can play in building the resilience of socio-economic and ecological systems as part of climate change adaptation strategies. Munang et al., (2013) stated that ecosystems provide services that play a part in responding to climate change, such as risk mitigation of natural hazards (floods, drought); food security, and livelihood diversification. An approach called Ecosystem-based Adaptation (EbA) has recently emerged as a viable alternative to tackle the threats of climate change in the context of a holistic adaptation strategy. EbA's approach is a nature-based solution (NbS) as an overarching concept to address societal challenges based on the idea that safe, and healthy ecosystems are more robust and therefore more adaptable to environmental stress, such as climate change (Munang et al. 2011). EbA's key premise, therefore, includes the conservation, restoration, and sustainable management of ecosystems and biodiversity that provides life-supporting (ecosystem services) systems that people need to survive as well as addressing climate-related risks and building the resilience of both ecosystems and societies through multi-sectoral and multi-level approaches (Lee & Sanderson, 2014, Fedele, 2019).

Several organizations such as the Intergovernmental Panel on Climate Change (IPCC), the Sendai Mechanism for Disaster Risk Management, the United Nations Convention on Biological Diversity; the United Nations Framework Convention on Climate Change (UNFCC, 2015); UN Environment, German cooperation agency (GIZ); Conservation Measures Partnership (CMP), International Institute for Environment and Development (IIED), IUCN, Eurac research, UN-EHS, among others have advocated ecosystem-based solutions to climate change adaptation and disaster risk reduction at the highest levels. Also, to respond to the requirement of the Paris Agreement adopted in 2015, for all Parties to engage in adaptation and mitigation planning and implementation through the country’s Nationally Determined Contribution (NDC), 24 of the NDCs mention EbA explicitly and 109 refer to using ecosystem services as a means for adaptation to climate change (UNFCC, 2015). For example, Togo planned in its Nationally Determined Contribution (NDC) to promote integrated and sustainable management of water resources and to strengthen the resilience of agricultural production systems through practices relying on nature (CPDN-Togo, 2015).

Despite the enormous benefits of taking an EbA approach to Climate risks reduction and the opportunity to accomplish numerous policy priorities, such as resolving simultaneous adaptation and mitigation, promoting socio-economic prosperity, and ensuring environmental security and biodiversity conservation, EbA strategies are not applied broadly, nor reliably to tackle climate change and its associated challenges (Munang et al. 2013, Harvey et al, 2014, Fecede, 2017, Reid et al, 2019). This challenge highlights the need to increase the understanding of how Ecosystem-based Adaptation strategies reduce the vulnerability of both ecosystems and communities to climate-related risks and of what factors influence the implementation of EbA strategies in climate risk reduction or management processes.

1.2. Research Problem

It is widely acknowledged that land is a crucial and valuable resource that plays an important role in generating food, fiber, fuel, and other ecosystem services necessary for human survival, fostering resilience to climate-related risk and contributing to climate change mitigation (Nkonya et al., 2011; Tagore, et al., 2012). However, the land is undergoing considerable degradation nowadays. According to Barrow (1994) in Sivakumar & Stefanski (2007), land degradation involves two interconnected, complex systems: the natural ecosystem and the human social system. Natural influences, through periodic stresses of extreme and recurrent climatic events, and human use and abuse of sensitive and vulnerable dry land ecosystems through land-use changes, and unsustainable land management negatively people's livelihoods and sustainable development (Stringer and Fleskens, 2014; Olsson et al., 2019).

Land degradation is defined as ''reduction or loss in arid, semi-arid, and dry subhumid areas, of the biological or economic productivity and complexity of rain-fed cropland, irrigated cropland, or range, pasture, forest, and woodlands resulting from land uses or a process or combination of processes, including processes arising from human activities and habitation patterns, such as (i) soil erosion caused by wind and/or water; (ii) deterioration of the physical, chemical, and biological or economic properties of soil; and (iii) long-term loss of natural vegetation'' (UNCCD, 1994). Over 250 million people are directly impacted by land degradation, according to UNCCD. Additionally, over a hundred countries and a billion people are at risk. These people include many of the world's poorest, most marginalized, and politically weak citizens.

Climate change is considered to exacerbate the rate and severity of various ongoing land degradation due to the gradual variation in temperature, precipitation, and wind, changes to evapotranspiration rates and biodiversity, the distribution and intensity of extreme events such as drought and floods, as well as a result of changes to environmental conditions that allow new pests and diseases to thrive (Reed and Stringer 2016). Climate-related land degradation is a common challenge that affects human society and its livelihoods especially rural communities due to their high dependency on land-based activities such as agriculture and forestry, for their livelihoods and well-being (Zommers et al., 2016; Fedele, 2019; Olsson et al., 2019), with consequences such as damage to croplands, reduction of agriculture production and yield, food insecurity and loss of livelihood for farmers, increase in low-income levels (Allen et al. 2001; Karami et al., 2009). Land degradation is prevalent in areas where sustainable land use maintenance is low compared to land use functions and services (Olsson et al., 2019). Climate-related land degradation is expected to have net negative impacts on agricultural productivity in most parts of Africa and alter the regional suitability of various crops, leading to an overall negative impact on long-term food productivity and food security. Estimates show that land degradation is now severe enough to reduce yields on approximately 16% of the agricultural land mainly cropland in Africa (Chinzila, 2017).

In Togo, the analysis of climatic data over the period 1961–2018 reveals unequivocally that temperature is on the rise, with an increase of 0.8 °C to 1.2 °C between the latitudes of the country. On the other hand, precipitation is generally decreasing in all parts of the country, with a territory with a range of decrease of from 15 mm to 98 mm of rainfall. The current climate trend in Togo causes extreme climatic events. These events are among others: floods, droughts, high temperatures, seasonal shifts, violent winds, and poor distribution of rainfall, with huge consequences on ecosystems especially croplands and livelihoods (QCN, 2022). Indeed, the accentuation of the phenomena of dry spells throughout the country and especially in the Savanna region, coupled with the disruption/shifting of seasons, the risk of flooding, and the irregularity of rainfall in a context of continued land degradation, suggests the increased vulnerability of this sector, which is vital for the survival of communities (QCN, 2022).

The Savanna region in Togo is characterized by extreme climatic variability with low and erratic precipitation, water scarcity, frequent droughts, and flood events, and extreme temperatures (Djaman and Ganyo, 2015; Pilo et al., 2021). The climatic conditions of the region have changed over the last few decades, with a decrease in rainfall and, in particular, a shortening of the rainy season and a wider variation of the rainfall. The irregular distribution of rainfall has an impact on crop and pasture yields, as well as water resources (Lare & Lamboni, 2015). In addition, this region is one of the areas in Togo with high susceptibility to land degradation due to the physical characteristics of its soils (low water retention capacity, fragile structure, a tendency to acidification), unsuitable human practices, and the change in climatic conditions. This land degradation includes loss of vegetation, soil erosion, loss of soil organic matter, and loss of biodiversity (Brabant, 1997). The increase in average temperatures causes an increase in evapotranspiration and soil drying, making them more vulnerable to erosion. This erosion process is accelerated by increased rainfall intensity and frequent strong winds. The soils lose their fertility progressively under the effect of water and wind erosion. (Abalo-Esso et al., 2021) . These challenges adversely affect farming, the primary source of livelihood in the area, and result in a decrease in yields, loss of livelihood, increase in low income, and food insecurity within communities (Pilo et al., 2021). According to existing climate scenarios, the magnitude of extreme climatic variability will rise compared to the reference situation (1995) in the Savanna region, especially greatest temperature variations is expected in the prefectures of Tône, Tandjoaré, Kpendjal, and Cinkassé, with consequences that would affect agroecosystems impacting production levels of the main crops by 5% by 2025, 7% by 2050 and 10% by 2100 (QCN, 2022).

Addressing climate change and related land degradation through agrobiodiversity and ecosystem services conservation to improve agricultural land resilience and productivity is crucial in the Savana region. According to FAO (2016), building the food and agriculture sector's resilience to climate change will require a comprehensive nature-focused transformation of the food system. An immediate and direct way to help farmers ensure their farm-based livelihoods in the face of increasing climate change and variability is to focus on helping them use farm management practices based on agrobiodiversity and ecosystem services that provide adaptation benefits (van Noordwijk et al., 2011; Vignola et al., 2015). Numerous studies have demonstrated that sustainable land management and the preservation of ecosystem services can help to lessen people's vulnerability to climate change and help in adaptation (Folke et al. 2010, Andersson et al. 2015). An approach called Ecosystem-based Adaptation (EbA) has recently emerged as a viable alternative to tackle the threats of climate change in the context of a holistic adaptation strategy. There are several definitions for EbA, but officially it is defined by the Convention on Biological Diversity (CBD) as “the use of biodiversity and ecosystem services to help people to adapt to the adverse effects of climate change, as part of an overall adaptation strategy that takes into account the multiple social, economic and cultural co-benefits for local communities” (CBD, 2009). EbA approach is a nature-based solution (NbS), as an overarching concept to address societal challenges based on the idea that safe, and healthy ecosystems are more robust and therefore more adaptable to environmental stress, such as climate change (Munang et al. 2014). EbA includes the conservation, restoration, and sustainable management of ecosystems and biodiversity that provides life-supporting (ecosystem services) systems that people need to survive as well as addressing climate-related risk and building the resilience of both ecosystems and societies through multi-sectoral and multi-level approaches (Fedele, 2019).

Despite the potential of EbA strategies to address social and ecological vulnerability and the impacts of changing climate, much work needs to be done to upscale the implementation of EbA strategies to buffer climate change and its related risks (Munang et al.2014). According to Lee and Sanderson (2014), one of the key obstacles in the implementation of EbA strategies is incorporating the concept into the decision-making process. However, knowledge about the existing EbA practices and farmers' decisions towards the implementation of these practices in addressing climate-related impacts in the study area remains scarce (Azouma, 2002; Munang et al. 2014; Ali, 2018; Dao et al., 2021; Adji et al., 2022). Then, there is a need to comprehend farmers' decision-making processes regarding the implementation of ecosystem-based adaptation strategies to address climate change risks to their agroecosystems. Therefore, the purpose of this study is to examine EbA implementation decisions to address climate risks among farmers in the Savanna region. Thus the following questions are addressed in this study: (i) What are the observed changes in climatic parameters and how do farmers perceive the risks related to these changes on agroecosystems? (ii) How do farmers use and perceive the effectiveness and co-benefits of ecosystem-based adaptation strategies in buffering the impacts of climate change on their agroecosystems? (iii) What factors are associated with decision-making toward implementing EbA strategies to reduce climate change risks on their agroecosystems?

The answers to these questions can help shape the design of ecosystem-based approaches that, along with other technical and policy measures, can lead to more sustainable agriculture and resilience in the face of climate change.

1.3. Research Aim, Objectives and Hypotheses

1.3.1. Research Aim and Objectives

The study's overarching aim was to investigate farmers' implementation of ecosystem-based adaptation strategies on their agricultural land to reduce climate-related risks in the Savanna region of Togo. This aim will be accomplished with the following specific objectives:

1. To explore both observed changes in climatic parameters and the farmers' perceptions about the risks related to these changes;
2. To assess farmers' perception of the effectiveness and co-benefits of existing Ecosystem-based Adaptation (EbA) practices to address climate change risks to agroecosystems;
3. To model farmers' decision-making toward the implementation of Ecosystem-based Adaptation (EbA) strategies to reduce climate change risks on agroecosystems.

1.3.2. Research Hypotheses

The main hypothesis that drives this research is as follows:

Farmers' decisions to implement Ecosystem-based adaptation practices to buffer climate change risks to their agroecosystems are significantly related to their perception of climate change risks, perception of Ecosystem-based Adaptation strategies in reducing vulnerability, and EbA behavioral factors.

The main hypothesis is supported by three secondary hypotheses:

- The study area is experiencing changes in rainfall and temperature patterns which is perceived by farmers to increase extreme events like floods and droughts threatening agricultural land, agricultural production, and food security in the study area.
- Farmers in the study area are implementing EbA practices on their farms and have a good understanding of the benefits and effectiveness of these practices in responding to climate change impacts.
- A combination of cognitive, behavioral, and socioeconomic factors strongly explain farmers' decisions to implement ecosystem-based adaptation practices to reduce the impact of climate change on their agroecosystem.

1.4. Significance of the study

In the Savanna region of Togo, several studies have been carried out on climate change adaptation in the agricultural sector, but little attention has been given to farmers' decision-making toward the adoption of Ecosystem-based Adaptation strategies at the farm level to suggest an effective adaptation approach for building the resilience of agricultural production systems while maintaining farm-based livelihoods in the study area. Thus, the findings of the current study come to fill these gaps. Our research provides new information on the use of Ecosystem-based adaptation practices by farmers in the Savanna region of Togo, as well as important insights into their socio-ecological effectiveness, co-benefits, and the factors underlying farmers' decisions toward their implementation in the context of climate change. Such information provides insights for developing integrated agriculture and climate change policies suitable for weather-induced disaster-prone areas such as the Savanna region. It should serve as new guidelines for ongoing and future comprehensive climate risk management in the agricultural sector in the Savanna region and must be properly absorbed by policymakers.

1.5. Thesis Organization

The thesis is organized into a total of six chapters. **The first chapter which is the current** general introduction of the thesis sets up the research problems and justification concerning the adaptation strategies for addressing climate-related land degradation by preserving agricultural biodiversity and ecosystem services to improve agricultural productivity. This chapter also develops research objectives and hypotheses of the various essays that comprise subsequent chapters of this thesis. The second chapter (Literature Review) presents the review of concepts, theories, methods, and findings of previous works relevant to this thesis as well as the physical and human characteristics of the study area. **Chapter 3** addresses specific objective 1, which focuses on the analysis of the different indicators of climate variability, identifies the key drivers of climate risks, and assesses the level of farmers' perception of climate risks. **Chapter 4** deals with specific objective 2 which seeks to evaluate the effectiveness and co-benefits of Ecosystem-based Adaptation practices adopted by farmers. **Chapter 5** covers specifically objective 3 which aims to model farmers' EbA adoption decisions. Finally, **Chapter 6** proceeds with a general discussion of the research findings, summaries, and relevant recommendations about each specific objective of the study. It also highlights key interpretations that can be applied, adopted, and disseminated to farmers and advisory support institutions in the Savanna region for decision-making on the adoption of ecosystem-based adaptation practices.

CHAPTER 2: LITTERATURE REVIEW

2.1. Concepts and Definitions

2.1.1. Climate Change Risk

Climate Change risk is the likelihood of specific climate-related impacts, which could influence resources, people, ecosystems, culture, etc. The climate risk concept allows for the inclusion of all elements of a socio-ecological system from climate-related hazards to social- and ecosystem-related vulnerability and exposure factors that contribute to risks (GIZ et al., 2018). Then, the risk of climate-related impacts within a social-ecological system results from the interaction of climate-related hazards (including hazardous events and trends) with the vulnerability and exposure of human and natural systems Risk related to climate change impacts results from dynamic interactions between climate-related hazards with the exposure and vulnerability of the affected human or ecological system to the hazards (see figure 2.1).

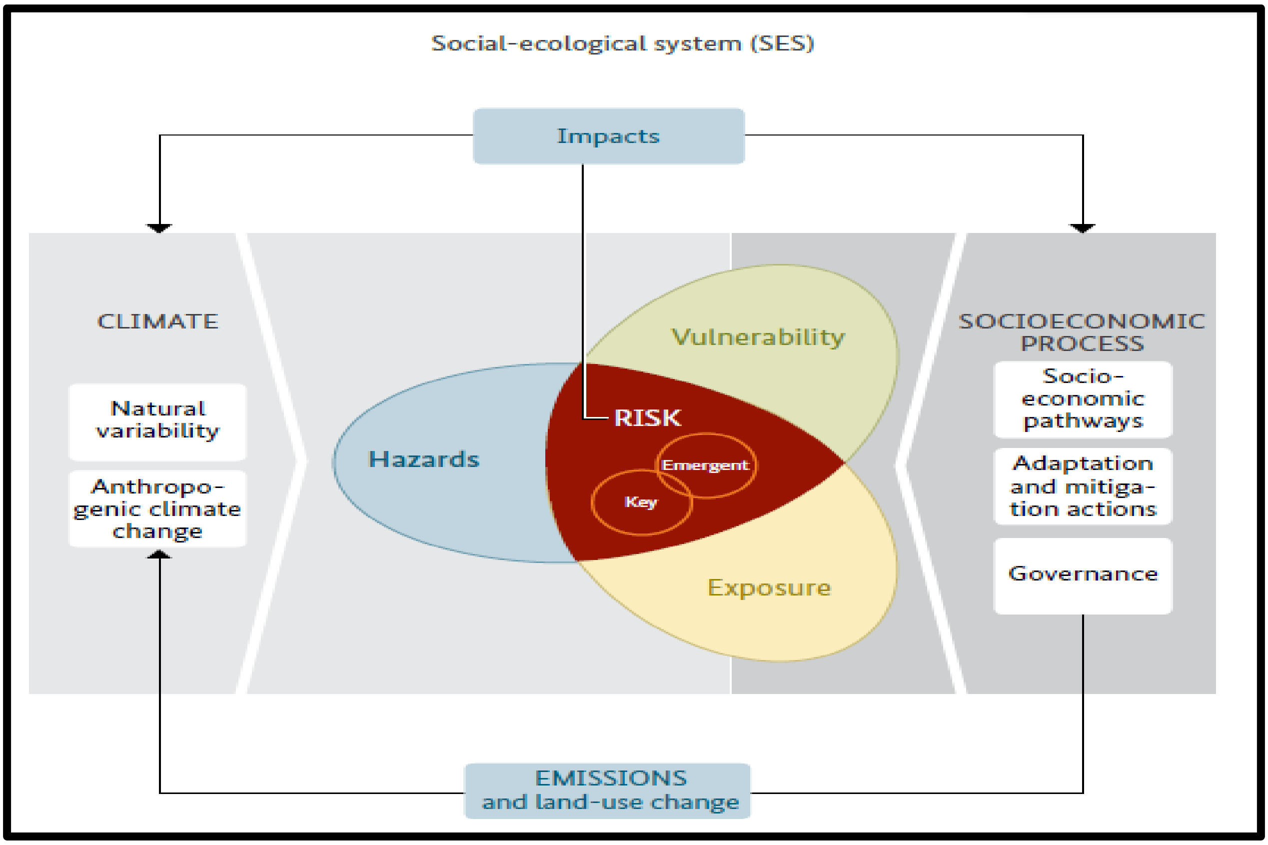

Figure 2.1. Illustration of the core concepts of the IPCC WGII AR5. (Source: IPCC 2014a, p. 1046)

Hazards, exposure, and vulnerability may each be subject to uncertainty in terms of magnitude and likelihood of occurrence, and each may change over time and space due to socioeconomic changes and human decision-making (Reisinger et al., 2020).

The term hazard in the IPCC (2014) report typically refers to physical events, trends, or their physical repercussions. Hazard is defined as the potential occurrence of a physical event, trend, or impact, whether it be caused by nature or by human activity, that could result in fatalities, serious injuries, or other health effects, as well as damage and loss to infrastructure, property, livelihoods, service provision, ecosystems, and environmental resources. According to GIZ et al. (2018), a hazard may be an extreme weather event (e.g. tropical storm, flooding), but can also be a slow onset trend (e.g. increase in average temperature, etc.).

Exposure is defined in IPCC (2014) as the presence of people, livelihoods, species or ecosystems, environmental functions, services, resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected. GIZ et al. (2018), refer to exposure as relevant elements of the socio-ecological system (e.g. people, livelihoods, assets, but also species, ecosystems, etc.) that could be adversely affected by hazards. The degree of exposure can be expressed by absolute numbers, densities, proportions, etc…

Vulnerability is defined as ‘the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt’(IPCC, 2014). The term "vulnerability" refers to characteristics of exposed socio-ecological system elements that have the potential to amplify (or diminish) the effects of a particular climate hazard. It includes both sensitivity and capacity, two important components. Sensitivity is characterized by the elements that have a direct impact on its outcomes. Environmental and physical characteristics of a system, such as the type of soil used in agricultural fields, its ability to retain water to prevent flooding, or the type of material used to construct dwellings, can all be considered sensitive factors as well as social, economic and cultural attributes (e.g. age structure, income structure). Capacity in climate risk assessment describes how well societies and communities can foresee and adapt to the present and future effects of climate change. It focuses on the people's ability to manage ecosystems rather than the capacity of ecosystems to respond to effects GIZ et al. (2018).

The term impacts primarily refers to the effects of extreme weather and climate events, as well as climate change, on natural and human systems. The effects on lives, livelihoods, health, ecosystems, economies, societies, cultures, services, and infrastructure caused by the interaction of climate changes or hazardous climate events occurring within a specific period and the vulnerability of an exposed society or system are generally referred to as impacts (IPCC 2014).

2.1.2. Social-Ecological System (SES)

There are no social systems without nature, according to Petrosillo et al (2015). Because of the interactions and "feedback" between ecological (biophysical) and social (human) subsystems, humans must integrate with nature (CCRN, 2014). This supports the social-ecological system theory, which emphasizes the interconnected definition of the "human-in-nature" perspective and two-way feedback interactions between the natural system (such as ecosystems) and the "human system" (such as communities, society, and the economy) (Berkes and Folke, 1998; Folke, 2006; CCRN, 2014; Petrosillo et al, 2015). The ecological component of the interactions provides crucial services to society and frequently results in feedback that can either amplify or suppress change. These interactions take place across multiple spatial and temporal scales (Levin et al., 2013; Petrosillo et al., 2015, Fischer et al. 2015) (see figure 2.2).

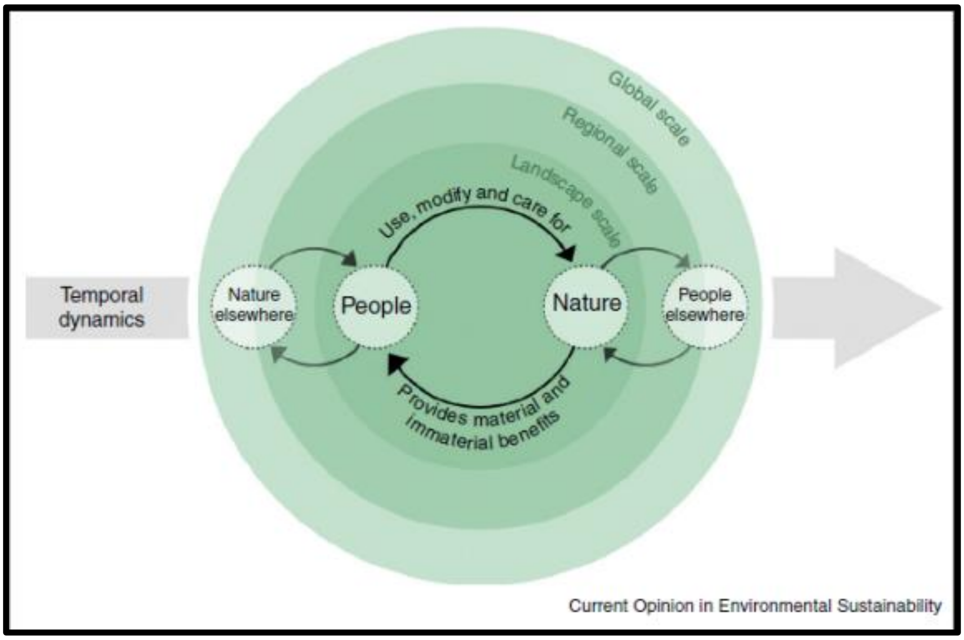

Figure 2.2. Social-ecological systems reciprocal interactions between people and nature, across various spatial and temporal scales. Source: Fischer et al., 2015

The SES has been built on theories of complex and adaptive systems that have originated from different scientific disciplines (Luhmann 1993; Petrosillo et al, 2015). These theories are based on concepts such as adaptive cycles, resilience, adaptability, transformability, and hierarchy (panarchy), and aim to provide a knowledge basis to manage complex adaptive systems and to achieve sustainable development in theory and practice (Petrosillo et al, 2015). Folke (2006) argues that social-ecological system approaches must be used to address the current global environmental challenges, including climate change, environmental degradation, and biodiversity loss.

2.1.3. Ecosystem services

DEWHA, (2009) defined an ecosystem as a living community that consists of populations of plants, animals, microorganisms, and the non-living environment that interact as a functional unit. An ecosystem works by constantly cycling energy and materials through living organisms that grow, reproduce, and die and have the potential to provide a variety of services including provisioning, regulating, cultural, and supporting services critical to human well-being, health, livelihoods, and survival (Costanza et al.,1997; MEA, 2005; DEWHA, 2009). The concept of ecosystem services (ES) was developed in the late 1970s to emphasize society's reliance on the benefits that nature provides to humans (De Groot et al., 2002). Ecosystem services are the benefits provided to humans as a result of resource transformations (or environmental assets such as land, water, vegetation, and atmosphere) into a flow of essential goods and services such as clean air, water, and food (Constanza et al. 1997). According to the Millennium Ecosystem Assessment, ecosystem services are the benefits people receive from ecosystems (MA 2005). Fisher and Turner (2008) expand on this definition, claiming that ecosystem services are aspects of ecosystems that are used (actively or passively) to produce human well-being. According to the Millennium Ecosystem Assessment (2005), ecosystem services fall into the following categories: provisioning services (e.g. food, water, wood, and fiber, fuel); regulating services (e.g. climate regulation, flood regulation, water purification); supporting services (e.g. nutrient cycling; soil formation, primary production, habitat provision); cultural services (e.g. spiritual, recreational, aesthetic, educational and cultural benefits) (Figure 2.3).

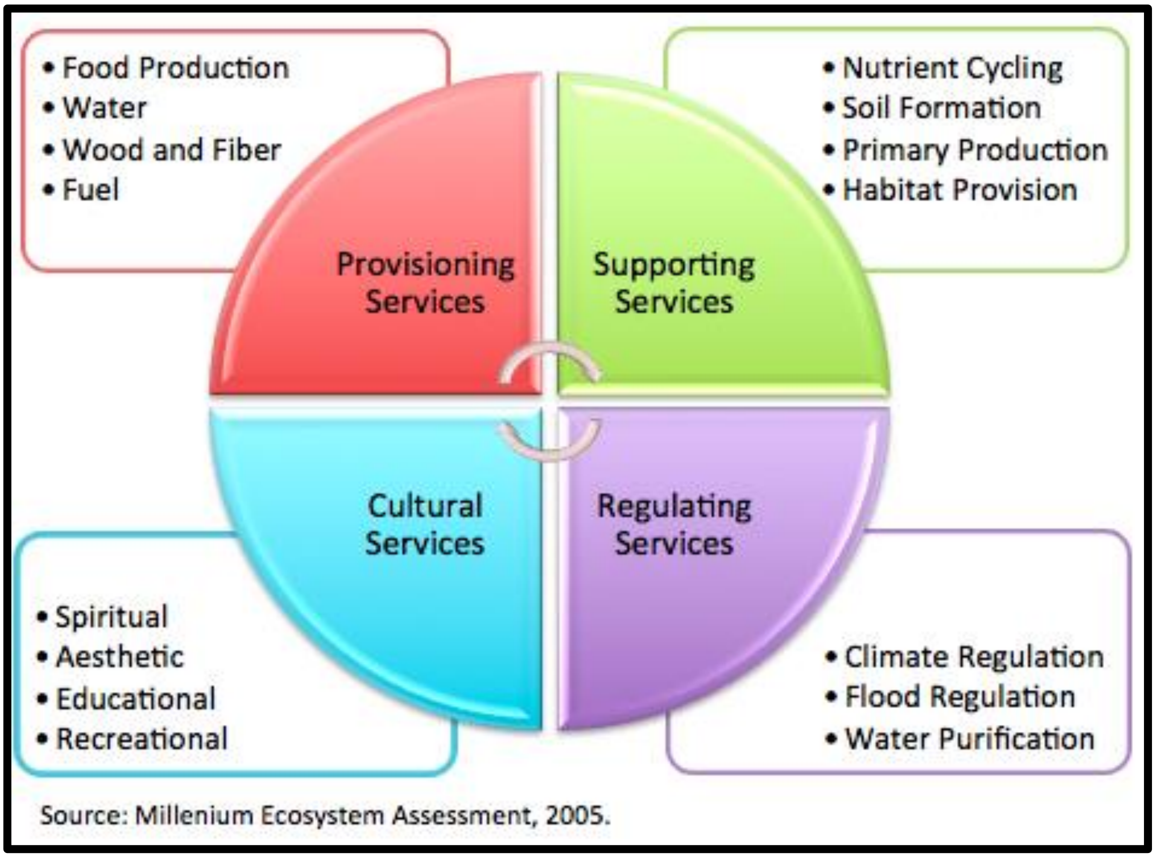

Figure 2.3. Ecosystem services categories and examples

Agro-ecosystems do not only provide agricultural commodities such as food and fiber, but also help protect biodiversity, water, carbon storage, and landscape amenity.

However, recent environmental change coupled with other stressors is affecting the ability of agro-ecosystems to continue to provide the quality and quantity of ecosystem services required for sustainable rural livelihoods (Gentle and Maraseni, 2012; Shrestha et al., 2012; Baral, 2013).

2.1.4. Ecosystem-based Adaptation (EbA)

Development and management actions can be structured to influence human behavior on ecosystems and their socio-ecological system (Gunderson, 2000). They include approaches so-called ecosystem-based adaptation (EbA) or nature-based solutions (NBS) to adaptation. Ecosystem-based Adaptation (EbA) has quickly emerged as a viable option to deal with the challenges of climate change in the context of a holistic adaptation strategy. While ecosystem services have always been used by societies, the term Ecosystem-based Adaptation was coined in 2008 by the International Union for Conservation of Nature (IUCN) and its member institutions at the UN Climate Change Convention Conference in 2008 (UNFCC, 2008). EbA was officially defined in 2009 at the UN Convention on Biological Diversity Conference as the use of biodiversity and ecosystem services as part of an overall adaptation strategy to help people adapt to the adverse effects of climate change (CBD, 2009). CBD's definition was later changed to make it more holistic. EbA was thus defined in 2010 as "sustainable management, conservation, and restoration of ecosystems as part of an overall adaptation strategy that takes into account the numerous social, economic, and cultural co-benefits for local communities" (CBD 2010, cited in Doswald et al. 2014: 185). It builds on a wide range of existing practices employed by the conservation and development sectors, such as Sustainable natural resource management, Sustainable Agriculture practices (SAP), Community-based natural resource management (CBNRM), and Community-based adaptation (CbA) (Swiderska et al., 2018). Since the evolution of the concept and practice of EbA, various principles, and standards have been developed to guide best practices for implementation (Andrade et al, 2011; FEBA, 2017; GIZ and CMP, 2020). These principles are complemented by safeguards, which are social and environmental measures to avoid unintended consequences of EbA to people, ecosystems, and biodiversity. Standards have also been developed to help practitioners understand what interventions qualify as EbA, including three elements and five criteria. EbA should fit these elements: Help people adapt to climate change; and active use of biodiversity and ecosystem services, in the context of an overall adaptation strategy. These three elements can be broken down into five key criteria, which can be used to ensure EbA practices are effective. EbA should: Reduce social and environmental vulnerability to climate change; Generate social benefits and support the most vulnerable. Restore, maintain, or improve ecosystems and biodiversity, be mainstreamed into policies at multiple levels, support equitable governance, and enhance capacities. Those standards must be addressed for an activity, initiative, project, approach, strategy, and/or practice to qualify as ecosystem-based adaptation (FEBA, 2017). EbA approaches have to be built based on a good understanding of risk (Fedele, 2019).

2.2. Overview of the Agriculture Sector in Togo

Agriculture is an important economic sector in Togo including crop production, livestock, and fishing farming. Agriculture employs approximately 70% of the working population with a GDP growth rate was 4.6% in 2021 compared with 4.0% in 2020 (MERF, 2023a) and &generated more than 20% of export revenues however, it is poorly structured and underdeveloped (MAEH, 2016). The country has a large amount of arable land and has agro-sylva-pastoral, fishing, and wildlife potential that is generally favorable to agricultural activities. It is practiced on 1.4 million hectares nationwide (out of a potential 3.6 million arable hectares), accounting for 39% of arable land and 25% of the country's total surface area. The lowland surface area is estimated to be 175,000 hectares, with irrigable land covering 86,000 hectares, of which 2,300 hectares are completely or partially hydro-agricultural development systems, representing a 2.6% equipment rate. Togo's agricultural production is dominated by food crops and exports (DSID, 2015).

Food crops account for 70% of all agricultural production and are mainly intended for domestic consumption and provide significant income to producers, due to the permanent demand. The main food crops are cereals (maize, sorghum, millet, rice), tubers (cassava, yams), and legumes (cowpeas, soybeans). On average, cereals account for 56% of the total calorific value of plant products and occupy around 60% of the land devoted to food crops. Average maize and rice yields are 1,230 kg/ha and 1,687 kg/ha in 2021, compared with 5,878 and 4,764 kg/ha worldwide (MERF, 2023b). In general, productivity and crop yields are low. Crop yields from one region to another are uneven, with the lowest production area being the Savanna region which is exposed to land pressure. They vary from 1 to 2 tonnes/ha for cereals 0.5 to 1 tonne/ha for pulses and around 10 tonnes/ha for tubers (cassava and yams). These yields represent less than 50% of the yield levels achievable under optimal growing conditions (MAEH, 2016).

In terms of livestock production, the trend in livestock numbers in Togo from 2011 to 2021 shows a steady increase in the number of cattle, from 424,527 in 2014 to 473,582 in 2019. The same trend is observed for ruminants (sheep/goats), which have risen from 3,485,365 in 2014 to 6,928,273 in 2021. Similarly, the number of pigs has risen from 931,014 to 1,129,336 between 2014 and 2021 (MERF, 2023b). Finally, the number of poultry increased significantly over the same period (from 14,613,344 to 30,672,748). However, the rate of coverage of meat products, and per capita consumption of meat and offal is estimated per inhabitant per year at 7.5 kg, whereas the recommended standard is 12 kg per inhabitant per year (MERF, 2023b).

As a result, every year the country imports live animals (around 30,000 head of cattle, 40,000 head of sheep and goats, 1 million poultry) and meat products (10,000 tonnes) to make up the shortfall.

In addition, fishing plays an important role in Togo's economy. It is mainly dominated by maritime fishing (60 to 80%). A comparison of production according to the type of fishing shows a clear predominance of small-scale maritime fishing and inland fishing. Inland fisheries production has risen from 5,000 tonnes in 2011 to 6,300 tonnes in 2021 whereas, fish farming production has risen from 20 tonnes in 2011 to 1,000 tonnes in 2021. As for industrial fishing production increased from 102 to 150 tonnes over the same period. For small-scale maritime fishing, the average production is 16,000 tonnes. Projections for 2023 are estimated at 20,050 tonnes, an increase of 3.08% compared with the previous season but down 13.98% on average for the last five years (DSID, 2022). The average coverage (2021) of fish products is around 5.8 kg/inhabitant/year instead of 12 kg/inhabitant/year. As an outcome, the country imports 40,000 tonnes of fish products each year to make up the difference (République Togolaise, 2023b). Overall, Togo still needs to make sustained efforts to achieve food self-sufficiency.

Despite its significant contribution to the overall economy, Togo's agriculture is primarily rain-fed agriculture dominated by small producers and thus fundamentally dependent on weather fluctuations with huge consequences on agriculture productivity. In addition to an initially very low level of productivity, Togolese agriculture faces enormous challenges in gaining access to productive resources as well as adequate technical support and appropriate technical training and the drastic effects of climate change observed in recent decades (Pilo, 2018). Recognizing its role in the economy, most national plans, and policies, including the current government roadmap 2025 and the agriculture development policy (2015-2030), consider the agricultural sector as the key engine of economic growth and the greatest potential sector to directly increase the income of the poor (MAEH, 2016). According to the Togo Comprehensive Africa Agricultural Development Program (CAADP), a 1% increase in agricultural GDP would result in a 2% reduction in the incidence of poverty at the national level (World Bank, 2017).

2.3. Historical and Projected Climatic Trends in Togo

An analysis of meteorological data over a relatively long period (1961-2018) reveals unequivocal evidence of climate change in the country, with very marked spatio-temporal variability. Temperatures are all on the rise, with an increase of 0.8°C to 1.2°C across the country's latitudes (Table 2.1).

Table. 2.1. Evolution of Temperature in Togo's different climatic zones (1961 –2018)

Synoptic stations	Mean temperature (°C) 1961-1985	Mean temperature (°C) 1986-2018	Difference (m)
Lome 06° 10'N-01°15'E	26,8	28	1,2
Atakpame 06° 10'N-01°15'E	25,8	27	1,2
Sokode 06° 10'N-01°15'E	26,2	27	0,8
Mango 06° 10'N-01°15'E	27,9	29	1,1

Source: QCN, 2022

The northern regions of the country experience faster rates of increase than the southern regions (World Bank, 2021).

Across all emissions scenarios, temperatures are projected to continue to rise in Togo, through the end of the century as seen in Figure 2.4.

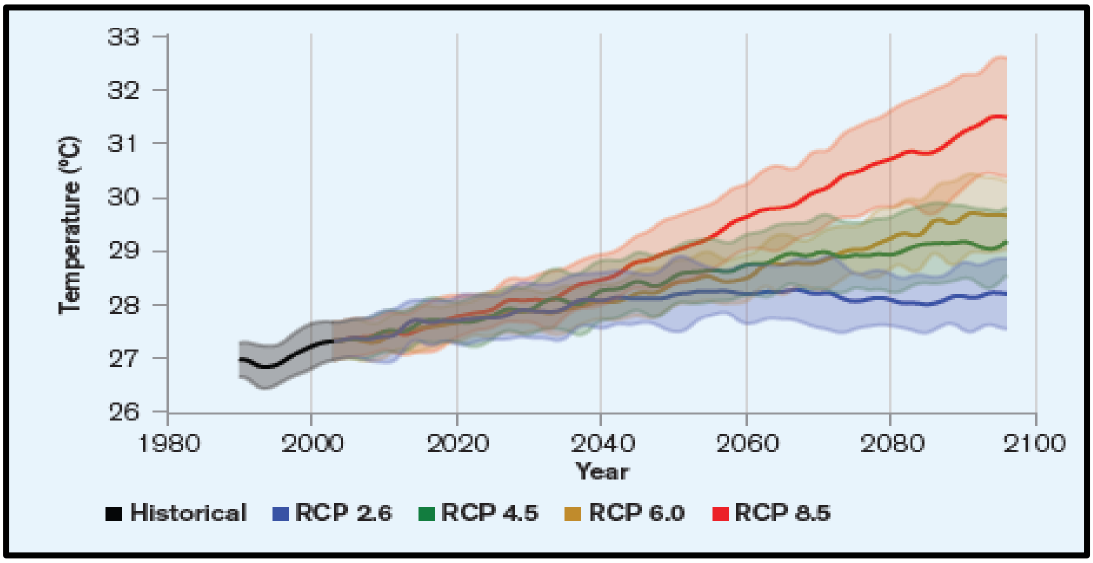

Figure 2.4. Historical and projected average temperature for Togo from 1986 to 2099
Source: (CCKP, 2021)

The results of the climate scenarios drawn up as part of the Fourth National Communication on Climate Change revealed that in the RCP 6.0 scenario, Average temperatures, meanwhile, will rise at all timescales, with increases of between 0.6°C and 0.7°C in 2025 and between 2.15°C and 2.75°C in 2100. In the RCP 4.5 scenario, Average temperatures will rise from 0.66 to 0.84°C in 2025, from 1.15 to 1.48°C in 2050, and from 1.53 to 1.96°C in 2100. According to QCN (2022), the scenarios developed show that, in comparison to the baseline situation (1995), the greatest temperature variations will be recorded in the prefectures of Tône, Tandjouaré, Kpendjal, and Cinkassé located in the Savanna region. In addition, the analysis of meteorological data over the period 1961-2018 shows a decreasing rainfall across the country, with decreases ranging from 15 mm to 98 mm (Table 2.2) impacting severely agriculture activities.

Table. 2.2. Evolution in rainfall in Togo's different climatic zones between 1961 and 2018

Synoptic stations	Mean Rainfall (mm) 1961-1985	Mean Rainfall (mm) 1986-2018	Difference (m)
Lome 06° 10'N-01°15'E	876.0	816.2	-59.8
Atakpame 06° 10'N-01°15'E	1363.3	1347.9	-15,4
Sokode 06° 10'N-01°15'E	1380.7	1282.9	-97,8
Mango 06° 10'N-01°15'E	1085.1	1038.3	-46,8

Source: QCN, 2022

Some studies in Togo carried out by (Klassou, 1996; Badameli, 1998; Adewi et al., 2010; Amouzou et al., 2013) revealed also a rainfall deficit since 1970. This high variability is frequently characterized by a late start and early end to the rainy season in comparison to the usual crop calendar, the onset of dry spells, and poor spatial and temporal distribution of rainfall, all of which disorient farmers in their usual crop, frequently affecting crops growth (MERF, 2022). This situation combined with high population growth, deforestation, very traditional farming techniques, and improper land use has resulted in massive land degradation through soil erosion and loss of fertile soil with extremely high agriculture yield losses (Koudahe et al., 2018). For instance, the study carried out by Ali, (2018) revealed that the intra-seasonal temperature and precipitation variability affect the potentiality of farmlands and reduce the yield of the three major food crops (maize, sorghum, and rice). Increasing intra-seasonal precipitation variability by one unit could reduce maize yield by 0.906, rice yield by 1.668, and sorghum yield by 0.0499 metric tons per hectare on average. Increasing intra-seasonal temperature variability by one could reduce maize yield by 8.51 sorghum yield by 3.062 metric tons per hectare on average (Ali, 2018).

Furthermore, there is significant uncertainty on the future of rainfall patterns for Togo with most scenarios pointing to an average projected increase in annual precipitation by the end of the century as seen in Figure 2.5.

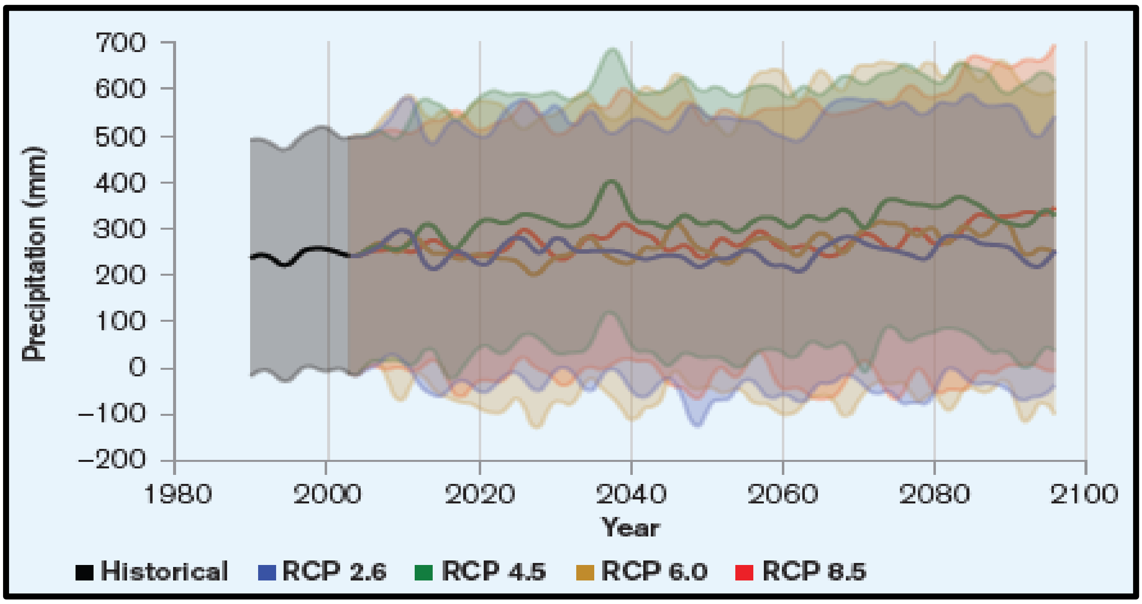

Figure 2.5. Historical and projected average rainfall for Togo from 1986 to 2099
Source: (CCKP, 2021)

According to QCN (2022), in the RCP 6.0 scenario, precipitation will vary between -0.08% and +0.35% by 2025 and from -0.3% to +1.26% by 2100 compared with the baseline of 1995 while in the RCP 4.5 scenario, precipitation will vary from -0.09% to +0.39% in 2025, from -0.16% to +0.67% in 2050 and from -0.21% to +0.89% in 2100.

The scenarios developed, whatever the assumptions, clearly show that climate change is a real concern for the country and that warming trends will increase in the short, medium, and long term with consequences that would be very damaging (QCN, 2022). The changes in the temperature and rainfall will lead to a loss of agricultural land and production potential. It has been suggested that the expected phenomenon of dry spells across the country, combined with the disruption/shifting of seasons, the risks of flooding, and the irregularity of rainfall in a context of continuous land degradation, will increase the agriculture sector's vulnerability and weakening the country's food security despite its importance to the country (World Bank, 2021).

2.4. Vulnerability of the Agriculture sector to climate change risks in Togo

According to the revised NDCs, the agricultural sector is extremely vulnerable to climate change in the country's two northern regions, with maximum vulnerability in the Savanna region. This equates to a "very high" potential impact and a low adaptation capacity. (MERF, 2021a). Future climate projections to 2050 under the RCP 6.0 scenario point to an even less bright future for Togo's agricultural sector. The increasing frequency of dry spells throughout the country, coupled with the disruption and shifting of the seasons, the risk of flooding, and the irregularity of rainfall in a context of continuing degradation of land, suggests the increased vulnerability of this sector, which is vital for the country (MERF, 2021a).

Despite efforts to adapt agriculture to current climatic and socioeconomic conditions, the effects of climate change are being felt acutely in the agricultural sector. Depending on the crop, dry spells can result in significant yield losses. Furthermore, due to changing climatic conditions, certain crops can no longer be grown in certain parts of the country. In addition, people living in the catchment areas of the country's major rivers are exposed to the effects and impacts of flooding, which erodes their livelihoods, including their farmland. In the livestock sector, climate change is leading to a fodder deficit (MERF, 2021a). On the one hand, this increases the risk of infestation of meat products in all regions of the country due to the uncontrolled use of natural or planted pastures, and on the other, the failure of livestock farmers to respect transhumance corridors. In terms of fishing, the use of poisoning techniques, combined with water pollution from leached soils, raises the risk of food poisoning and bioaccumulation (MERF, 2021a). This situation is reducing producers' incomes, exposing people to food insecurity, and influencing their livelihoods.

2.5. Climate Change Risks Adaptation for Togo's Agriculture Sector

Munang et al., (2014) and Fedele (2019) stated that as agroecosystems degrade or fragment, they provide fewer resources to sustain farmers' livelihoods. It has been widely recognized and highlighted in United Nations agencies (UN Environment, UN Framework Convention on Climate Change, UN Convention on Biological Diversity), non-governmental organizations (NGOs) portfolios, and in several international agreements, such as the Sendai Framework on Disaster Risk Reduction, the Paris Agreement, that sustainable land management can play a crucial role in building the resilience of socio-economic and ecological systems as part of climate change adaptation. Thus, the protection and conservation of agricultural land ensure the provision of ecosystem services that contribute to climate change adaptation, risk reduction from natural hazards (floods, drought), food security, and livelihood diversification. Like many countries of west African countries, Togo, specifically highlights sustainable land management (SLM), an ecosystem-based management approach in their national contributions to climate actions as adaptation components for the agricultural sector (MERF, 2021). Also, the country has committed to the sustainable agriculture land management process in the National Policy for Agricultural Development 2015-2030 (MAEH, 2016). Various actions are being planned in the country to improve agricultural land resilience and adapt the agriculture sector to climate change including soil and water conservation approach, integrated soil fertility management approach, agrobiodiversity conservation approach, construction and/or improvement of reservoirs for micro-irrigation in rural areas across the country, using sustainable management of the natural resource on which the agriculture sector relies on (MERF, 2015). This overall goal for the agriculture sector to address climate change demonstrates that the country recognizes the role of ecosystems in reducing climate-related risks (e.g.: land degradation, the decline in agriculture production and yield, loss of agriculture livelihood, and food insecurity).

2.6. Perception of Climate Change Risk on Agriculture

Risk is one of many factors influencing the success of climate change adaptation efforts in agricultural communities (Bartels et al., 2013). When assessing climate impacts, the term "risk" is frequently used to describe the possibility of negative effects on people's lives, livelihoods, health, and well-being, ecosystems and species, economic, social, and cultural assets, services (including ecosystem services), and infrastructure from a climate-related hazard (IPCC, 2018). Farmers' judgments about climate change-related threats to cropping systems are termed "risk perceptions of climate change" (Slovic, 2000). The characteristics of the individual, their experiences, the information they receive, and the cultural and geographic context in which they live all affect and shape risk perception (van der Linden, 2015; Whitmarsh and Capstick, 2018).

Farmers' perceptions of climate change risk are distinctive in that they distinguish between actual real-world hazards, like climate change, and intuitive assessments of those dangers (Rosa, 2003). Mankand (2016) stated that farmers' perceptions of the risk have an impact on how they manage that risk (Mankad, 2016). Farmers employ a variety of strategies to reduce the effects of agricultural risks depending on how they perceive those potential risks (Martin, 1996; Meuwissen et al, 2001; Flaten et al, 2005; Bergfjord, 2009). Risk perception has emerged as a key determinant to understanding farmers' adaptation decision-making, and for educators and scientists, a crucial component in efforts to develop adaptation interventions that more accurately reflect farmers' needs. (Arbuckle et al., 2013, 2015, Abid et al., 2016 ; Dorward et al., 2020, Khanal et al., 2021 ; Ahmed et al., 2021; Likinaw et al., 2022). According to Greiner et al. (2009), understanding how farmers view risk is essential for developing and implementing policies and programs that support both improved agricultural management and natural resource conservation, but also for determining research gaps and future directions (Hoque et al., 2019). However, measuring the relationship between climate change risk perceptions and adaptation responses is complex. It combines behavioral components from belief formation with outcome assessments as a result of actions and weather events (Van der Linden, 2017). It is crucial to comprehend and identify the climatic factors that farmers take into account when formulating their opinions on climate change (Zamasiya et al., 2017; Likinaw et al., 2022).

Several methods are used in the literature to comprehend how farmers perceive the risk of climate change. Studies on climate change risk perceptions frequently employ the Standardized climate change risk perception index (SCCRPI) (Iqbal et al., 2016; Sullivan-Wiley and Gianotti, 2017; Ahmed et al., 2021; Zobaer et al., 2022; Likinaw et al., 2022). The probability or likelihood of risk events and the seriousness of the consequences of those events are combined to create the SCCRPI, which is a metric or index (Li et al., 2018). Instead of a precise measurement of probability or consequences, data in risk perception studies are primarily obtained by asking respondents' perceptions about risks using ordered qualitative scales where they can express their subjective views on the incidence of climate change risk and, as well, their concern regarding the magnitude of the gain/loss caused by the risk (Frondel et al., 2017; Cullen et al., 2018; Ahmed et al., 2021).

2.7. Ecosystem-based Adaptation (EbA) Strategies in Agriculture

Ecosystem-based Adaptation in agricultural systems is defined as the use or benefiting from biodiversity, ecosystem services, or ecological processes (at the plot, farm, or landscape level) to help increase crops' or livestock's ability to adapt to climate variability (Vignola, 2015). EbA in agriculture encompasses a wide range of actions aimed at preserving and strengthening ecosystem services that support agricultural productivity and resilient food production (Ghanbariet al., 2021). According to Harvey et al. (2017), there is a diverse range of agricultural practices based on the management of ecosystem services and biodiversity. Existing and relevant ecosystem-based management approaches, such as agroecology, sustainable land management (SLM), integrated plant nutrient management, conservation agriculture, and agroforestry, can provide guiding frameworks for the application and scaling up of EbA in cultivated ecosystems when integrated into climate change adaptation planning processes (Abdelmagied and Mpheshea, 2020).

The use of agroforestry to prevent soil degradation, and erosion, and protect the land from impacts of floods, extreme temperatures, and other climate impacts on livestock and crops; the use of crop diversification, intercropping, and crop rotation within fields, as well as soil conservation practices for preventing soil erosion and maintaining soil (Shah et al., 2019; Harvey et al., 2017; Jackson et al., 2010; Lin, 2007; Tengo and Belfrage, 2004) are some examples of ecosystem-based adaptation practices. Other examples include minimal soil disturbance and permanent soil cover to improve soil conditions, reduce land degradation, and increase yields through, and crop rotations. Other best practices include soil and water conservation measures (contour farming, terracing, infield water harvesting, and run-off regulation), and integrated soil fertility management (manuring and composting through crop-livestock integration and agroforestry) (Abdelmagied and Mpheshea, 2020).

Like many countries in Africa, Togo, specifically highlights sustainable land management (SLM), an ecosystem-based management approach in their national contributions to climate actions as adaptation components for the agricultural sector (République Togolaise, 2021). Also, the country has committed to the sustainable agriculture land management process in the National Policy for Agricultural Development 2015-2030 (MAEH, 2016). Various actions are being planned in the country to improve agricultural land resilience and adapt the agriculture sector to climate change including soil and water conservation approach, integrated soil fertility management approach, agrobiodiversity conservation approach, construction and/or improvement of reservoirs for micro-irrigation in rural areas across the country, using sustainable management of the natural resource on which the agriculture sector relies on (MERF, 2015).

2.8. Effectiveness of Ecosystem-based Adaptation Practices

Identifying effective EbA practices in the context of climate change necessitates the use of comprehensive assessment frameworks to evaluate the effectiveness of those practices in supporting adaptive capacity and resilience while providing a variety of benefits. Several frameworks were developed to address this need. For instance, Munroe et al. (2011) and Doswald et al. (2014) assessed the state of the evidence-based effectiveness of EbA initiatives through a framework developed with stakeholders. However, such an assessment was limited to a systematic map of EbA-relevant peer-reviewed literature and a sample of grey literature to provide a methodical overview of the state of EbA's effectiveness. According to the authors, effective EbA would reduce people's vulnerability on environmental, social, and economic levels as well as provide benefits. Reid and Alam (2014) conducted an EbA assessment in two Action Research for Community Adaptation in Bangladesh (ARCAB) sites; they evaluated how effectively EbA supports adaptive capacity and resilience in such communities. In this second assessment framework, EbA's effectiveness is viewed only in terms of ecosystem health. The authors argued that effective EbA should have two key components: the maintenance of ecosystem services and ecosystem resilience.

Recent EbA works further the analysis to include measurable parameters; among these, Bertram et al. (2017) developed a framework for defining qualification criteria and quality standards to guide to assess the effectiveness and the strength of an EbA intervention and a baseline on how an EbA intervention can be improved. Three key elements were featured to measure the effectiveness of EbA projects at national to local levels: 1) EbA helps people adapt to climate change; 2) EbA makes active use of biodiversity and ecosystem services; and 3) EbA is part of an overall adaptation strategy. Each element contains one or two criteria and various indicators that must be met. The assessment framework is provided to help decision-makers design high-quality EbA measures during the planning phase of a project and improve the quality of measures during the implementation phase. Reid et al. (2018) provided a framework for assessing the effectiveness of EbA approaches for overcoming barriers to EbA implementation and influencing policy. In this latter framework, EbA effectiveness is broadly classified along four axes, namely 1) effectiveness for human communities; 2) effectiveness for the ecosystem; 3) financial and economic effectiveness; and 4) policy and institutional aspects. The framework is being applied to strengthen the evidence and inform policy by consolidating and comparing evidence from 13 existing EbA project sites in Asia, Africa, Central, and South America. This framework was developed primarily to assist policymakers in determining when and how the EbA initiative is effective. However, it can also be used to develop indicators that can help measure initiative effectiveness and support adaptive project management over time when planning and implementing new EbA projects. Vignola et al. (2015), along the same line, developed a framework for identifying effective EbA practices specifically for smallholder farmers. The authors perceive that effective ecosystem-based agricultural practices can improve ecosystem resilience and service provision, increase adaptation benefits to climate change, and improve smallholder farmers' livelihood and food security. The proposed framework is seen to be a useful tool to stimulate careful consideration of agricultural practices that are suitable or effective for smallholder farmers to reduce vulnerability to climate change while also conserving the capacity of agroecosystems to provide both on- and off-site ecosystem services and could be applied to the wide variety of agricultural systems that exist globally (Vignola el al., 2015).

Although there are many frameworks to assess the effectiveness of EbA practices, they share some similarities, such as EbA measures that improve ecosystems' capacity to produce services, which in turn improves humans' well-being, adaptive capacity, or resilience, and reduces their vulnerability.

2.9. Gender Considerations in Agricultural Ecosystem-Based Adaptation

Gender issues are directly related to men's and women's roles and responsibilities in the farming household, as well as decisions about allocating resources and adopting technologies in farming systems (Beuchelt, 2016). The issue of gender perspectives on sustainable farming systems in the context of climate change has been the subject of several studies (Dharamshi et al., 2023; Mussema, 2020; Lien & Brown, 2020; Baćanović and Murić., 2018; Oloukoi et al., 2014; Hassan and Nhemachena, 2008) among others and confirmed that men and women are affected differently by climate change and have their preferences concerning the adoption of conservation and sustainable practices to manage climate change due to gender roles and responsibilities, access, and control of resources, education, and other institutional factors (access to credit, technology, and input). Both men and women play critical roles in the conservation and sustainable use of biological diversity, in the development of resilient livelihoods, and in the transformation of food systems (Amogne et al., 2018). According to Aguilar, L., Granat, M., & Owren, (2015), EbA is very important from a gender perspective as women are generally the primary custodians of local and traditional knowledge due to the close linkage and stronger relationships with natural resources.

2.10. Decision-Making Theories of Sustainable Technology Adoption in Agriculture

Nowadays, more emphasis is being placed on sustainable agricultural technologies to adapt to climate change while increasing agricultural productivity, ecosystem resilience, and farmers' livelihoods, particularly the adoption of ecosystem-based agriculture or sustainable agriculture technologies. The primary advantages of these technologies or practices include increased food production while preserving soil and water resources, preserving soil fertility, improving farm system resilience to climatic risk, and capacity to sequester carbon and mitigate climate change (World Bank, 2006; FAO 2009; IFAD 2011). Farmers' decisions to adopt new technologies are influenced by the dynamic interaction of technology features and a variety of conditions (social, economic, institutional, bio-physical) (Loevinsohn et al., 2012). According to Teklewold et al. (2013) and Melesse (2018), factors influencing technology adoption in agriculture can be divided into three categories: (i) producer and farm characteristics (e.g. education level, experience, age, gender, level of wealth, farm size, labor availability, resource endowment, risk aversion); (ii) technology features (e.g. complexity, performance, cost, period of investment recovery, susceptibility to environmental hazards); and (iii) institutional environment (eg. availability of credit, access to information on the technology, infrastructure, extension support). As a result, the technology adoption process becomes quite complex and far from simple (Bilali et al., 2021).

Many previous studies investigated farmers' behavior and decision-making regarding the adoption of sustainable agriculture technologies (Bayard and Jolly, 2007; Vignola et al., 2010; Mutyasira et al., 2018; Bonke & Musshoff, 2020; Waseem et al., 2020; Coulibaly et al., 2021; Mahdavi, 2021; Sok et al., 2021; Nguyen & Drakou, 2021) through several descriptive theories that have been developed to explain the factors underlying technology adoption qualitatively. These progress from Rogers' (1962) theory of innovation diffusion to the theory of planned behavior (Ajzen, 1991), via the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975) and the technology acceptance model (TAM) (Davis, 1989). These conceptual approaches and models cross various disciplines (for instance, sociology, psychology, innovation, sustainable agriculture management, etc…) and differ in terms of theoretical assumptions, goals, variables, and evaluation methods (Bilali et al., 2021).

2.10.1. Theory of Diffusion of Innovations (DIT)

Everett Rogers' (1962, 1995) Innovation Diffusion Theory (IDT) or Theory of Diffusion of Innovations (DIT) seeks to explain why, how, and at what rate new technologies and innovations spread. Adoption, according to Rogers (2003), is the decision to fully utilize innovation as the best course of action available whereas diffusion is the process by which a new idea spreads over time among the members of a social system by using specific channels. The four key components of the innovation diffusion model are innovation, communication channels, time, and social system. In this context, research on innovation diffusion seeks to explain the factors that influence user adoption of new technologies. DIT combines three major components: innovation characteristics, adopter characteristics, and the process of innovation decision-making (Taherdoost, 2018). In terms of the innovation-decision process, five steps (understanding, persuasion, decision, implementation, and confirmation) occur over time through various communication channels (Rogers, 2003).

Regarding the component of innovation characteristics, five main constructs have been proposed (relative advantage, compatibility, complexity, trialability, and observability/results demonstrability) (Sila, 2015). Rogers (1995, 2003) distinguishes five types of adopters: innovators, early adopters, early majority, late majority, and laggards (see Figure 2.6).

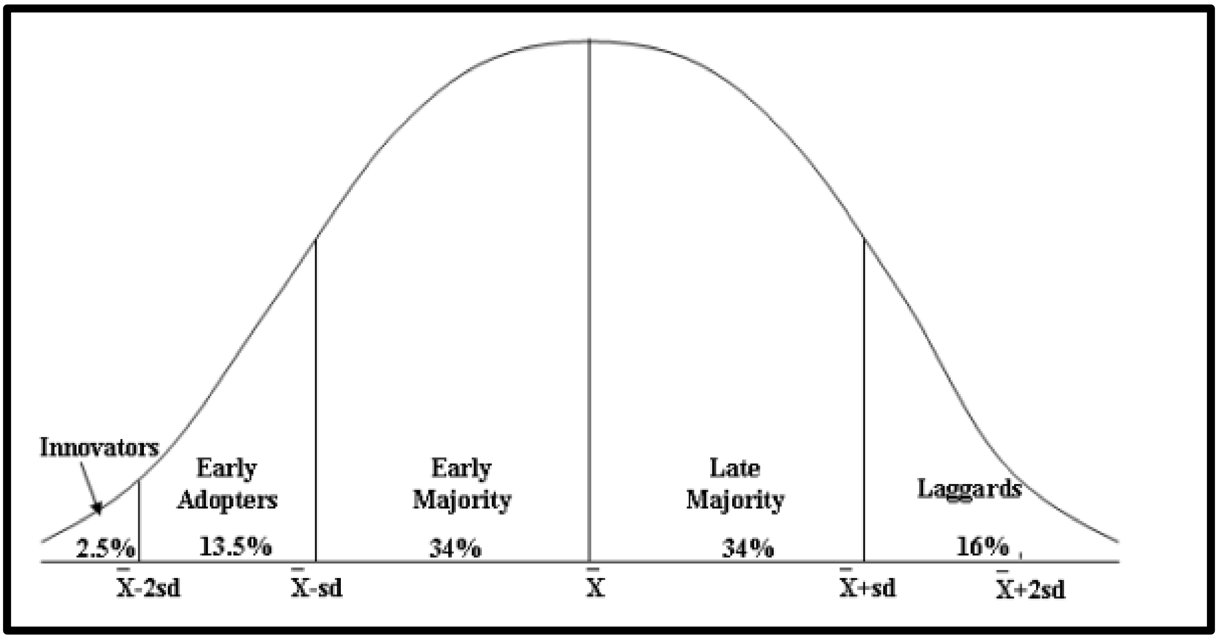

Figure 2.6. Adopter Categorization based on Innovativeness (Source: Diffusion of Innovations, fifth edition by Everett M. Rogers, 2003

In each adopter category, individuals are similar in terms of their innovativeness: "Innovativeness is the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a system" (Rogers, 2003, p. 22). Braak (2001) described innovativeness as "a relatively stable, socially constructed, innovation-dependent characteristic that indicates an individual's willingness to change his or her familiar practices" (p. 144). For Rogers, innovativeness helped in understanding the desired and main behavior in the innovation-decision process. Thus, he categorizes the adopters based on innovativeness. DIT has been used to study a wide range of technologies and innovations since the 1960s, ranging from agricultural machines to organizational innovations (Tornatzky and

Klein, 1982). It was used to investigate the adoption of land, soil, and water conservation practices, among other things (Mango et al., 2017).

DIT explains the adoption process and predicts adoption rates (Askarany et al., 2012; Hameed et al., 2012), but it does not take into account how attitude and intention influence innovation adoption (Karahanna et al., 1999; Muchena et al., 2005). It focuses on technological characteristics, personal characteristics, and environmental factors, but it has less explanatory power when it comes to predicting adoption outcomes (Taherdoost, 2018).

2.10.2. The Theory of Reasoned Action (TRA)

The theory of reasoned action (TRA) is essentially a set of interconnected concepts and hypotheses proposed and developed by social psychologists to understand and predict human behavior (McKemey and Sakyi-Dawson, 2000). It arose from eminent psychologists Fishbein and Ajzen's long-standing collaborative research (Fishbein and Ajzen 1975) in response to the failure of broad social attitudes to predict behavior, and they proposed that the intention to perform a given behavior is the most immediate antecedent and the best predictor of actual behavioral performance. It attempts then to explain all human behavior and could be adapted in case studies dealing with the determinants of technology adoption. Individuals' relationships between beliefs, attitudes, norms, intentions, and behaviors, according to this theory, underpin the adoption of technological innovation. The TRA assumes that most behaviors of interest to social and behavioral scientists are completely under volitional (self) control, and thus, once an intention is formed, the behavior is expected to be initiated under appropriate circumstances (Sok et al., 2021). According to the TRA, one's behavioral intention to adopt technology is the strongest or most proximal predictor of volitional behavior. Behavioral intention is thought to be influenced by both an individual and a normative influence A person's attitude towards performing the volitional behavior is the individual influence on intention. The normative influence on intention is referred to by Fishbein and Ajzen as one's subjective norm. Attitude refers to an individual's positive or negative feelings towards a specific behavior. These are known as behavioral beliefs. (see Figure 2.7).

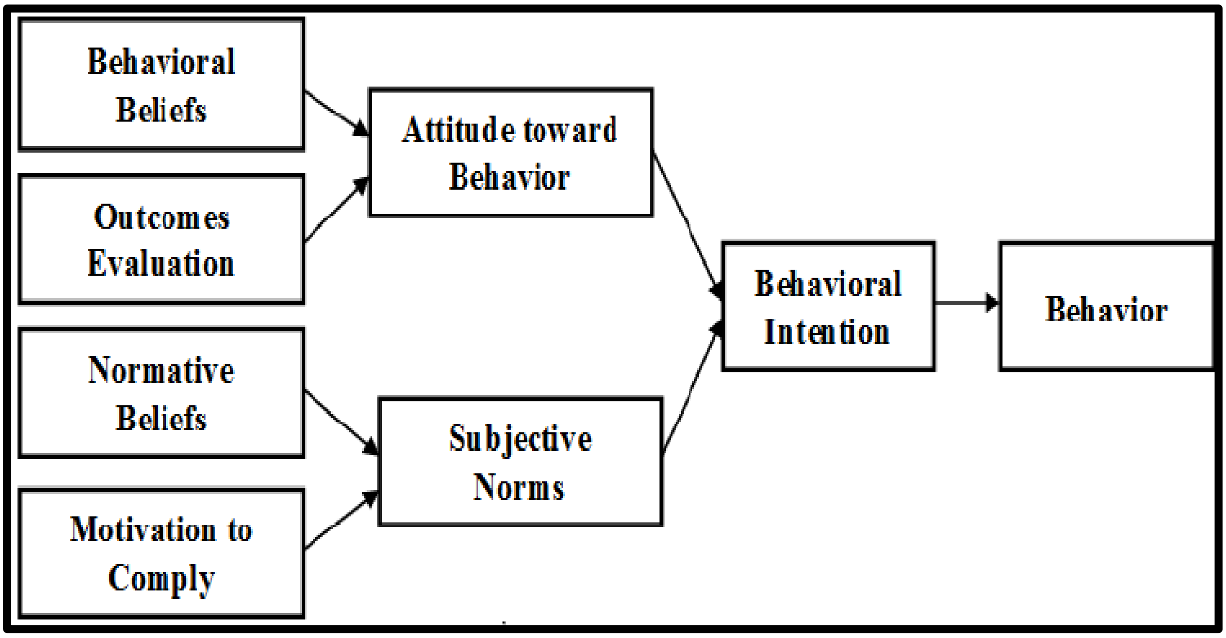

Figure 2.7. Theory of Reasoned Action – TRA (Fishbein & Ajzen, 1975)

When a person evaluates a behavior positively, he or she will intend to perform it. An individual's attitude is determined by his or her belief about the consequences of performing the behavior (behavioral beliefs), which is weighted by his or her evaluation of these consequences (outcome evaluations). Thus, attitude is a person's primary belief about whether the outcome of his or her actions will be positive or negative (Hardeman et al., 2002; Fishbein and Cappella, 2006).

Subjective norm refers to an individual's perception that the majority of people around him/her believe he/she should or should not exhibit the behavior (Fishbein and Ajzen 1975). As a result, the subjective norm is influenced by the individual's environment (family, friends, colleagues, neighbors, etc.). It refers to the pressure felt by the latter and emanating from his surroundings before manifesting or not manifesting a behavior. It also depends on the motivation of the individual to conform to the expectations of those around him (Aronson et al., 2005). TRA is a broad model that was not created to investigate any specific behavior or technology (Davis, 1989). Other variables that influence intention, such as experience, fear, and mood, are not taken into account by the theory (Bilali et al., 2021). According to Taherdoost (2018), the main disadvantages of TRA are that it ignores the role of habit, cognitive deliberation, and moral factors.

2.10.3. Technology Acceptance Model (TAM)

The technology acceptance model (TAM) was developed by Davis (1989) and is strongly linked to Fishbein and Ajzen's (1975) theory of reasoned action. It applies specifically to technology adoption behavior and was originally developed to explain the acceptance of information systems by their users and the determinants of their use (Davis, 1989). In contrast to the TRA, the Technology Acceptance Model (TAM) excludes the construct of the subjective norm in explaining intention (Bilali et al., 2021). TAM includes fundamental user motivation variables (i.e. perceived usefulness, perceived ease of use) as well as outcome variables (i.e. behavioral intention, technology use) (Davis, 1989) (see figure 2.8).

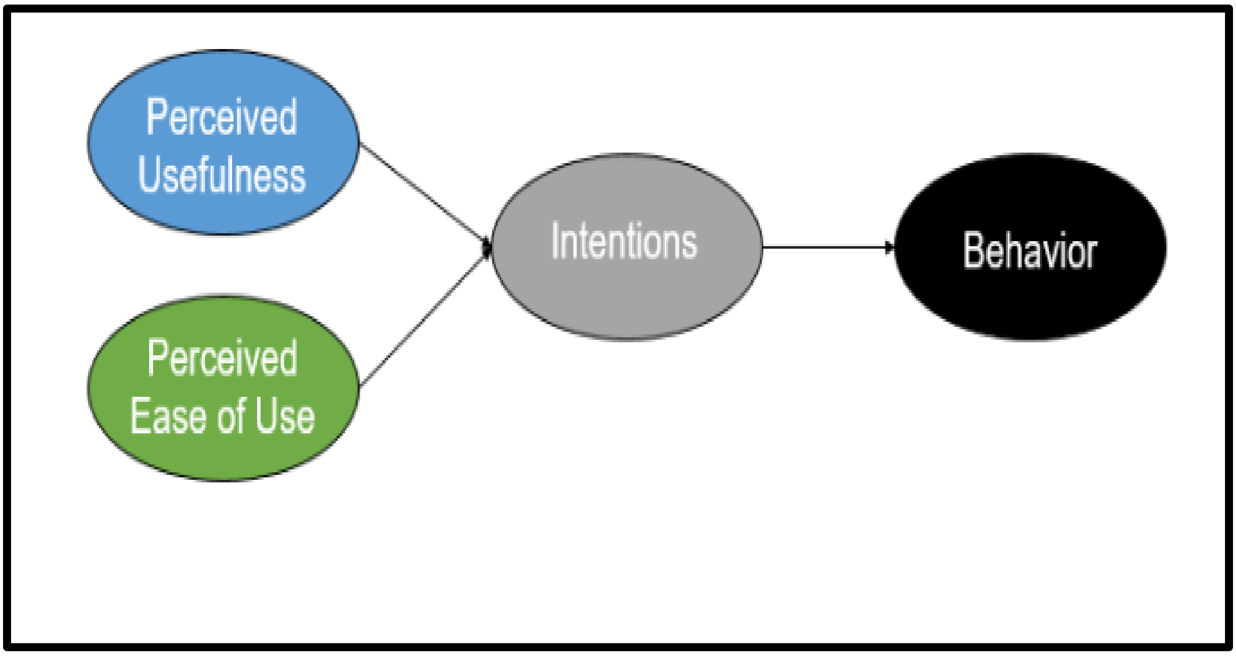

Figure 2.8. Technology Acceptance Model (Davis, 1989)

The main variables/beliefs that explain the intention and, consequently, behavior are perceived ease of use (PEU) and perceived usefulness (PU) (Maranguni & Grani, 2015). In general, PEU refers to the effort associated with the use of technology, whereas PU considers the outcomes and benefits of using technology, particularly in terms of performance. External variables, such as self-efficacy (SE), subjective norms (SN), and facilitating conditions (FC), explain the variation in PEU and PU (Schepers & Wetzels, 2007). Contextual factors and personal capabilities are examples of external variables.

TAM was used to examine, among other things, the adoption of biological control on rice in Iran (Bagheri et al., 2016), mobile phones in Sub-Saharan Africa (Kabbiri et al., 2018), precision agriculture in Iran (Tohidyan Far & Rezaei-Moghaddam, 2017), and pasture-based grazing systems in Ireland (McDonald et al., 2016). According to (Alambeigi and Ahangari, 2016) this theory could explain 64% of the actual behavior of agricultural experts in using information and communication technologies. Aubert et al. (2012), in their research, discovered that perceived usefulness and perceived ease of use positively influenced the adoption of precision farming techniques. Their findings also revealed variances in adoption behavior of 64% and 46% for these two variables, respectively. TAM, according to some authors, has a higher predictive power than TRA. According to Gefen and Straub (2000), while perceived usefulness has a significant effect on the adoption of technology, the effect of perceived ease of use may vary depending on the type of task performed. This prompted Chen and Tan (2004) to caution against generalizing the findings of studies that used the technology acceptance model.

One of TAM's main shortcomings is that it ignores the social influence (subjective norms) on technology adoption. Furthermore, TAM does not address extrinsic motivations, making the model inappropriate in situations where technology is used not only to accomplish specific tasks but also to meet certain emotional needs (Taherdoost, 2018).

2.10.4. Theory of Planned Behavior

The Theory of Planned Behavior (TPB), is now one of the most influential socio-psychological models used to understand human behavior. To account for the TRA's limitations, Ajzen (1991) added a new variable to the theory of reasoned action: the perceived control over behavior that precedes behavioral intentions The perceived control over behavior is dependent on the availability of skills and resources, as well as their perceived importance in achieving outcomes. Indeed, TPB's core constructs include, in addition to "attitude towards behavior" (or "behavioral attitude") and "subjective norms," the "perceived behavioral control" (Ajzen, 1991). Thus, attitude, subjective norms, and perceived control are the primary variables that influence and predict behavioral intentions (Ajzen, 1991). (see Figure 2.9).

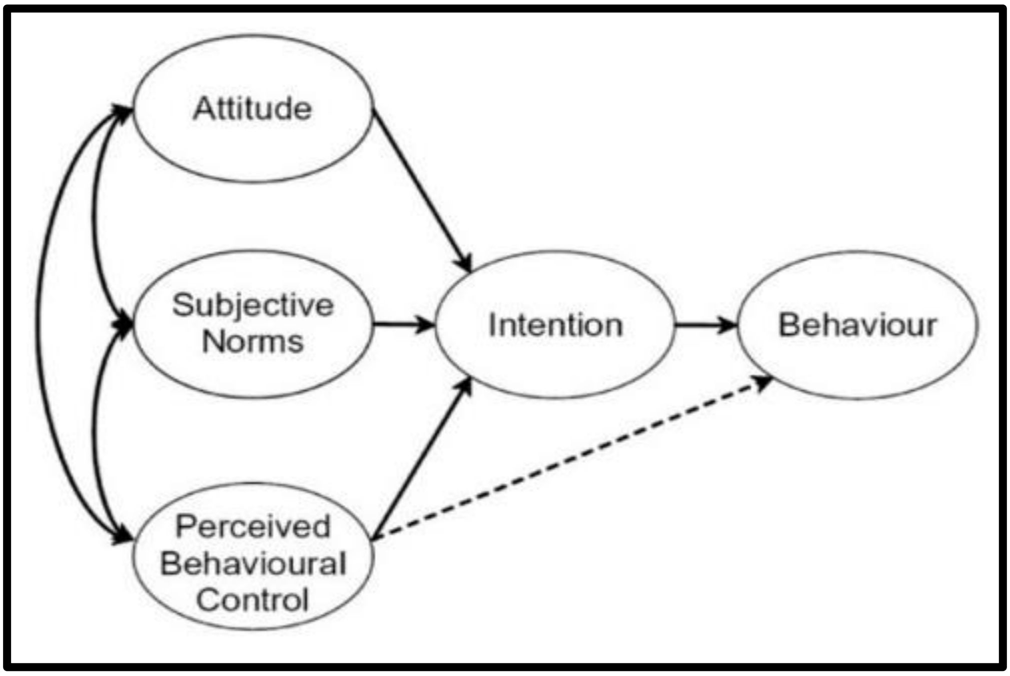

Figure 2.9. Theory of Planned Behavior (Ajzen, 1991)

TPB assumes that an individual's affects their behavior. TPB considers a specific consumer/behavior user and provides a framework for analyzing the determinants of that behavior. In the TPB, 'intention' is viewed as what the individual intends to do. It is the source of motivation that has an impact on behavior. In turn, it is assumed that intention is determined by three types of constructs (Attitude, Subjective norms, and perceived behavioral control). The first construct, **attitude towards the behavior (ATT)**, represents the degree to which a person evaluates a behavior favorably or unfavorably. It is made of an affective attitude which is related to whether the behavior is enjoyable or not and the instrumental attitude which is related to whether the behavior is beneficial or harmful (Ajzen, 1991). The second construct, **subjective norm**, refers to an individual's perception of social pressure to engage in a particular behavior. It consists of beliefs about social expectations as well as the motivation to meet those expectations (Ajzen, 1991). In other words, because people are context-dependent, important others' opinions matter in shaping an individual's intention to use new technologies (Venkatesh & Davis, 2000). Finally, **perceived behavioral control (PBC)** refers to a person's perception of his/her capability to perform the behavior. It increases when people believe they have more resources and confidence (Ajzen, 1985; Hartwick & Barki, 1994; Lee & Kozar, 2005).

The TPB has been used to study farmers' intentions, decisions, and adoption behavior in a variety of agricultural areas (Borges et al. 2014), conservation agriculture (Avemegah, 2020; Beedell and Rehman 2000), soil conservation (Wauters et al. 2010), agricultural product diversification (Seger et al. 2017, Hansson et al. 2012) water conservation practices (Yazdanpanah et al. 2014), and organic farming (Lapple and Kelly, 2013). It has also been used in several studies to explain farmers' environmental behavior, specifically why they adopt or do not adopt conservation practices (Wauters et al. 2009; Beedell and Rehman 2000; Rehman et al. 2004; Yazdanpanah et al. 2014). While the TPB is a good framework for studying farmers' intentions and actual behavior (Wauters et al. 2009; Beedell and Rehman 2000; Borges et al. 2014; Werner et al. 2017; Deng et al. 2016), findings suggest that the theory of planned behavior's predictive power varies by population, geographic location, and the specific behavior being studied.

Regarding model limitations, TPB does not take into account other factors that may influence behavioral intention to perform a behavior, such as risk perception. Furthermore, it does not account for economic or environmental factors (Truong, 2009).

2.11. Factors Affecting Farmers' Sustainable Technology Adoption in Agriculture

Sustainable technology adoption in agriculture such as sustainable agriculture practices ecosystem-based adaptation practices or climate-smart agriculture practices, according to researchers, may strengthen people's resilience to climate change, aid in soil degradation, and support agricultural output in a cost-effective, productive, and profitable manner (Wollni & Andersson 2014; Ngwenya et al. 2017; Aryal et al. 2020; Coulibaly & Diakité, 2021). Since the 1950s, scientists have been studying farmer acceptance of novel agricultural techniques (Manzano, 2016). The adoption of new agricultural practices could be influenced by several factors. Understanding the role of these factors would contribute to the success of projects aimed at their introduction and dissemination.

The decision to implement sustainable techniques in agriculture is based on several criteria (Kassie et al. 2015). Several scientific studies have attempted to explain the factors that influenced the widespread adoption of those techniques or practices among farmers. According to Coulibaly & Diakité (2021), these variables are frequently classified into four groups: farmers' factors, farm factors; psychosocial factors, and exogenous factors. Karali et al (2011), revealed that economic, demographic, social, cultural, psychological, technological, and ecological factors influence farmers' responses to climate change. According to Keshavarz and Karami (2014), the needs of the individual, as well as cognitive factors (such as prior values, beliefs, and experiences), affect the farmers' decisions under climate change.

2.11.1. Farm Households' Socioeconomic Characteristics

The socio-economic characteristics of farm households could influence their decision to adopt new technologies in agriculture. Several authors have conducted empirical studies on the adoption of sustainable agriculture management technologies in general, and water and soil conservation technologies in particular and found that several farm households' socioeconomic factors influence the adoption of these technologies including gender, age, education, gender, household/labor size, and farming experience as factors influencing farmers' decisions (Kebede et al.,1990; Knox and Meinzen-Dick 1999; Croppenstedt et al., 2003; Chirwa, 2005; Alene and Manyong, 2006; Ayele, 2008; Hisali et al., 2011; Hailu et al., 2014; Jha & Gupta, 2021). According to Uddin et al. (2014), age, family size, farm size, education, family income, and cooperative involvement are all influential characteristics of farmers who use climate change coping strategies. Farmers' assets, such as farm size and machinery, as well as access to credits that influence farm income and farmer off-farm income, all play an important role in coping with CC effects (Feder et al., 1985; Sambodo, 2007; Keshavarz et al., 2010; Hisali et al., 2011;). According to (Belay et al, 2017; Amare & Simane, 2017), socioeconomic models showed that education, family size, gender, age, livestock ownership, farming experience, frequency of contact with extension agents, farm size, access to market, access to climate information, and income were the most important factors influencing farmers' choice of climate change adaptation practices. Also, Anzum et al (2023) determined the socio-economic factors that influence the farmers in choosing the right adaptation decisions and found that household age, education, family income, family member, farm size, farming experience, organizational participation, and training received have a significant influence on farmer’s adaptation choices.

2.11.2. Perception of Sustainable Technologies in Agriculture and Adoption Decision

The farmer's decision to adopt new technology is influenced by their cognitive evaluation. Farmers' willingness to use sustainable technologies or practices in agriculture increased when they were perceived to be preferable in terms of environmental consequences, yield response, ease of use, and economic advantage, among other factors (Coulibaly & Diakité (2021). According to Rajendran et al. (2016), farmers are shown to favor the adoption of sustainable technologies when these were seen to prevent or mitigate climate hazards associated with their traditional agricultural techniques. Meshesha et al., 2022, found that farmers' positive perception of the benefits of Climate-Smart Agriculture innovations for increasing crop productivity, reducing agricultural vulnerability to climate change, and reducing/removing GHG emissions from the farm increased their adoption of Climate-Smart Agriculture (CSA) that include improved variety, row planting, crop residue management, crop rotation, compost, soil and water conservation, intercropping and agroforestry. Other authors (Cole, 2010; Sheng et al., 2019; Piñeiro et al., 2020) have shown that farmers' perception of future benefits of sustainable practices increases their likelihood of adoption. According to Delfiyan et al. (2021), the efficacy and cost of adaptation responses had a significant impact on farmers' adaptive decisions.

2.11.3. Farmers' Climate Change Risk Perception and Sustainable Technologies Adoption Decision

One of the most important factors influencing farmers' decisions to use resilient technology, particularly when confronted with climate change, is their risk perception (Kao, 2022; Azizi-Khalkheili., 2021). According to (Reid et al., 2007; Mubaya et al., 2012;) If farmers do not perceive climate change issues as a serious threat, they are less likely to adapt to it. Grothmann & Patt (2005) defined the relative risk perception as the perceived probability of being exposed to climate change impacts and appraisal of how harmful these impacts would be. According to Ludewigs (2006), farmers are generally more concerned with minimizing risks rather than maximizing profits. Barak, (2006) suggested that when studying farmers' adaptation to climate change, it is critical to understand the relationship between risk perceptions and behavioral decision-making.

Ahmed et al. (2022) investigated how climate change perceptions of agricultural risk affect adaptation to climate change through technology adoption in Bangladesh and discovered that farmers' adoption of technology is significantly influenced by their perception of climate change risk. Also, (Kao, 2022) investigated farmers' ability to perceive climate risks and their implications in the decision to adopt resilient technologies in Togo and revealed that farmers' decision to adopt resilient technologies is heavily influenced by their estimates of the risk posed by climate change. Furthermore, Menapace et al. (2013) focus on producer risk behavior and demonstrate that risk perceptions are linked to adaptation technology adoption. Greimer et al. (2009) discovered that the main sources of risk perceived by farmers in adopting good agricultural practices are primarily the risk of drought, which leads them to adopt good water and moisture conservation practices.

2.12. Presentation of the Study Area

2.12.1. Location of the Study Area

The study was carried out in fifteen (15) localities in the Savana region of Togo (figure 2.10).

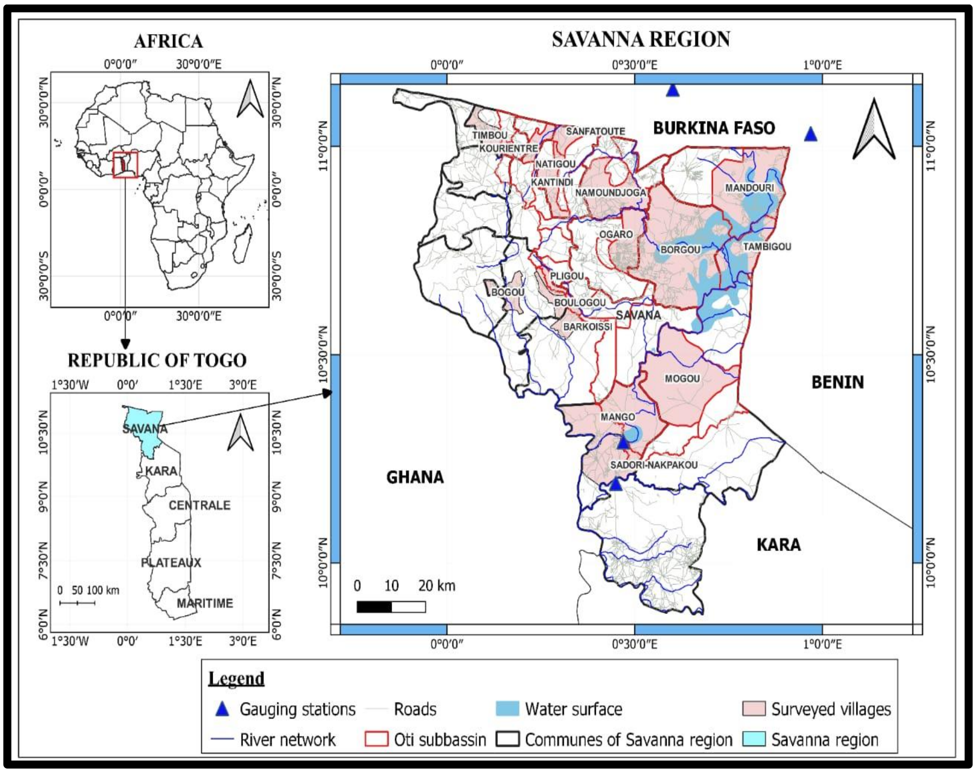

Figure 2.10. Geographical location of the study area

The Savana region is located more than 600 km from the coast in the northern part of Togo. It extends between 0 ° and 1 ° east longitude and 10 ° and 11 ° latitude North. It is bordered to the north by Burkina Faso, to the east by Benin, to the west by Ghana, and the south by the Kara region It covers an area of 8,400 km2 (15% of the national territory) a third of which is occupied by wildlife reserves. It is watered by the Oti River and its tributary. Administratively, the region is subdivided into 69 counties grouped into 7 prefectures, including Cinkassé, Kpendjal, Kpendjal-Ouest, Tône, Tandjouaré, Oti Nord, and Oti Sud (INSEED, 2020). Agriculture and livestock farming are the main economic activities, providing almost 96% of employment and 90% of farmers' income (Soviadan et al., 2019). However, the region is characterized by high poverty (the highest in the country) (65,1%) (INSEED, 2020) and, a 43% prevalence of moderate or severe food insecurity (FAO, 2022). In addition, the region is characterized by a strong and continuous degradation of arable land due to human activities with high exposure to climate variability and its related risks leading to a decrease in agricultural productivity (Brabant et al., 1994, Barry et al., 2005).

2.12.2. Climate Conditions

The north of Togo, and in particular the entire Savanna region is characterized by a Sudanian tropical climate, which is distinguished by an unimodal rainfall regime, consistently high temperatures, as a result of high insolation, and low relative humidity.

High temperatures characterize the research area. The average monthly temperature ranges between 25°C and 34°C, with an annual average temperature of around 30°C. Maximum temperatures are extremely high between March and April, with monthly averages exceeding 30°C (32.5°C and 31.5°C in March, respectively; 32.6°C and 31.5°C in April in Dapaong and Mango). This period corresponds to the dry season's hot period, which lasts from mid-February to April. However, temperatures gradually decrease in magnitude from this point forward, reaching their first minimum in August-September (approximately 26°C in Dapaong and 27°C in Mango), coinciding with the period of heavy rainfall. Temperatures rarely exceed 30°C during the rainy season, which lasts from May to October. These temperatures change moderately from November to mid-February, a relatively short period. This is a period of harmattan influence when the relative humidity drops to around 11%. The graph below depicts the monthly average temperature evolution at the Dapaong and Mango stations over 37 years (1965 to 2014). Finally, the analysis of Figures 2.11 and 2.12 show that this thermal regime is characterized by alternating hot phases at high temperatures and cold phases; this weakens the soils, makes them prone to erosion, and affects plant growth.

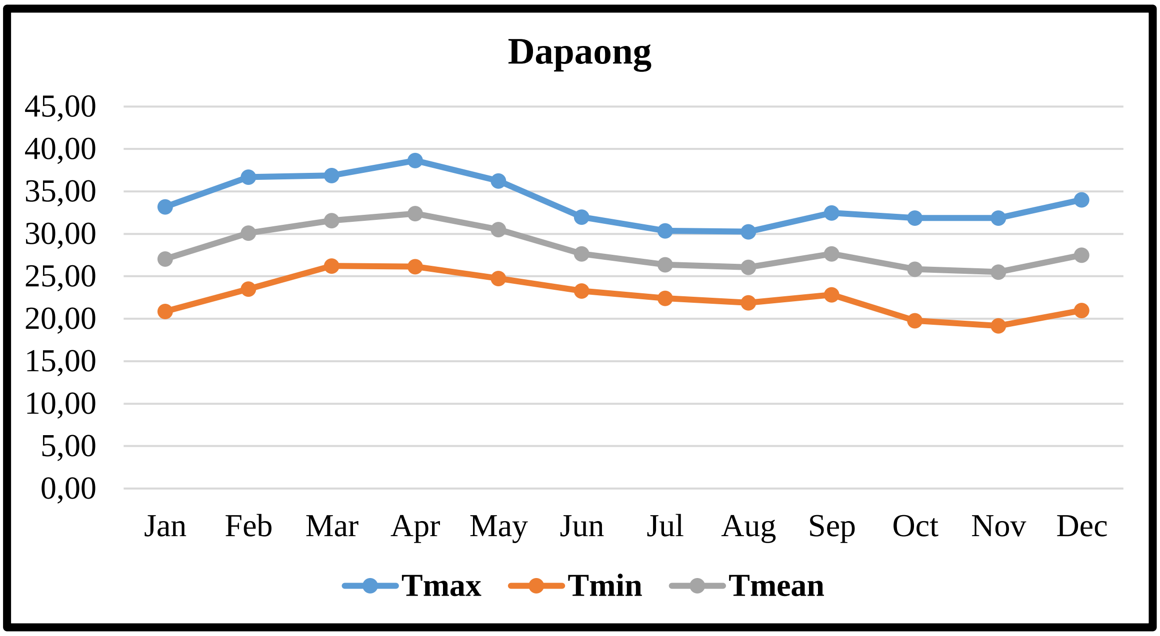

Figure 2.11. Monthly inter-annual temperature averages for the period 1981-2018 at Dapaong station.

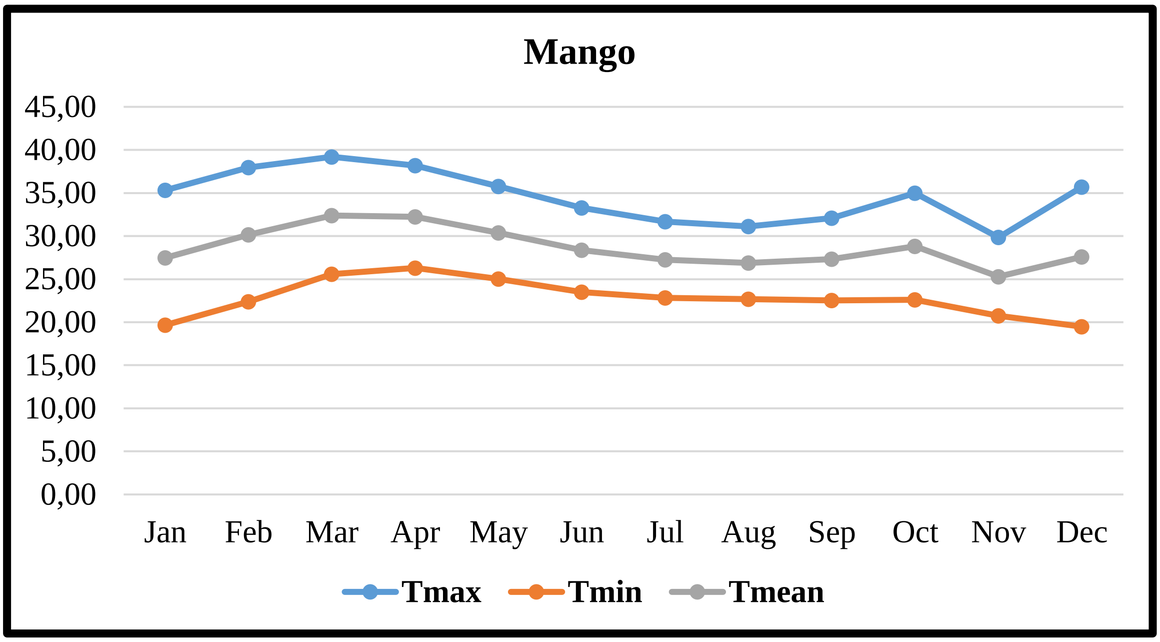

Figure 2.12. Monthly inter-annual temperature averages for the period 1981-2018 at Mango station

In addition, the Savana Region has an unimodal rainfall regime with two distinct seasons. The contrasting nature of the rainfall regime is reflected in a short rainy season lasting approximately 5 months (May/June to September) subject to monsoon passage and a fairly long dry season lasting nearly 7 months (November to April/May) characterized by a notable absence of rainfall. The dry season is challenging for both plants and animals to overcome and even threatens their growth. The harmattan's combined effects with the drought's restrictions on the vegetation cause many plants to suddenly wilt and lose their leaves. According to Gaussen's relationship, P=2T, as shown in the ombrothermal diagrams below, there are 6 months in which the monthly average temperature curve (the thermal) is above the rainfall graph. These are the so-called " ecologically dry months". At the Dapaong station (figure 2.13) and Mango station (figure 2.14) these are the months of November, December, January, February, March, and April.

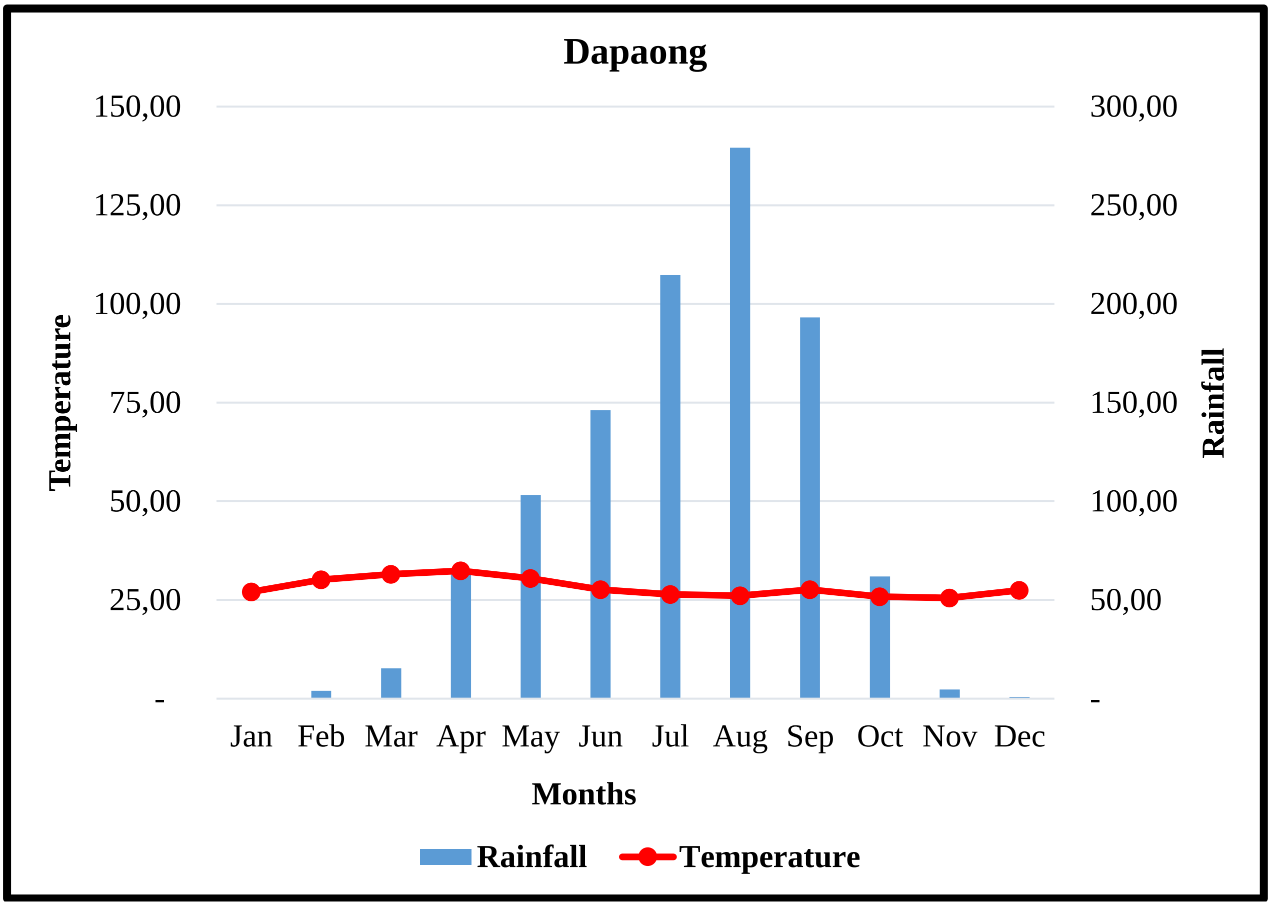

Figure 2.13. Ombro-thermal diagram of monthly average (1981-2018) at Dapaong station

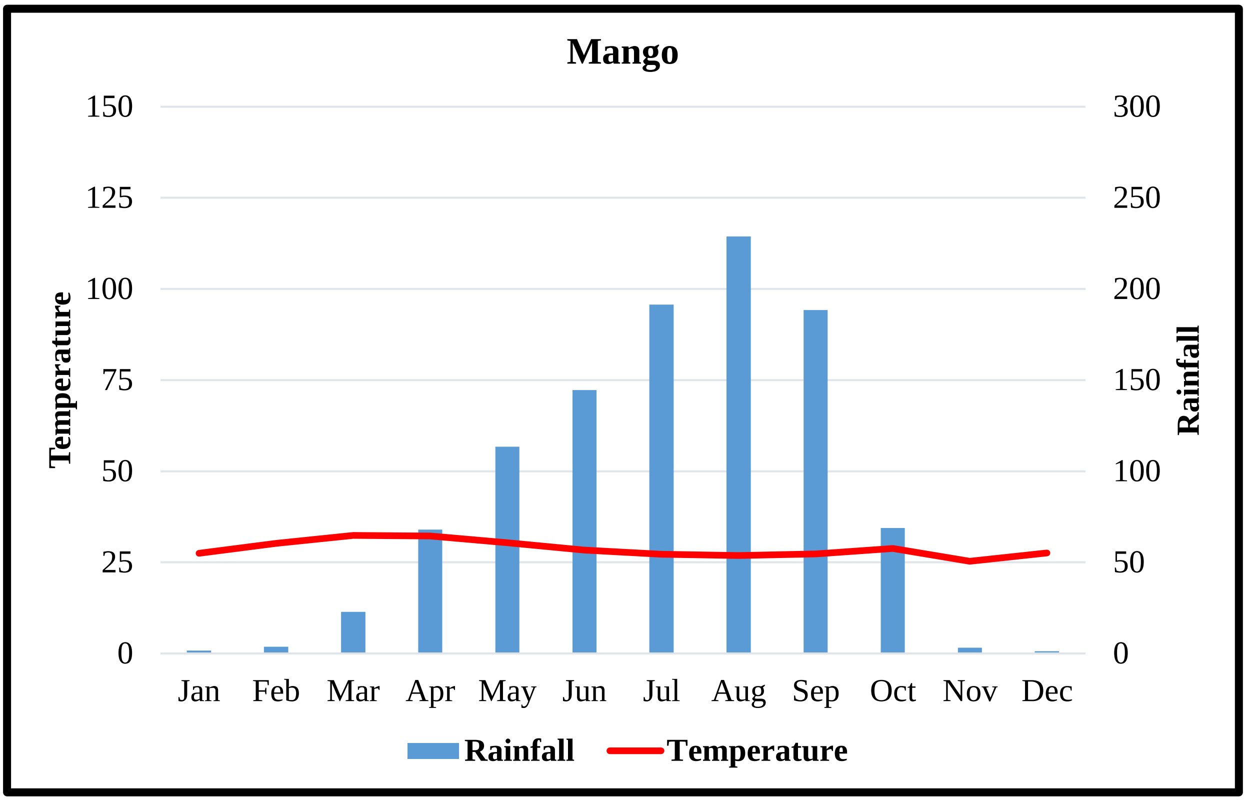

Figure 2.14. Ombro-thermal diagram of monthly average (1981-2018) at Mango station

The study area benefits from low rainfall, with an annual average of around 1000 mm, due to its location in the semi-arid climatic zone.

Furthermore, the relative humidity of the air is heavily influenced by the study area's seasonal rhythm and rainfall. As a result, except during rainy seasons, it rarely exceeds 60%. It varies in inverse proportion to temperature. During the season of extremely high temperatures and harmattan weather, the air humidity in the entire region is relatively low On the other hand, humidity is very high during the rainy season and can reach well over 80% (Laré, 2017). Humidity levels are relatively low in the dry season, and high in the rainy season with maximum levels recorded in June, July, August, and September. The very low relative humidity, combined with strong winds and high temperatures, imposes very severe aridity conditions during January, February, and March. This has serious consequences for animal and plant life.

Moreover, the region experiences high insolation which results in high temperatures with low annual thermal amplitudes. The dry season (November to February) has the highest values. High insolation increases the intensity of both surface water evaporation and plant transpiration. As a result, most rivers, dams, and wells dry up during this period of high insolation, resulting in increased water scarcity for human needs and animal watering. In short, during the dry season, low relative air humidity combined with high insolation values and high temperatures exacerbates plant water stress. Also, in the study area, the evapotranspiration demand at various stations reaches significant levels during the dry season. Between November and May, potential evapotranspiration values range from 5 to more than 7 mm/d. During the driest months (December to March), evaporative demand reaches significant instantaneous values (more than 7 mm/d). During the rainy season, however, the ETP in the Savanna Region is much lower, hovering around 4 mm/d (Laré, 2017).

2.12.3. Natural Environment

The soils of the Savana region are mostly tropical ferruginous soils (leached) and poorly developed soils resulting from erosion on the edges of watercourses. The northwestern part of this region is extremely underdeveloped. According to the ORSTOM degradation index, Togo's north-western region has the highest percentage of degraded and severely degraded land (Brabant, 1996).

The Savana region is in the ecological zone I (Ern, 1979), which corresponds to the northern plains and is primarily covered by dry Savanna. The region's natural vegetation is dominated by a fairly homogeneous landscape of sparsely wooded Savanna, with some remnants of gallery forest along the banks of the Oti River, containing species such as Berlinia grandiflora, Diospyros mespiliformis, Daniellia Oliveri, and others (Brunel et al., 1984; Tchamie, 2006). A few patches of forest can also be found on the mainland, at higher elevations, and along waterways. Deforestation, agriculture, and other factors have nearly eliminated primary vegetation. A "steppe Savanna" with thorny shrubs grows on eroded soils in the northern part of the region. Acacia ataxacantha, Acacia dudgeonii, Acacia gourmaensis, Acacia hockii, Acacia pennata, and other xeric species grow in this Savanna. The rest of the study area is dominated by tree formations, particularly in the western sector (Tandjoaré, Tône, Cinkassé, and parts of Kpendjal prefectures), the Oti reserve, the former Galangashi classified forest, and the eastern sector (Mandouri-Oti).

The cultivated land hosts useful woody plants in the form of agroforestry parks with Parkiabiglobosa (néré) and Vitellariaparadoxa (karité), with shrub stumps cut down each year of different species (Guierasenegalensis, Piliostigmareticulatum, etc.), complemented by other useful trees such as Adansoniadigitata (baobab), Borassusaethiopum (roan), Tamarindusindica (tamarind), etc., depending on local conditions. These parks, which are critical for soil fixation and fertility reproduction, are showing significant signs of deterioration (severe pruning and cutting of trees, destruction of young plants from spontaneous reseeding by tilling the soil with a ridge).

In general, the rate of deforestation is high, and removals from the use of wood resources for energy are significant. Given the decline in wood resources, a significant proportion of millet and sorghum stalks are used as cooking fuel. Many animal species have disappeared from the area over the past two decades, in connection with population growth, hunting, and fishing, competition for resources between large herbivores and the human population, and the reduction of uncultivated areas.

Water availability in the region depends on climatic (rainfall) and geological (structure and texture, nature of the bedrock) conditions. As an integral part of the Volta basin, the Savana region is watered by Oti rivers and its tributaries.

Crossing the North-East - South-West region, the Oti rises in Benin on the eastern slopes of the Atakora range under the name of Kpendjari. It is the most important watercourse flowing through Mandouri - Mango plain with a very low flow rate. The most important tributaries on the right bank are Ouké Oualé, near Mandouri, the Sansargou, the Namiélé, and the Koukombou, forming the border with border with Ghana. The Oti River has its source at an altitude of 600 m in the Atakora in the North of Benin. It crosses Togo over a distance of 167 km and marks the border with Ghana over 176 km. It receives on its left bank, tributaries with an abundant flow coming from the well-watered mountain: Koumongou and Keran. The drainage regime of the Oti is tropical, linked to the rainfall regime. The rising period is observed between August and September. The low water period is in the dry season. The Oti is a fairly abundant but very irregular river. It has long periods of low water with sometimes complete drying up. The average monthly flow observed in March (minimum low water level) reaches only 3,6 m³/second, that is to say, 500 times less than the average flow of September, the main month of rising, which testifies to its very great seasonal irregularity. The Oti has a relatively permanent flow because of the periodic regulation of its flow by the waters of the Kompienga dam in Burkina Faso, while all the other tributaries dry up during the dry season.

2.12.4. Demographic and Socioeconomic Characteristics

The population of the study area has increased, from 828224 inhabitants in 2010 to 1143520 inhabitants in 2022, with annual growth rates of over 2.70% and a density of 96 inhabitants per km² (INSEED, 2023). The number of women exceeds the number of men by a wide margin, with a proportion of 52% for women and 48% for men (INSEED, 2023). The Total Fertility Rate (TFR) is 6 children per woman while the intermediate value of around 5 children per woman is found in other regions (Tchalla, 2022).

The vast majority of the region's population is employed in the primary sector (86% of the population), and high population growth only increases human pressure on natural resources (soil and vegetation) through agricultural exploitation. Agriculture and livestock breeding are the main economic activities, providing 96% of employment and 90% of farmers' income. It is important to note that the development of this agricultural activity is mainly based on food crops, essentially rainfed. These include cereal crops (millet, sorghum, maize, rice, etc.), legumes (cowpeas, voandzou, beans, groundnuts), tubers (yams, sweet potatoes, taro), and cotton. In addition to these main rainfed crops, there are market garden crops (onions, tomatoes, carrots, lettuce, etc.) produced in the dry season around developed water points or permanent water reservoirs. Livestock production is mostly associated with crop production or sometimes alone. It is practiced by almost all farmers.

Despite the economic importance of the primary sector and the fact that the majority of the population are farmers, agricultural activity is unfortunately carried out in a technological environment that was previously traditional, with the use of outdated equipment such as the hoe, the cutter, the axe, the sickle, etc. This situation is accentuated by the variability of rainfall and the exponential growth of the rural population, with the corollary effect of over-exploitation of agricultural land.

2.13. Summary

In short, this chapter covers the conceptual framework of the research and the characteristics of the study area. The chapter presents then the definitions of the main concepts, methods, and results of previous work relevant to the thesis. It presents also a general analysis of the agricultural sector in Togo in the context of increasing population needs, while the means of production, such as land resources, are constantly being degraded, leading to an increasing decline in agricultural yields. It describes also the climate-related risks in the agricultural sector and the adaptation options and measures for managing climate risks in the agricultural sector in Togo. The analysis of the literature review clearly shows that climate-related risks on agroecosystems are sensitive issues to which many authors have not remained indifferent. And, various authors have demonstrated the potential of Agricultural ecosystem-based adaptation (EbA) strategies for building the resilience of agricultural production systems while maintaining farm-based livelihoods.

CHAPTER 3: CLIMATE-RELATED RISKS ON AGROECOSYSTEMS: CLIMATIC TRENDS, AND FARMERS' RISK PERCEPTIONS

3.1. Introduction

The increased intensity and frequency of extreme weather events, as well as climate variability with associated impacts on ecosystems, and human livelihood activities and strategies, have sparked widespread concern (Kahsay et al., 2019). Rainfall and temperature are essential climatic variables that are frequently used to characterize climate change and variability (Sharma et al., 2016; Gedefaw et al., 2018). Climate change is defined by the Intergovernmental Panel on Climate Change as statistically significant variations in climate that persist for an extended time, typically decades or longer (IPCC, 2007). Any changes in rainfall characteristics such as intensity, duration, and frequency as well as warming temperature impact and are expected to have the most significant impacts on agricultural production, livelihoods and food security of people in the developing world, particularly in West Africa, due to their high dependency on rain-fed agriculture and their extensive dependence on agricultural practices for livelihoods (Oranu et al., 2018; Sanou et al., 2018; Chapagain et al., 2021).

Togo, like other West African countries, is experiencing the effects of climate change such as rising temperatures, flooding, drought, poor rainfall distribution, shorter growing seasons, etc. Indeed, the average temperature increase varies from 0.8 to over 1.2°C across the country's latitudes, and average rainfall is generally down at all points in the region, ranging from 15 to 98 mm (QCN, 2022). These events have had an impact on rain-fed agriculture in the country, which depends on the seasons. The economy of Togo is largely dependent on agriculture and the majority of rural households primarily depend on low-productivity rainfed agriculture particularly vulnerable to the effects of climate change, with enormous consequences on agriculture income, livelihood, and food security (World Bank, 2011). For several consecutive years now, Togo has been subject to climate risks due to an alteration in the distribution of rainfall with extreme droughts and floods events and a decrease in the number of rainy days across the country, impacting intensively agriculture livelihoods and the agroecosystems on which farmers rely (Djaman and Ganyo, 2015; Kwami, 2018). For example, the 2010 floods caused damage and losses to farmers at all stages (sowing, heading, harvesting, etc.); livestock and their habitats as well as food stocks were affected. The 2010 floods destroyed 4,737.79 ha of maize fields in the north of the country, affecting 16,179 farmers. At the national level, the last periods of drought or irregular rains affected nearly 1,498,234 people, or 20.2% of the total population, and decreased the agricultural production of nearly 93.8% of farm households. Drought-related losses from 2013 to 2014 are estimated at approximately 8 billion CFA francs or 13,924,077.39 USD (République Togolaise, 2018). These impacts are expected to worsen in the future as changing climate alters rainfall and temperature patterns across the country, particularly in the Savanna region (Republique Togolaise, 2023a).

The Savanna region in Togo is considered the most vulnerable to climate change in the country, with a high potential impact on agroecosystems and a low capacity to adapt (République Togolaise, 2023). This region is experiencing a strong influence and persistent rainfall variability and temperature extremes with less and erratic rainfall than usually expected particularly shorter rainy seasons, and poor rainfall distribution affecting crops and pasture yields which put most rural households in the region at risk of food insecurity (Pilo et al., 2021; Badameli and Kadouza, 2020; Djaman and Ganyo, 2015, Lare and Lamboni, 2015). Various studies have been conducted to investigate spatial and temporal variability of rainfall and temperature in the Savana region among others (Essotalani et al., 2010; Badjana et al. 2012; Somiyabalo 2019; Kankpénandja et al., 2020, Yao et al., 2023), have shown evidence of rainfall variability and increase trend of temperature in the region. Gadédjisso-Tossou (2015), Sanou et al. (2018), and Lus et al. (2018) have included farmers' community perceptions, to show the link between climate change evidence with observed data and farmer perception; These studies have helped assess how farmers' risk perception influence climate change adaptation. According to Mehmood et al. (2022), farmers' decisions to implement climate change adaptation strategies are directly related to their perception of climate change, its impacts, and related risks. Although farmers' perceptions of climate change risks are a prerequisite for the adaptation strategy (Tripathi & Mishra, 2017; Kahsay et al., 2019), little is known about whether actual climate risks are perceived equally or differently among farm households. There is increasing interest in integrating local farmers' climate change perception with nearby weather monitoring station data to improve farmers' adaptation strategies. As a result, understanding and characterizing farm households' perceptions of climate change risks in agroecosystems is critical for improving adaptation policy for addressing the challenges that climate change poses to agriculture activities in the Savanna region in Togo. Therefore, the objective of this study is to explore both observed changes in rainfall and temperature and farmers' perceived risks related to those climatic changes in the Savanna region. Specifically, this study seeks to answer the following questions:

Q1.1 How does the rainfall and temperature pattern change over time in the study area?
Q1.2 What are the perceived key drivers of climate change risk on agroecosystems?
Q1.3. How do climate change risk perceptions vary among farmers' households?

From these questions, three specific objectives have been drawn:

OS1.1 To examine change in rainfall and temperature patterns for (1961-2021);
OS1.2 To assess the perceived key drivers of climate change risk on agroecosystems;
OS1.3. To categorize farmers on the level of perception of climate change risks.

Three specific hypotheses were developed based on the objectives of structuring this study.

H1.1. There is evidence of rainfall variability and temperature increase between 1961 and 2021 in the Savanna region.
H1.2. Among key drivers, the following are perceived to lead to climate change risks on agroecosystems: increased frequency of drought and flood events, exposition of farmers and their croplands to climate-related hazards, loss of ecosystem services provided by cropland for farming, increased soil erosion, decrease in soil fertility, unsustainable farming practices, strong dependency on agricultural income, and decrease in agriculture yield and income.
H1.3. Farm households perceive climate change risk differently depending on personal experience and capacity.

3.2. Methodology

3.2.1. Data Collection

3.2.1.1. Climate Data

To analyze the climatic features and trends, daily precipitation and daily temperature (Maximum and minimum) data from Dapaong and Mango stations were obtained from the National Meteorological Service of Togo. The length of records for precipitation was 60 years (1961 to 2021). The missing precipitation data were filled through linear interpolation of the same month's data of the contiguous years on either side of the missing value.

3.2.1.2. Participatory Workshop

A local stakeholders' workshop was held in January 2021 to qualitatively identify the key drivers of the risk of climate-related impacts on agriculture. The workshop involved 21 participants (men and women) from key local NGOs (working in the field of climate change and sustainable agriculture), agricultural local public institutions, community leaders, and farmers' organizations to broaden their knowledge. Those local stakeholders were identified in each of the seven districts of the study area under the assistance of extension agents based on their experience and technical expertise in the field of climate change and agriculture. The workshop was conducted entirely in French. The workshop began with introductory talks during which the climate risk concept and its components (hazards, exposure, and vulnerability), as well as climate impacts, were clarified by using the Intergovernmental Panel on Climate Change (IPCC) AR5 approach of risk. According to IPCC (2014), the concept of climate change risk is a function of hazard, exposure, and vulnerability (IPCC, 2014). Afterward, the participants were divided into three groups of seven. Each group is made up of members of non-governmental organizations (NGOs), community leaders, farmer organizations, and agricultural local public institutions. Each group was asked to answer three questions: (1) what are the major changes observed in the climate conditions and their related hazards affecting agroecosystems during the last 20 years? (2) Which major impacts related to the identified climate hazards have affected agroecosystems during the last 20 years? (3) Which major social and ecological vulnerability factors contribute to climate change risks on agroecosystems in the study area? (4) What are the major exposed elements of agroecosystems at risk? The top-ranked answers provided by each group for each of the four questions were considered to develop the household survey questionnaire.

3.2.1.3. Household Survey

Fifteen most susceptible localities of the Savanna region were carefully chosen for a household survey (Table 3.1). The localities were purposively selected based on their vulnerability to frequent climatic events (e.g. droughts and floods) and their agricultural importance.

Table 3.1 Distribution of respondents per Surveyed localities

Districts	Surveyed localities	Number of respondents
Tandjouare	Pligou	20
	Bologou	23
Tone	Sanfatoute	21
	Kourientré	26
	Kantindi	29
Cinkassé	Timbou	35
Kpendjal	Tambigou	21
	Mandouri	24
	Borgou	43
Kpendjal-Ouest	Namoudjoga	23
	Ogaro	22
Oti	Barkoissi	21
	Mango	39
	Sadori	39
Oti-sud	Mogou	39
Overall	**15**	**425**

The survey questionnaire was designed using the information gathered during the participatory workshop. The data was collected through a structured questionnaire using a simple random sampling technique. Face-to-face interviews were conducted in this survey. The questionnaire contained several questions based on the information collected during the local stakeholders' workshop session. **1)** demographic and livelihood strategies of the respondents, **2)** farmers' perception of climatic changes. The respondents were requested to appraise their view on the identified changes in climate parameters based on the extent to which they influence their agroecosystem. A five-ranking scale was adopted to estimate their perception levels. The

ranking scale ranged from 0 (no perception) to 4 (very high perception). **3)** Perception of the impacts deriving from changes in climate parameters and hazards on agroecosystems, **4)** farmers' perception of key drivers determining vulnerability and exposure of agroecosystems to climate change risks. The respondents were asked to give their views based on the subjective degree of agreement for each factor related to hazard, exposure, and vulnerability identified during the participatory workshop. Hence, a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5), was adopted to estimate households' perception levels.
Before starting the household survey, the interviewers were properly trained. Under the supervision of the researcher, the data of 60 farmers were pre-tested. Eligible interviewees were the head (male or female) of an agricultural household in the survey area and had lived there for at least 20 years before the survey data. A total of 425 farm households were surveyed following Cochran's formula with 60 households in each locality.

$$\boldsymbol{S = \frac{Z^2PQ}{E^2}} \qquad (\mathbf{1})$$

where, S = sample size per locality, Z = deviation set at 1.96 corresponding to a confidence level of 95 percent; P = the number of households in the locality; Q = 1 – P; E = margin of error which is equal to 5 percent.

To eliminate the language barriers between the interviewers and farmers, the interviews were carried out in local languages like Moba, Tchokossi, and French.

3.2.2. Data Analysis

3.2.2.1. Analysis of Rainfall and Temperature Characteristics and Trends

The evolution of the different normal of cumulative annual and seasonal rainfall and mean temperature was investigated to determine whether there was an increase or decrease in rainfall and temperature throughout (1961-2020). To examine spatial variation of rainfall incidence in the study area, the Rainfall Anomaly Index (RAI) developed by van Rooy (1965) has been used to analyze the intensity and frequency of the rainy and dry years in the study area. The precipitation values for the study period were ranked in descending order of magnitude, with the highest precipitation ranked first and the lowest precipitation ranked last.

For the period under consideration, the average of the ten highest and ten lowest precipitation values was calculated. The mean of ten extremes is used to compute the positive and negative RAI indices using the following equations.

$$\boldsymbol{RAI = +3\frac{RF-MRF}{MH10-MRF}} \qquad \text{(Positive anomalies)} \tag{2}$$

$$\boldsymbol{RAI = -3\frac{RF-MRF}{ML10-MRF}} \qquad \text{(Negative anomalies)} \tag{3}$$

Where: RAI = the rainfall anomaly index; RF = the rainfall for the year in question; MRF = the mean actual annual rainfall for the total length of the period; MH10 and ML10 = the mean of ten (10) highest and lowest values of rainfall (RF) respectively of the period.

The RAI classification is used to determine the extremes of rainfall in the study area over decadal and annual time frames. The following range from ≥3.0 (extremely wet) to ≤-3.00 (extremely dry) **(**Table 3.2**)** was used to describe the variation in rainfall. Trend lines were fitted on the anomaly graphs to show changes in rainfall over time.

Table 3.2. RAI classification by van Rooy, 1965

RAI range	Class description
≥3.0	Extremely wet
2.00 to 2.99	Very wet
1.00 to 1.99	Moderately wet
0.50 to 0.99	Slightly wet
0.49 to -.49	Near Normal
-0.50 to -0.99	Slightly dry
-1.00 to -1.99	Moderately dry
-2.00 to -2.99	Very dry
≤-3.00	Extremely dry

To demonstrate rainfall and temperature reliability, the Standard Deviation (SD) and Coefficient of Variation (CV) were calculated. CV is calculated as follows:

$$\boldsymbol{\sigma = \frac{\sqrt{\sum(\mathbf{Y}-\bar{Y})^2}}{\mathbf{N}}} \tag{4}$$

$$\boldsymbol{CV = \sigma * 100/}\bar{Y} \tag{5}$$

Where: $\bar{Y}$ = mean, σ = Standard deviation, N = sample size (number of years of available rainfall data)

Furthermore, the number of rainy and dry days during the rainy season was examined. Dry days are those with a total rainfall of less than or equal to 1mm (Doukpolo, 2014).

3.2.2.2. Climate Change Risk Perception Index for Farmers

The Standardized Climate Change Risk Perception Index (SCCRPI) is used in this study to determine the most influential changes in climate parameters on agriculture production and livelihoods based on farmers' perceptions. In various studies on climate change risk perceptions, the standardized climate change risk perception index (SCCRPI) is widely used (Iqbal et al., 2016; Sullivan-Wiley and Gianotti, 2017; Ahmed et al., 2021; Zobaer et al., 2022; Likinaw et al., 2022) to gain a better understanding of how farmers perceive climate change risks. The SCCRPI is a metric or index that combines the probability or likelihood of risk events with the severity of risk event consequences (Aven, 2016; Li et al., 2018). The respondents were asked to rate the extent to which the major changes in climate parameters had an impact on their agricultural production and livelihood. For ease of analysis, we have denoted values to respective perception scales in increasing order such as 0 for no perception, 1 for low perception, 2 for medium perception, 3 for high perception, and 4 for very high perception. The Standardized Climate Change Risk Perception Index (SCCRPI) was calculated using the following equation from (Ahmed et al., 2021).

$$\boldsymbol{SCCRPI = \frac{CCRPn * 0 + CCRPl * 1 + CCRPm * 2 + CCRPh * 3 + CCRPvh * 4}{Respective\ highest\ CCRPS\ value} * 100}$$

Where SCCRPI is the Standardized Climate Change Risk Perception Index,

CCRPn is the number of respondents who have no perception,

CCRPl is the number of respondents having low perception,

CCRPm is the number of respondents having medium perception,

CCRPh is the number of respondents having high perception and

CCRPvh is the number of respondents having a very high perception.

The Total CCRPS value was calculated by multiplying respective perception values with total perception frequency against each statement, and the Respective highest CCRPS value was calculated by dividing the total CCRPS value by the highest maximum boundary value and multiplying by 100. Since we have 425 respondents, the Climate Change Risk Perception Score (CCRPS) for any identified change in climate condition could range from 0 to 1700, with 0 being the minimum and 1700 being the maximum, where 0 indicates a minimum level of risk perception and 1700 indicates a maximum level of risk perception. The analyses were done in Excel software.

3.2.2.3. Measuring Farmers' Climate Risk Perception Level

The current study used PCA, a widely used data dimension reduction technique, to identify the variables that explain the variability in farmers' perceptions of climate risk. The PCA results were used to classify households into different climate risk perception groups using cluster analysis.

The principal component analysis (PCA) is a data exploration tool based on ordination that converts a set of potentially correlated variables into a set of uncorrelated variables that capture the variability in the underlying data. PCA is a non-parametric analysis that is unaffected by any hypothesis about the probability distribution of the data (Abdi & Williams, 2010). PCA employs orthogonal linear transformation to identify a vector in N-dimensional space that accounts for as much of the total variability in a set of N variables as possible in the first principal component (PC), where total variability within the data is the sum of the variances of the observed variables after each variable has been transformed to have a mean of zero and a variance of one (Hatcher, 1997). Then, a second vector (second PC) orthogonal to the first is sought to account for as much of the remaining variability in the original variables as possible. Each subsequent PC is linearly uncorrelated to the previous ones and accounts for as much of the remaining variability as possible (Jolliffe, 2002). PCA was used as a data reduction tool in this study to identify relationships between variables and the components to be kept. Varimax rotation was used as the type of orthogonal rotation in this analysis. In addition, the Kaiser-Meyer-Olkin (KMO) adequacy measure was used to determine the appropriateness of applying PCA and Bartlett's test of sphericity to test for the presence of correlation between the variables (Hair et al., 2009). A KMO value greater than 0.5 and a significance level for Bartlett's test less than 0.05 indicate that there is a significant correlation in the data. To gain a better understanding of the components or factors received the factors corresponding to eigenvalues 1 are suggested (Hair et al., 2009). The Varimax rotation method was used to perform an orthogonal rotation.

K-mean Cluster Analysis (KCA) is a clustering method that divides n observations into k clusters, with each observation assigned to the cluster with the closest mean. The value of k is determined by repeated exploratory uses of K-means clustering (i.e., k = 2 to 10) (Everitt et al., 2011). Before running the K-mean cluster, the hierarchical cluster was run to determine how many clusters should be considered in the KCA. The analyses were done using SPSS version 26.

3.3. Results

3.3.1. Rainfall and Temperature Characteristics

3.3.1.1. Inter-Annual Precipitation Characteristics

The annual rainfall means, the annual rainfall median, the rainfall Standard Deviation, and the Coefficient of Variation were used to examine rainfall fluctuation from (1961 to 2021). Table 3.3 shows that the Mango station has the highest average rainfall (1069.5mm). The median is lower than the average at all two stations, indicating an uneven temporal distribution of rainfall in the study area. When a CV is ≤20 it means that rainfall variability is reliable but when ≥20 it indicates unreliable (Tume and Nyuyfoni, 2021). Hence, rainfall variability is reliable for Dapaong and Mango respectively with values of 20% and 17.86% thus explaining the contrasting nature of the rainfall.

Table 3.3. Indicators of rainfall fluctuation

Stations	**Indicators**			
	Mean annual rainfall (mm)	**Median (mm)**	**Standard deviation**	**Coefficient of variation (%)**
Dapaong	1049.73	1040.60	210.09	20%
Mango	1069.5	1052.5	191.06	17.86%

The interannual rainfall trend depicts a slight increase at Dapaong from 1961 to 2021 with an increase of 17.90% in rainfall between the period (1961-1990) and (1991-2020) (figure 3.1).

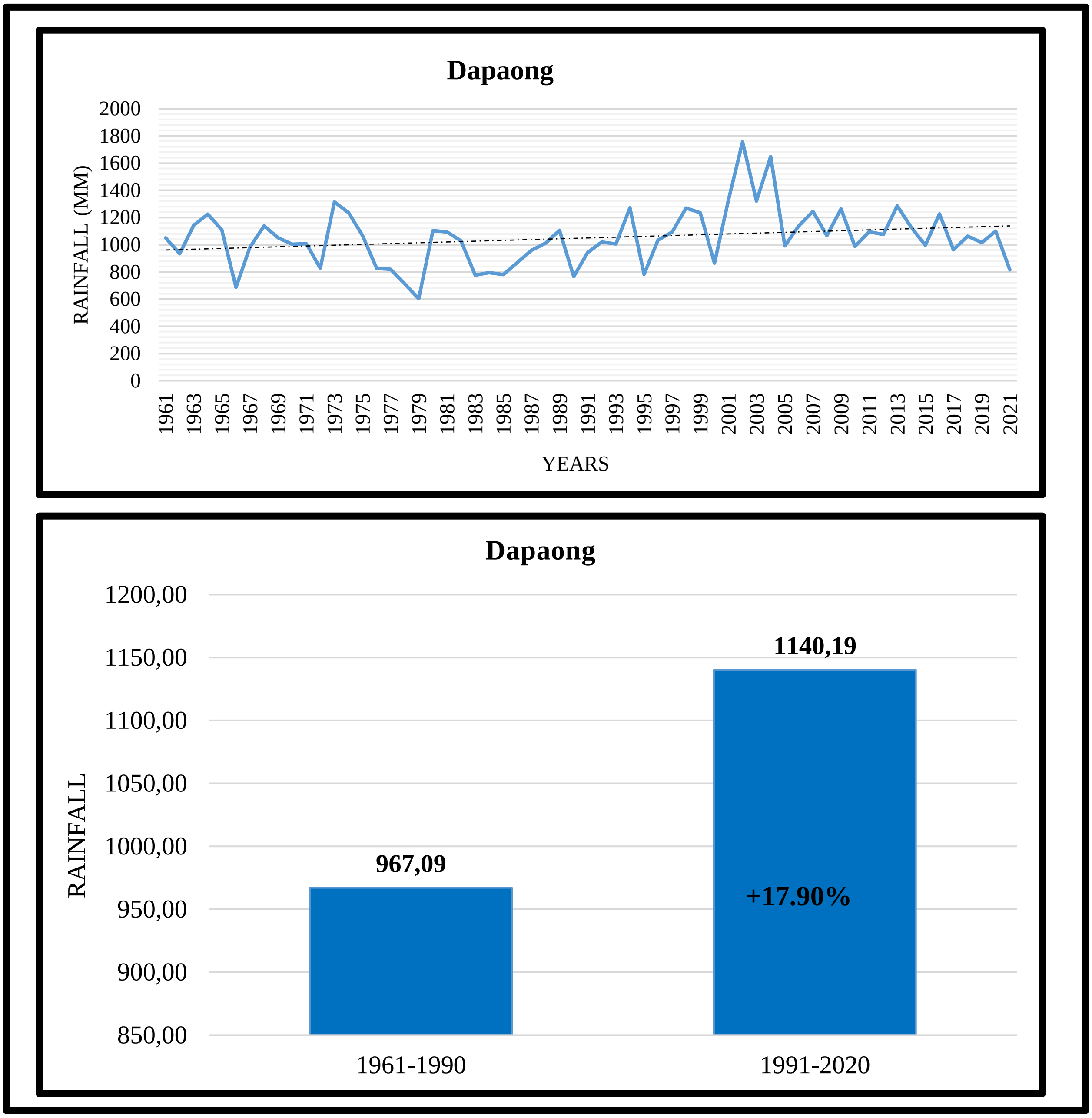

Figure 3.1. Inter-annual rainfall variation over the period (1961-2021) at Dapaong station

The highest rainfall amount measured in Dapaong was in 2002 at around (1756.6mm) and the lowest was in 1979 (603 mm). Whereas at Mango station, a slight decrease in rainfall is observed over the same period with a decrease of 5.60% of rainfall between the period (1961-1990) and (1991-2020). The highest rainfall amount was measured in 1969 (2009.20mm) and the lowest was in 2001 (747.40mm) (figure 3.2). This observation conceals strong seasonal and district disparities in the Savanna region.

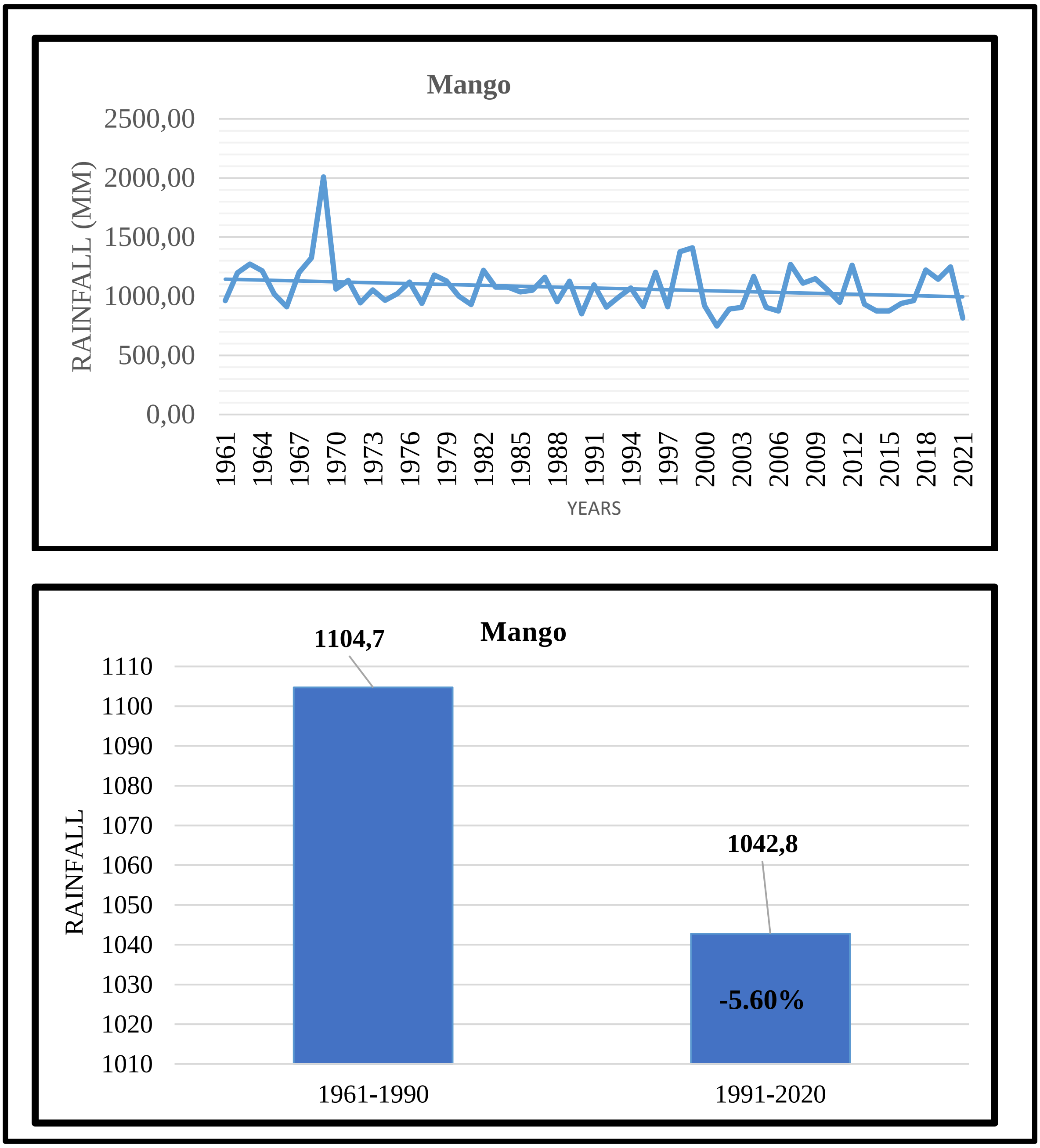

Figure 3.2. Inter-annual rainfall variation over the period (1961-2021) at Mango station

3.3.1.2. Inter-Annual Rainfall anomaly index (RAI)

The inter-annual rainfall anomaly graph was used to determine normal, wet, and dry years, for the considered period of sixty years (1961-2021) (Figures 3.3 and 3.4).

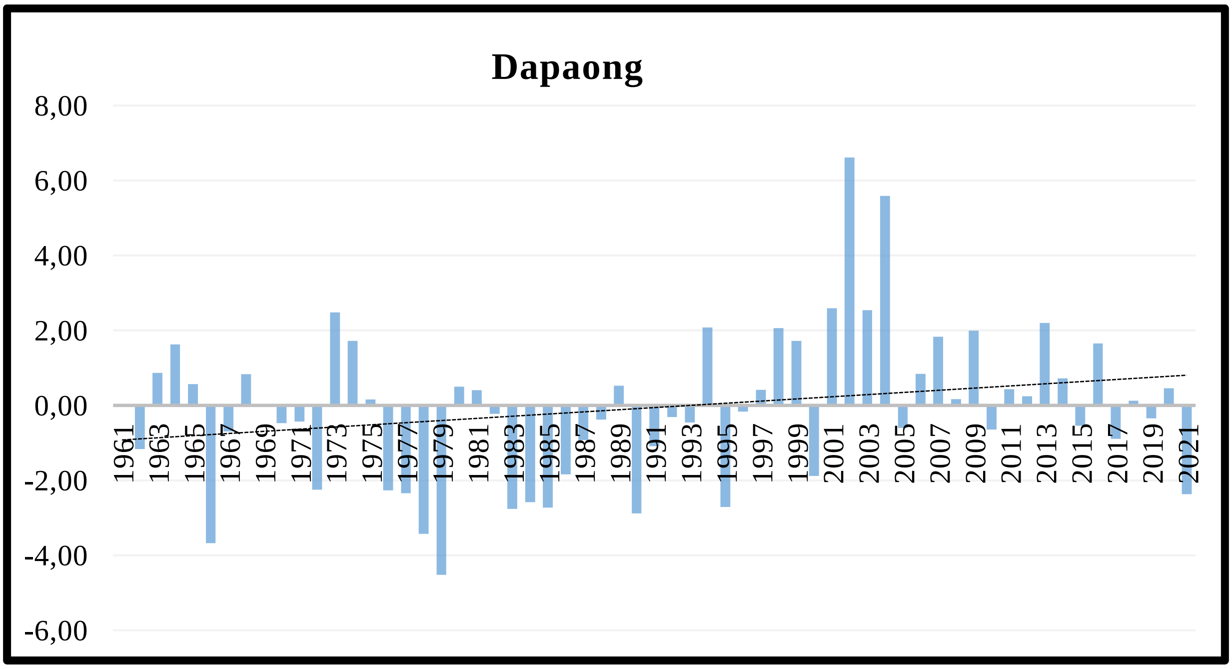

Figure 3.3. Inter-annual rainfall anomaly at Dapaong station over the period (1961-2021)

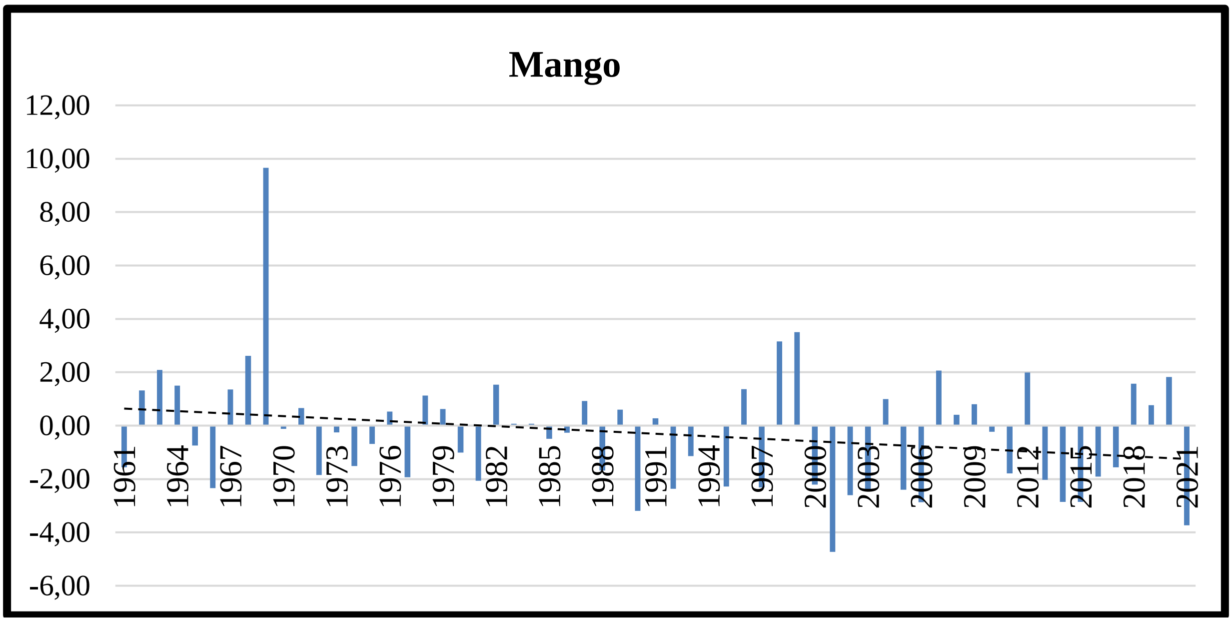

Figure 3.4. Inter-annual rainfall anomaly at Mango stations over the period (1961-2021)

The trend line in the graphs determines if each zone is experiencing rainfall deficits or surplus. The results confirmed that overall, the general trend is upwards in Dapaong and downwards in Mango. This trend is marked by a cyclic pattern of variations with alternating drier, normal, and wetter years. The results show that at the Dapaong, during the period under consideration (1961-2021) (see Appendix 1), 21 years were wet years with two (2) years being extremely wet ranging from 1647.3 mm to 1756.6 mm, six (6) years being very wet ranging from 1270.3 mm to 1321.6 mm, another six (6) years with moderately wet condition ranging from 1223.5 mm to 1262.9 mm, seven (7) years of slightly wet condition ranging from 1103.5 mm to 1142 mm. The highest wet year was in 2002 (1756.6 mm) and the lowest wet year was in 1963 (1142 mm). Seventeen (17) years of normal condition were depicted with rainfall amounts between 1003 mm and 1098.7 mm. There have been 22 years of dryness conditions, with four (4) years that were extremely dry with rainfall amounts between 603 mm and 710.7 mm, eight (8) years that were very dry with rainfall amounts between 765.3 mm and 827.6 mm, four (4) years that were moderately dry with rainfall amounts between 765.3 mm and 827.6 mm, four (4) years that were moderately dry with rainfall amounts between 863.6 mm and 942.6 mm, and six (6) years were slightly dry with rainfall amounts between 957.8 mm and 996.1 mm. The highest dry year was in 1979 (603 mm), and the lowest one was in 2015 (996.1 mm).

At the Mango station, however, during the same period (see Appendix 2)**,** there have been 24 years of wetness conditions, including three (3) years that were extremely wet with rainfall amounts between 1376.5 mm and 2009.2 mm, three (3) very wet years with rainfall amounts between 1270.7 mm and 1324.1 mm, eleven (11) years that were moderately wet with rainfall amounts between 1159.8 mm and 1262.7 mm, and seven years that were slightly wet with rainfall amounts ranging from 1103.5 mm to 1147.8 mm. The highest wet year was in 1969 (2009.2 mm) and the lowest wet year was in 2009 (1147.8 mm). There were nine (9) years of nearly average weather, with rainfall totals ranging from 1036.2 mm to 1096.1 mm. In the 24 years of dryness, there have been three (3) extremely dry years with rainfall amounts ranging from 747.4 mm to 851.9 mm, fourteen (14) very dry years with rainfall amounts ranging from 874.3 mm to 913 mm, eight (8) moderately dry years with rainfall amounts ranging from 938.1 mm to 991.7 mm, and two (2) slightly dry years with rainfall amounts ranging from 1018.7mm to 1023.1 mm. The lowest dry year was in 1975, and the highest one was in 2021 (747.4 mm) (1023.1 mm).

The RAI analysis then showed that at Dapaong during the 60 years taken into account (1961-2021), 21 years had wetter conditions with varying intensities (extremely to slightly), 17 years had conditions that were close to normal, and 22 years had dry conditions with extreme to slight intensities (Figure 3.5).

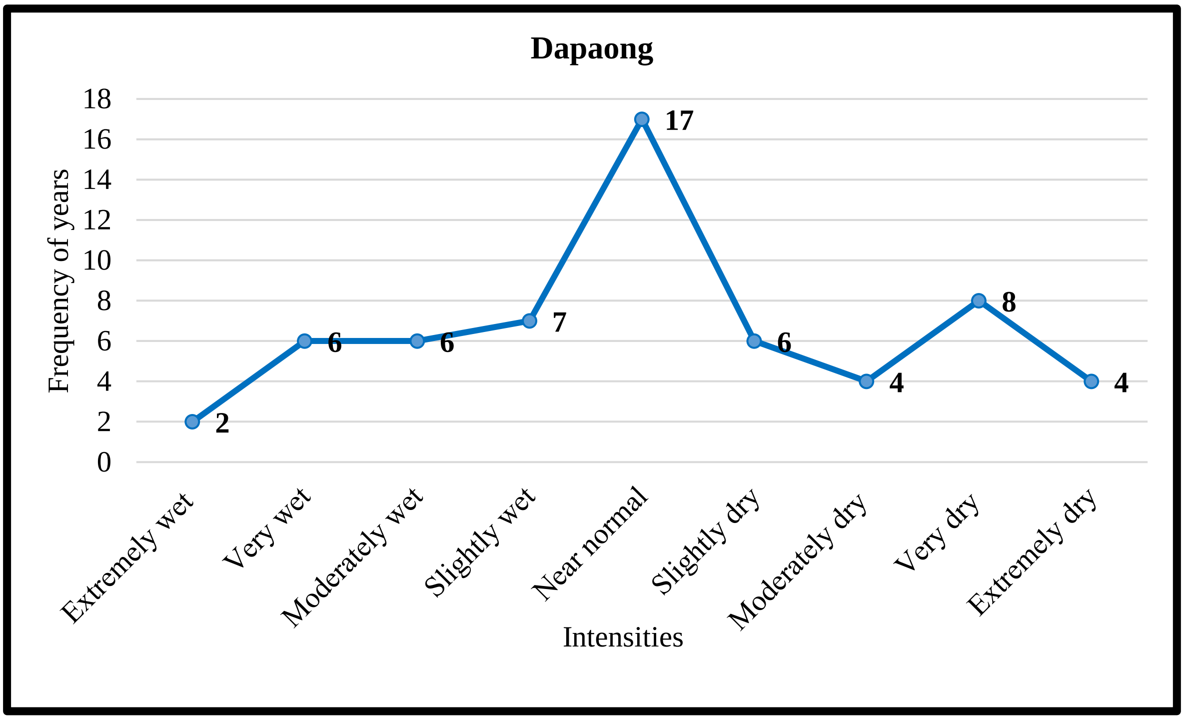

Figure 3.5. Frequency distribution of rainfall anomaly index of Wet, Dry, and Normal years in Dapaong from 1961-2021 (60 years)

Whereas at the Mango, 24 years experienced wetter conditions with varying intensities (extremely to slight), 9 years experienced conditions that were relatively close to normal, and 27 years experienced dry conditions with extreme to slight intensities (Figure 3.6).

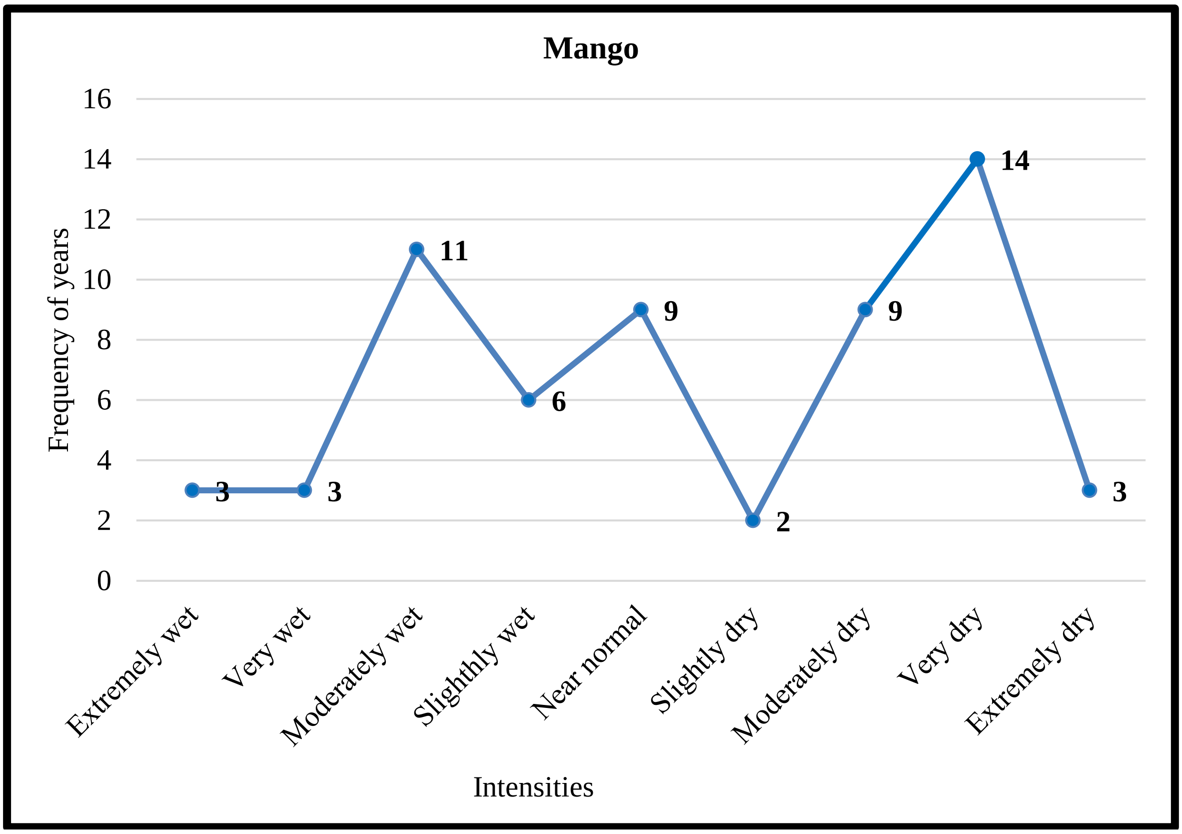

Figure 3.6. Frequency distribution of rainfall anomaly index of Wet, Dry, and Normal years in Mango from 1961-2021 (60 years)

3.3.1.3. Inter-Annual Variability in the Number of Rainy and Dry Days During Wet Season

Figure 3.7 shows both an annual variation and trend in the number of rainy and dry days over the rainy season (from April to October) at Dapaong and Mango stations. The downward trend in the number of rainy days is more noticeable at the Dapaong station. The number of rainy days varies throughout the series from 39 to 83 days in Dapaong, and from 49 to 83 days in Mango. Whereas, the upward trend in the number of dry days is more visible at the Mango station. The number of dry days varies throughout the series from 134 to 172 days in Dapaong, and from 131 to 165 days in Mango. This situation explains the shortening of the agricultural season and the increase in dry days in the Savanna region. Furthermore, studying the monthly distribution of the number of dry and rainy days allows one to comprehend the seasonal irregularity of the rainfall distribution.

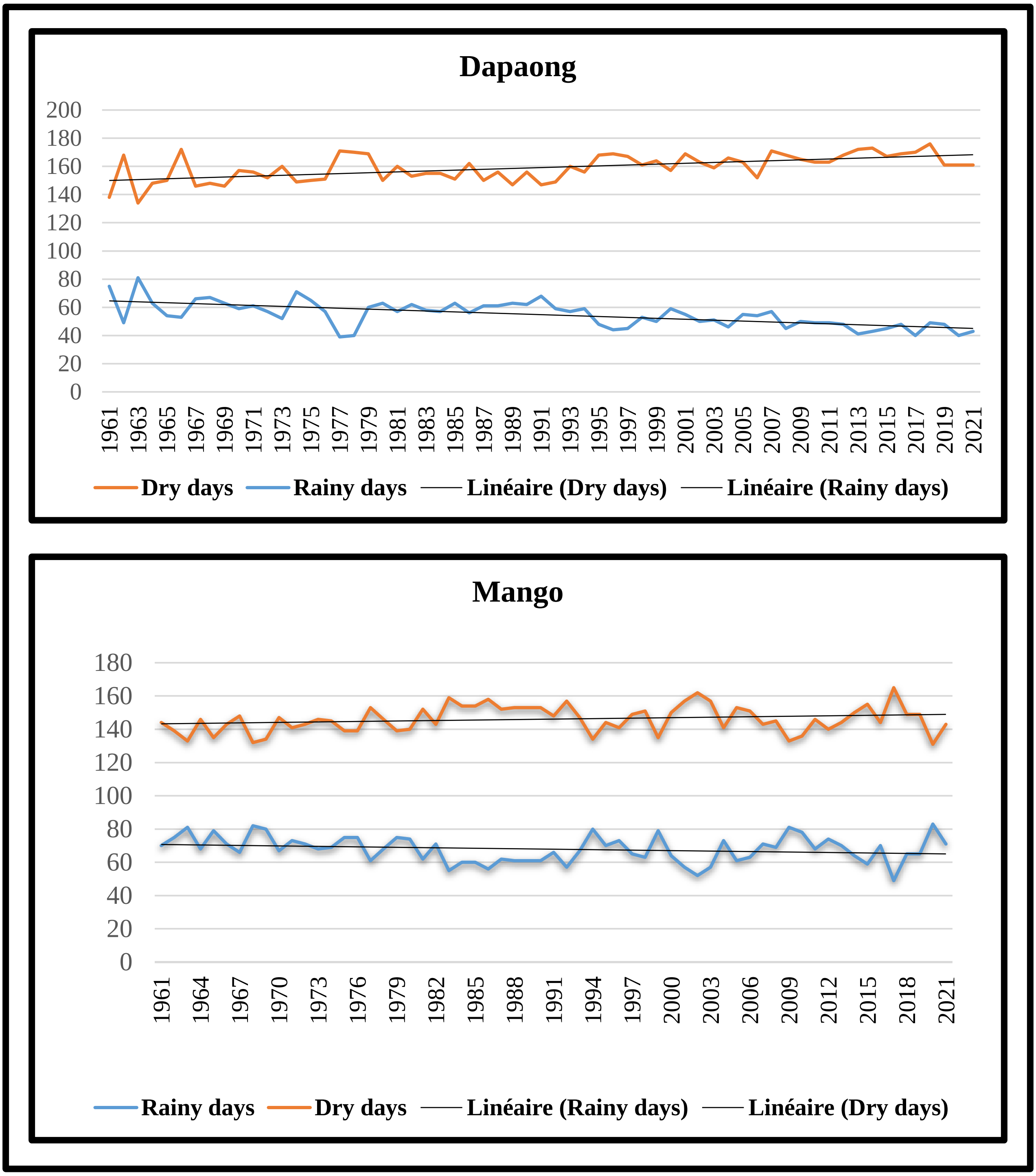

Figure 3.7. Annual variation in the number of rainy and dry days over the rainy season at Dapaong and Mango station (1961-2021)

Furthermore, Figure 3.8 revealed an increased trend of the annual maximum number of consecutive dry days ranging from 14 to 18 days and a decreased trend of the annual maximum number of consecutive wet days ranging from 4 to 11 days from 1961 to 2020.

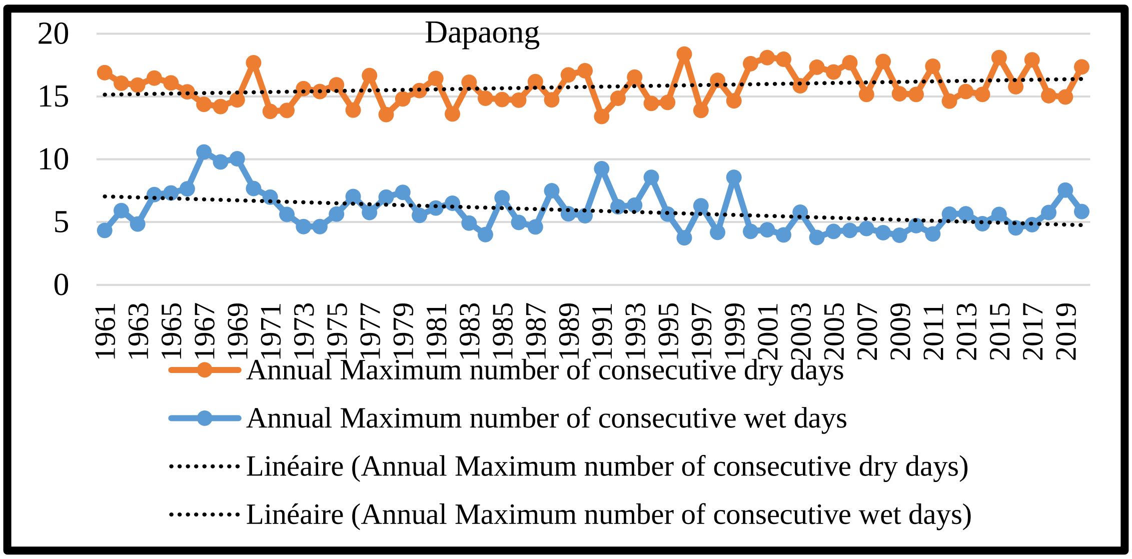

Figure 3.8. Annual maximum number of consecutive dry and wet days at Dapaong station

In addition, figure 3.9, also depicts an increasing trend in annual average maximum 1-day rainfall ranging from 9,38mm to 21.10 mm throughout 1961-2020.

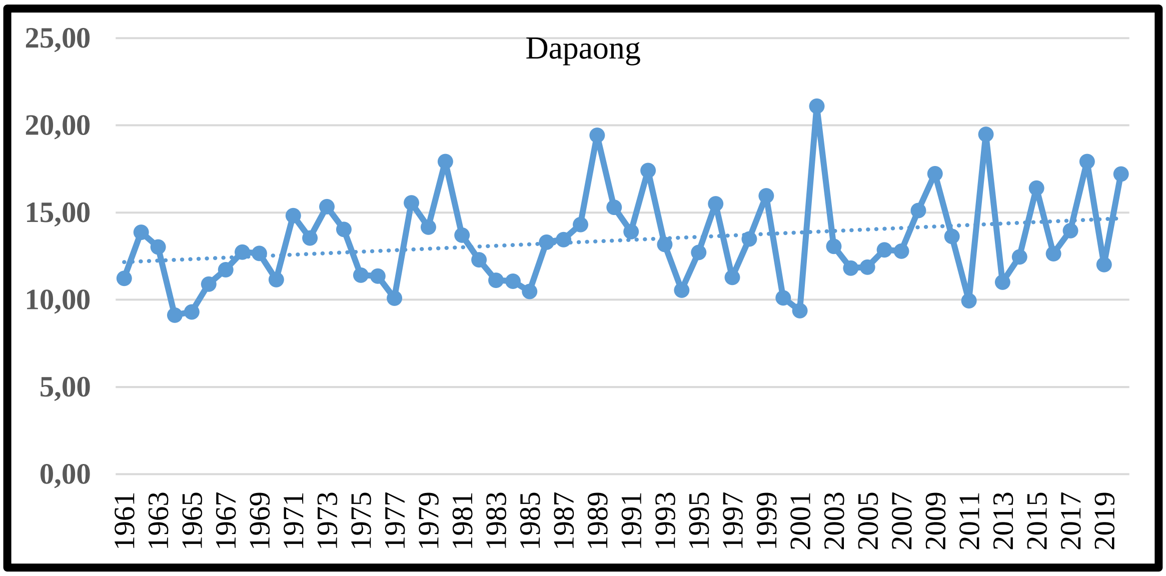

Figure 3.9. Annual Average maximum 1-day rainfall at Dapaong station

Moreover, the results in Table 3.4 show that the months considered as rainy unfortunately have more dry days than rainy days. For instance, August which records the maximum rainfall amount in the year has on average (1961-2021) 14 days of wet days both in Dapaong and Mango. The differences between the number of rainy days and the number of dry days are negative throughout the rainy season. At the two stations, the months of April, May, June, July, and October have the driest days (20-26 days without rain).

Table 3.4. Distribution of the Average number of wet and dry days in the wet season (from 1961-2021 in Dapaong and Mango)

		April	**May**	**June**	**July**	**August**	**September**	**October**	**Total**
Dapaong	NRD	4	7	9	11	14	12	5	63
	NDD	26	24	21	20	17	18	26	152
	Difference	-22	-17	-12	-9	-3	-6	-21	-89
Mango	NRD	4	8	10	11	14	15	7	68
	NDD	26	23	20	20	17	16	24	146
	Difference	-22	-15	-10	-11	-3	-1	-17	-78

NRD: Number of rainy days; NDD: Number of dry days

This situation shows the poor distribution of rainfall leading to an increase in the duration of dry spells, a shortening of the rainy season, and an increase in rainfall extreme events in the Savanna region.

3.3.1.4. Inter-Annual Mean Temperature Characteristics

In terms of the 30-year average, Figure 3.9 shows that the new temperature normal calculated for the period 1991-2020 in Dapaong is (28.07°C), up +0.12°C from 1981-2010, and in Mango is (28.98) up to +0.30°C from 1981-2010. This shows the increasing pattern of the temperature in the study area during the period under consideration.

According to previous analyses, there is evidence of current deterioration in rainfall and rise in temperature as determining factors of the Savanna region's climate change phenomenon. However, agriculture in the Savanna region is heavily reliant on the consistency of rainfall and temperature patterns. This situation may have a significant impact on agricultural activities and farmers' livelihoods.

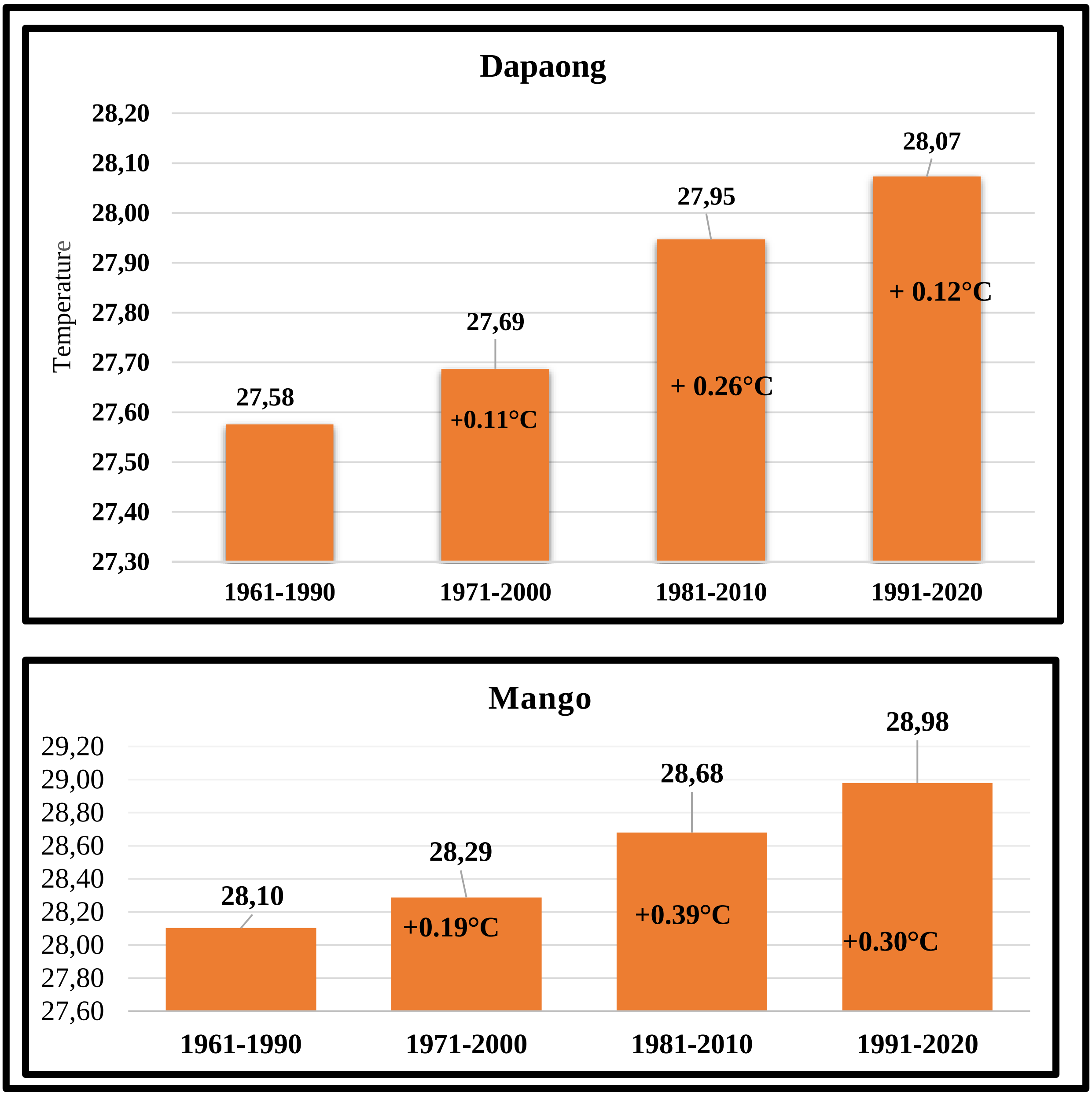

Figure 3.10. The normal evolution of the average annual temperature (1961-2020) at Dapaong and Mango

Farmers' perceptions of climate change, its impacts, and risks to agriculture are important to understand how they appraise the situation and how this may influence their decision to cope or adapt.

3.3.2. Farming Communities' Perception of Climate Change Risks

3.3.2.1. Socio-Demographic Characteristics of the Respondents

The results presented in Table 3.5 show that the majority of respondents are males (72.9 %) and more than twice of females (27.1%) with the average age of the respondents being 43.

Most of the respondents belong to the Moba ethnic group (64.7%). The respondents have an average of three years of education, implying that the vast majority have not completed primary school. Also, more than half of the total number of respondents (66.7%) have between 6-15 numbers of people in their household. The maximum household size is 20 and the minimum is 2 with an average of 10 people in the household.

Table.3.5: The socio-demographic characteristics of respondents

Variables	Frequency	Percentage (%)	Mean
Gender			
Male	310	72.9	
Female	115	27.1	
Ethnicity			
Moba	275	64.7	
Mossi	15	3.5	
Tchokossi	122	28.7	
Others	13	3.1	
Household size			
<= 5	1	0.2	
6-15	318	66.7	
16 +	106	33.1	
Age			43
Education			3

3.3.2.2. Livelihood Strategies and Access to Agricultural Services of the Respondents

The result presented in Table 3.6 reveals that The most common livelihood strategy of the household is crop farming activities (100%), with food crops accounting for 96% of all significant cultivated crops (maize, rice, sorghum; millet, and beans being the main cultivated food crops), on an average farm size of 4.96 hectares. The respondents have an average of 26 years of farming experience with an average labor force of approximately 5 people. The majority of them (50%) were members of farming associations and had access to extension services. 74 % of the respondents depend highly on farming activities for their annual income.

Table 3.6: Livelihood strategies and access to agriculture services of the respondents.

Variables	Frequency	Percentage (%)	Mean
Livelihood strategies of the respondents			
Agriculture	425	100	
Livestock	306	72	
Fishing	26	6	
Crafts	37	9	
Trade	86	20	
Food processing	19	5	
Selling of non-timber forest products	8	2	
Others	31	7	
Type of agriculture production of the respondents			
Food crop	395	96	
Cash crop	158	39	
Market gardening	112	27	
Tuber crop	85	21	
Type of food crop produced by the respondents			
Maize	357	94	
Millet	152	41	
Sorghum	201	53	
Rice	222	58	
Beans	161	42	
Type of livestock farming produced by the respondents			
Goat	208	68	
Cattle	191	63	
Pig	62	20	
Poultry	274	90	
Dependency of household income on agriculture activities			
Very low dependency (less than 25%)	14	3	
Low dependency (25-50%)	39	9	
Moderate dependency (50-75%)	54	13	
High dependency (75%-100%)	315	74	
Agricultural services			
Agricultural Group membership	213	50	
Extension services	212	50	
Input subsidies	235	55	
Credit	151	36	
Irrigation	44	10	
Climate information	128	30	
Farming characteristics			
Farming experience	425		26
Farm size (hectare)	425		4.96
Farm labor force	425		5

accounting for (75% to 100%) of their income. The other 25% get their income from other sources besides farming, including livestock activities with poultry, goat, and cattle being the main breeding, trading, craftsmanship, and fishing. 36 % of the respondents have access to agricultural credit, 30% to climate information, and 10% to irrigation facilities.

3.3.2.3. Mode of Land Ownership

In terms of land acquisition, land tenure systems underpin various modes of access to land, which are inextricably linked to social contexts and thus to individuals' social identities. The field surveys allowed for the identification of land access modes, which are inheritance (79%), borrowing (1%), donation (14%), and renting (6%) **(**Figure 3.11).

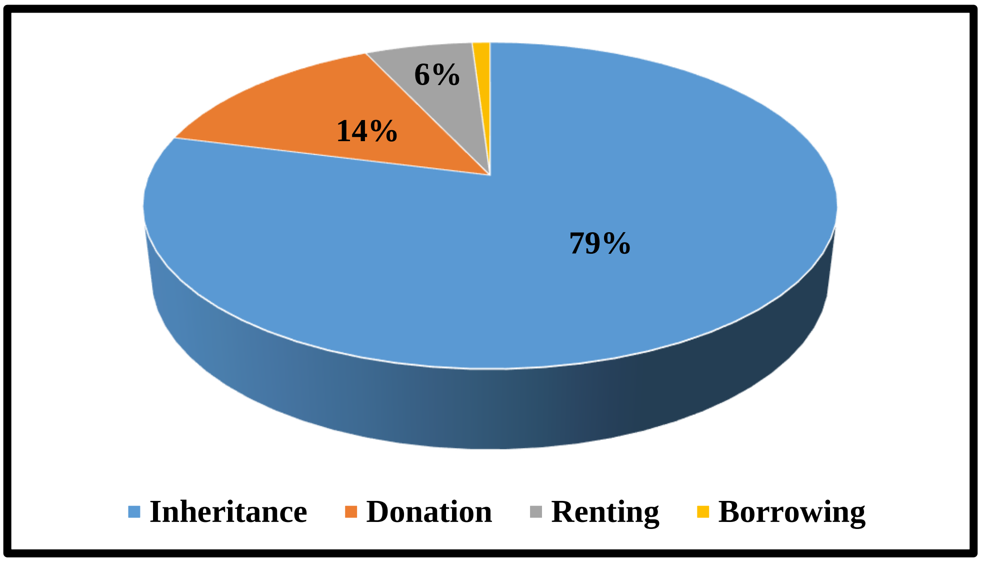

Figure 3.11. Mode of land ownership

Inheritance is the most common mode of land ownership in the study area: access to land is determined by a person's position within the family in this mode. The farmer's land is part of the family's land heritage, and land is passed down patrilineally. The acquisition of land by inheritance marks the transition from collective to individual land ownership. In the case of borrowing, the borrower negotiates with the lender, who agrees to give up a portion of his property for free in exchange for a fixed or open-ended operation. In the case of donation, some farmers may benefit from the donation of plots of land ahead of a family, for a variety of reasons. Loans and donations, on the other hand, are two methods of gaining access to land in which, regardless of the length of the exploitation, the beneficiary will never become the owner of the transferred plot. Land rental is a non-customary land practice. This method of accessing land is now increasingly common in the study area. Owners who cannot exploit all their land and who do not have the means to finance the season's agricultural production rent out part of their land in return for monetary compensation or service delivery (plowing, agricultural inputs). The duration of the exploitation of a rented plot is relatively short. It generally ranges from one to two agricultural seasons.

3.3.2.4. Local Stakeholders' Perceptions of the Key Drivers of Climate Change Risks

A participatory workshop was held to gather qualitative information from local stakeholders on the perceived key drivers of climate change risk. The participants were divided into three main groups of seven consisting of members of non-governmental organizations (NGOs), community leaders, farmer organizations, and agricultural local public institutions. Table 3.7 summarizes the information gathered from each group. This includes hazard, exposure, and vulnerability drivers as well as climate impacts that contribute to the climate change risks on agroecosystems. The workshop participants asserted that five major changes in climate conditions—erratic rainfall, warmer temperatures, an increase in extreme rainfall events, a shortening of the rainy season, and an increase in the duration of dry spells—are responsible for the increase in flood and drought events in the study area. Increased flood and drought events, according to the participants, have a variety of negative impacts on agroecosystems. These impacts include decreased water availability, decreased soil moisture, increased pest, and crop diseases, destruction of crops and farmland, damage to stored agricultural products, increased soil erosion, decreased soil fertility, decreased crop production and yields, and decreased agricultural income.

Additionally, relevant drivers determining the vulnerability of the social-ecological system (SES) were identified. In total, twelve social and ecological vulnerability drivers were identified. The drivers include loss of ecosystem services provided by cropland for farming, increased cropland degradation, cultivated land size, strong dependency on agricultural income, unsustainable farming practices, lack of access to sufficient farm labor, lack of knowledge on

Table 3.7. The top-ranked responses to group questions (data refers to participatory workshop)

	What are the major changes observed in the climate conditions and their related hazards?		**Which major impacts related to the identified climate hazards affecting agroecosystems during the last 20 years?**	**Which major social and ecological vulnerability factors contribute to the climate change risks on agroecosystem?**	**What are the major exposed agroecosystems elements at risk?**
	Changes in climate condition	**Climate-related hazards**			
Group 1	• Erratic rainfall • Warmer temperature • Increase in extreme rainfall events	• Increased drought events • Increased flood events	• Decrease in soil moisture • Increase in the rate of soil erosion • Soil fertility decline	• Loss of ecosystem services provided by cropland for farming • Strong dependency on agricultural income • Unsustainable farming practices • Lack of access to sufficient farm labor	• Cropland • Farmers
Group 2	• Shortening of the rainy season • Warmer temperature • Increase in extreme rainfall events	• Increased drought events • Increased flood events	• A decline in crop production and yields • Increase incidence of pest and crop diseases • Cropland and farm destruction	• Increased cropland degradation • Lack of Knowledge of sustainable land management practices • Lack of improved seeds • Lack of access to climate information	• Cropland • Farmers
Group 3	• Increase the duration of dry spells • Erratic rainfall Increase in extreme rainfall events	• Increased drought events • Increased flood events •	• Decrease in water availability • A decline in agricultural income • Damage to stored agricultural products	• Lack of access to irrigation • Cultivated land size • Lack of access to agricultural assets • Lack of access to financial safety net	• Cropland • Farmers

sustainable land management practices, lack of improved seeds, lack of access to climate information, lack of access to irrigation, lack of access to agricultural assets, and lack of access to the financial safety net. For example, the stakeholders highlighted that as the population of the study area is increasing, agricultural practices have changed, with the disappearance of fallow land, conversion of forested land, the reduction of crop residues returned to the soil, and the cultivation of land that is too poor or degraded. The combination of these practices results in a decrease in soil cover and a decrease in the rate of organic matter in the soil, accentuating the phenomenon of soil erosion and the degradation of soil fertility resulting in lower crop production and yields.

3.3.2.5. Farmers' Perceptions of Climate Change, Hazards, and Impacts on Agroecosystems

Approximately 97.2% of household respondents reported perceiving a change in temperature and rainfall over the last 20 years. In our study, we used the Likert scale to assess farmers' perceptions of the influence of those changes on their agricultural livelihood based on their own experience. To gain a better understanding, SCCRPI was calculated using frequency analysis from Equation (6) on the five major changes in climate conditions identified during the participatory workshop (Table 3.7). According to the SCCRPI, the values ranged from 49.18 to 92.12 (Table 3.8), demonstrating the influence of all five major changes in climate conditions on agroecosystems perceived by farmers in the study area.

Table 3.8. Perception of change in climate conditions affecting agroecosystems

Perceived changes in climate parameters	**Very high Perception (4)**	**High perception (3)**	**Moderate perception (2)**	**Low perception (1)**	**No perception (0)**	**SCCRPI**	**Rank**
Increased duration of dry spells	348	37	12	15	13	92.12	1
Erratic rainfall	330	50	15	17	13	91.00	2
Increase in extreme rainfall events	255	17	14	126	13	73.71	3
Shortening of the rainy season	221	29	16	146	13	69.47	4
Warmer temperature	102	11	32	267	13	49.18	5

After calculating the respective index values for each climatic change, we ranked them based on the highest index from 1 to 5 for better understanding and interpretation (Table 3.7). Farmers ranked the increased duration of dry spells highest among climatic changes considered, followed by erratic rainfall, an increase in extreme rainfall events, a shortening of the rainy season, and warmer temperatures.

Furthermore, farmers perceive that those changes have serious consequences on the occurrence of drought and flood events that severely affect agroecosystems in the study area.

Figure 3.12 shows that both drought and flood have been perceived to become more intense, frequent, prolonged, and severe over the last 20 years.

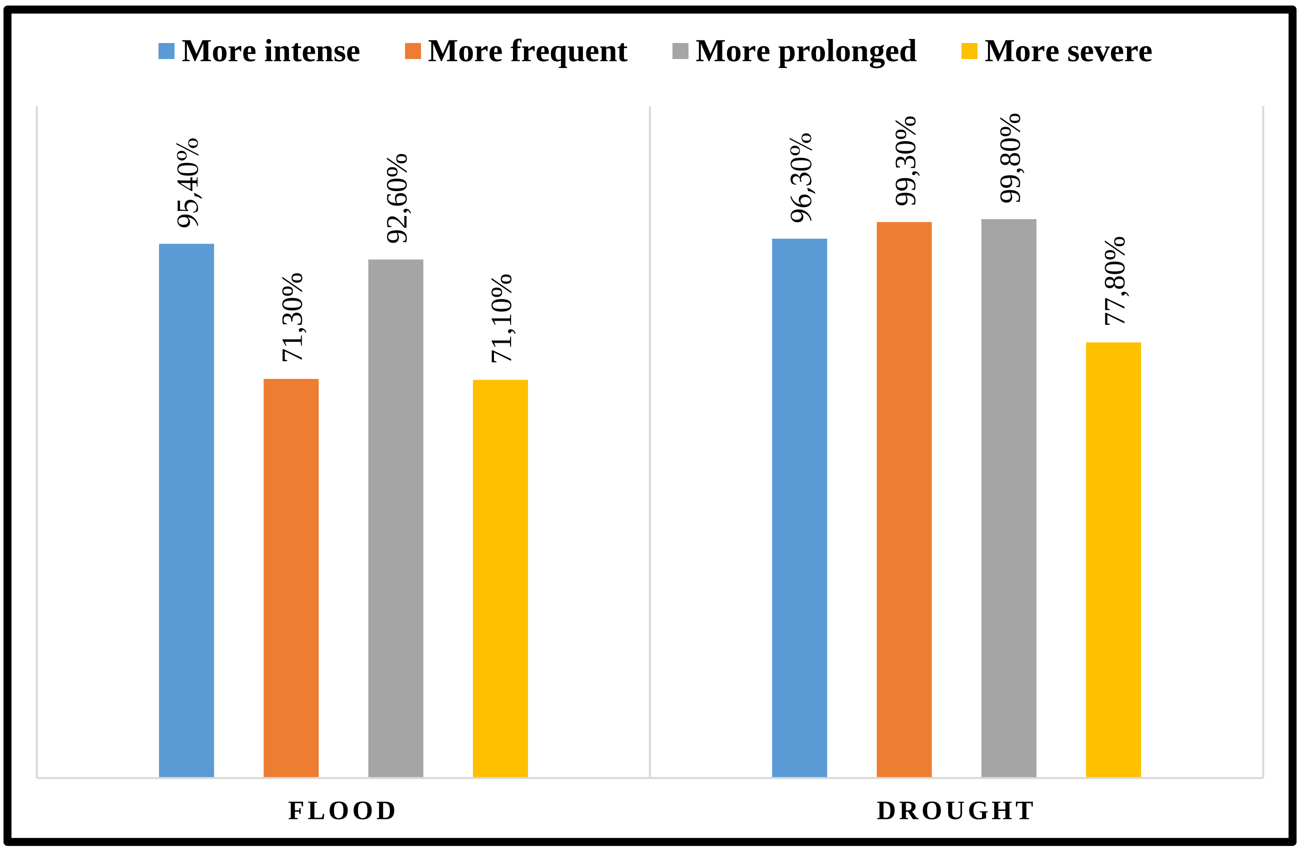

Figure 3.12. Farmers' perception of the occurrence of flood and drought hazards

Figure 3.13 revealed that among the impacts identified during the participatory workshop (Table 3.6)**,** the most significant impact perceived by farmers is a decrease in agricultural income (99%), followed by a decrease in crop production and yields (93%), soil fertility decline (92%), decrease in water availability (90%), an increased rate of soil erosion (88%), crop and farmland destruction (80%), decrease in soil moisture (76%), damage stored agricultural products (74%), and increased incidence of pest and crop disease (28%) as the most prominent impacts of climate change on agroecosystems.

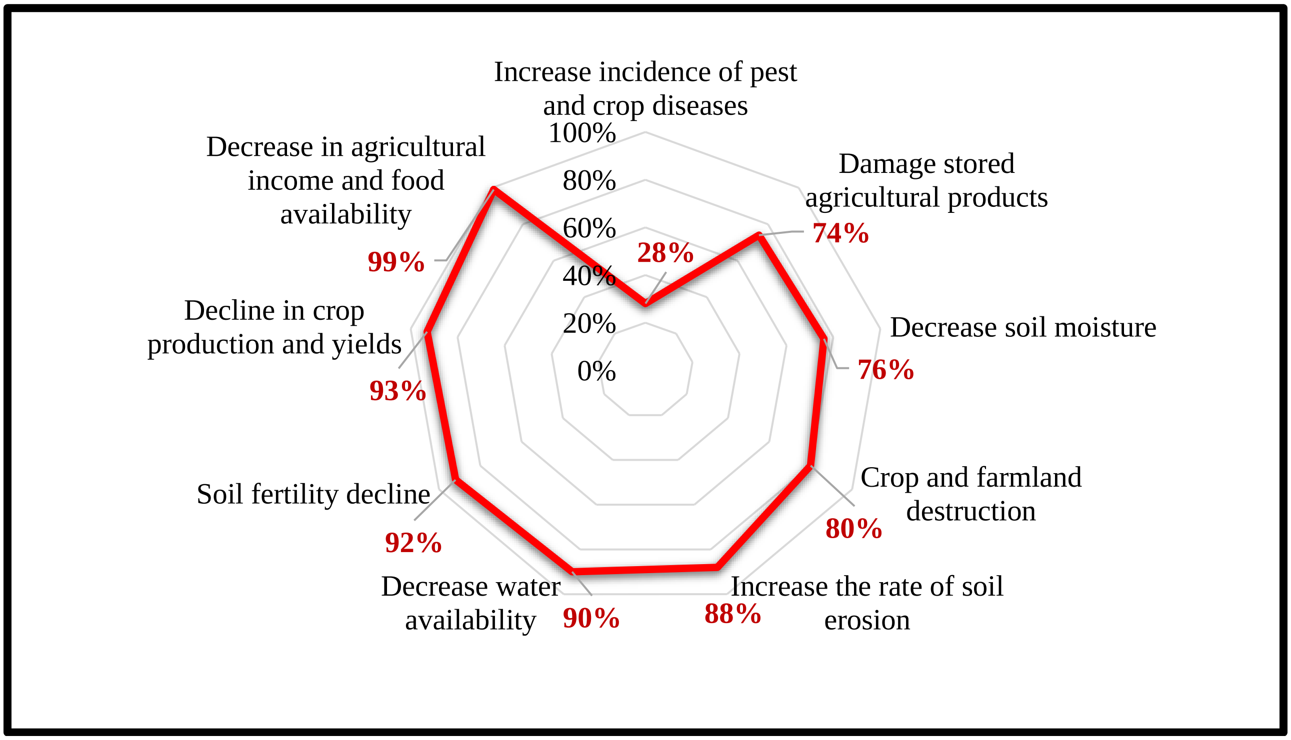

Figure 3.13. Farmers' perception of the major climate impacts on agroecosystems

3.3.2.6. Evaluation of Farmers' Climate Change Risks Perception

In this section, the study measured the level of farmers' climate change risk perception among surveyed farmers based on hazard, vulnerability, and exposure drivers identified during the participatory workshop (Table 3.7). A total of 16 items have been considered. Each surveyed farmer gave a subjective degree of agreement for each of sixteen statements based on five Likert scale points, where 5 points stood for "strongly agree," 4 for "agree", 3 for "neither agree nor disagree", 2 for" disagree" and 1 point for "strongly disagree".

Principal Component Analysis (PCA) was used as a data reduction tool to identify relationships between variables and the components to be kept. The evaluation of the data assumptions for PCA is shown in Table 3.9. It includes the Kaiser-Meyer Olkin (KMO) value, which is used to determine whether the PCA is useful for these variables. According to the results, the KMO value is 0.726, indicating that PCA is appropriate. Furthermore, Bartlett's test is used to determine whether or not there is an interrelationship between variables.

Table 3.9. Evaluation of the data assumptions for Principal Component Analysis.

Test of the correlation between variables.	**Results**	**Conclusion**
Kaiser-Meyer-Olkin (KMO)	Value = 0.726	Satisfied. PCA is appropriate for the analysis of these variables
Bartlett's Test of Sphericity:	Chi-Square= 1058.407; df = 120; P-value.=.000*	Satisfied. Variables are correlated

*actual p-value is less than 0.01

The result shows that the p-value for Bartlett's test of sphericity is less than 0.01; thus, the requirement for variable interrelationship is met in this study.

One method for determining whether variables are significant for principal component analysis is to examine their Measure of Sampling Adequacy (MSA). It is suggested that an MSA value of less than 0.50 which is unacceptable has to be excluded from further analysis because the correlations between Xi and the other variables are unique, meaning that they are unrelated to the remaining variables outside of each simple correlation. The Anti-Image Correlation Matrix is shown in (see Appendix 3). The overall MSAs of the individual variables are displayed on the matrix's main diagonal. It can be observed that the MSA values for the sixteen variables are all greater than 0.50, then acceptable for the final analysis of the data.

The Varimax rotation method was used to determine how many components should be retained. There are a total of 16 variables loaded into specific components. The components were chosen based on the total eigenvalue ≥1 criterion, as well as the variance explained by the factors when they were combined. The first seven components were retained, accounting for 75% of the variance in the data (see Appendix 4). Table 3.10 shows the variables grouped into their respective factors and renamed according to their collective representation. Seven factors were retained based on their Eigenvalue: **(1)** climate-related hazards; **(2)** Exposed elements at risk; **(3)** Cropland sensitivity; **(4)** Social sensitivity; **(5)** Sustainable agriculture barriers, **(6)** Lack of access to Agricultural facilities, and **(7)** Lack of access to financial protection and climate information. The first principal component, “climate-related hazards”, comprises two variables: increased drought events and increased flood events. This described the households' perception of climate hazards affecting their agricultural livelihood. It accounted for 15.95 percent of the total variance. The second component, "Exposed elements at risk," includes two variables: exposed farmers and exposed croplands, which accounted for 13.68 percent of the total variance. The third component, “cropland sensitivity”, accounted for 12.10 percent of the total variance. It comprised the loss of ecosystem services provided by land for farming activities and cropland degradation and described the perception of households on their cropland health. The fourth component, "social sensitivity," is made up of three variables: unsustainable farming practices, and strong dependency on agricultural income and cultivated land size. It described the perception of households on the pressure they put on their cropland. This factor accounted for 10.75% of the total variance. The fifth component, “Sustainable agriculture barriers” is comprised of two variables: lack of knowledge of sustainable land management practices and lack of access to improved seeds. It accounted for 9.29 percent of the total variance and described the sustainable agriculture capacity of households. "Lack of access to agricultural facilities," the sixth component, is made up of three variables: lack of access to agricultural production assets, lack of access to sufficient farm labor, and lack of access to irrigation. This describes the farming capacity of a household and accounted for 8.09% of the total variance. The seventh and last component, “Lack of access to financial protection and climate information”, consists of two variables: lack of access to financial safety nets, and lack of access to climate information. It accounted for 5.21 percent of the total variance.

Table 3.10. The rotated component matrix: Factor analysis for farmers' perception of the drivers of climate risk

No	Drivers contributing to climate change risks on agroecosystem	Principal components						
		Climate -related hazards	**Exposed elements at risk**	**Cropland sensitivity**	**Social sensitivity**	**Sustainable agriculture barriers**	**Lack of access to Agricultural facilities**	**Lack of access to financial protection and climate information**
X1	Increased drought events	**.864**	.077	.112	-.036	-.013	.060	.006
X2	Increased flood events	**.852**	-.027	.030	-.020	.045	.081	-.015
X3	Exposed farmers	-.006	**.791**	-.021	-.028	.048	.062	-.051
X4	Exposed cropland	.061	**.790**	.094	-.026	-.017	.074	.020
X5	Loss of ecosystem services provided by cropland for farming	.006	.056	**.597**	.043	-.001	-.198	.473
X6	Increased cropland degradation	.087	-.007	**.846**	-.092	.000	-.001	.050
X7	Unsustainable farming practices	.050	.136	.019	**.878**	.134	.152	-.037
X8	Strong dependency on agricultural income	.178	.049	.085	**.800**	.146	.009	.060
X9	Cultivated land size	.129	.033	-.007	**.779**	.240	-.035	.077
X10	Lack of knowledge of sustainable land management practices	.044	.016	.057	.092	**.906**	-.079	.093
X11	Lack of access to improved seeds	-.392	-.021	.225	-.131	**.544**	.361	-.272
X12	Lack of access to agricultural assets	.075	-.040	.039	-.082	-.024	**.577**	-.041
X13	Lack of access to sufficient farm labor	.111	.255	.323	.230	-.098	**.800**	.301
X14	Lack of access to irrigation	.049	.050	.069	.062	.047	**.814**	.011
X15	Lack of access to financial safety net	-.010	.294	-.037	-.029	.083	.064	**.662**
X16	Lack of access to climate information	-.112	.112	.234	-.167	.237	.181	**.580**

The results from the PCA were used to classify households into different risk perception categories using cluster analysis. Table 3.11 depicts the classification of cluster households. Based on the component scores, the households were divided into three risk perception groups (clusters) Clusters 1, 2, and 3 accounted for 65.9%, 21.4%, and 12.7% respectively. These three clusters were labeled as Cluster 1 "high climate risk perception households," which included farmers who perceived a high or very high perception of the influence of changes in climate conditions on their agroecosystems, Cluster 2 "moderate climate risk perception households," which included farmers who perceived a moderate perception of the influence of changes in climate conditions on their agroecosystems, and Cluster 3 "low climate risk perception households," which included farmers who perceived a low perception of the influence of changes in climate conditions on their agroecosystems. The F values of the components "Sustainable agriculture barriers" have a greater influence in deciding the clusters (291.898), followed by cropland sensitivity (58.412), exposed elements at risk (12.337), social sensitivity (3.768) and the least important factor influences the clusters is lack of access to agricultural facilities (3.086).

Table 3.11. Characterization of individual clusters based on component scores

Components of Household's climate change risk perception	Cluster 1 (65.9%)	Cluster 2 (21.14%)	Cluster3 (12.7%)	F	P-Value
	High climate risk perception households	Moderate Climate risk perception households	Low Climate risk perception households		
Climate-related hazards	0.15124	1.41800	-0.4165	3.236	0.000
Exposed elements at risk	0.10438	0.26613	-1.48457	12.337	0.000
Cropland sensitivity	0.34512	0.12442	-0.8263	58.412	0.040
Social sensitivity	0.19574	-0.93161	-0.01049	3.768	0.032
Sustainable Agriculture Barriers	3.81686	-0.00717	-0.21883	291.898	0.000
Lack of access to agricultural facilities	0.56685	0.20459	-0.06964	3.086	0.024
Lack of access to financial protection and climate information	0.03392	0.44873	-0.0181	3.710	0.047

Figure 3.14 shows that the households in Cluster 1 (high climate risk perception households) are the households with a high perception of sustainable agriculture barriers, the least

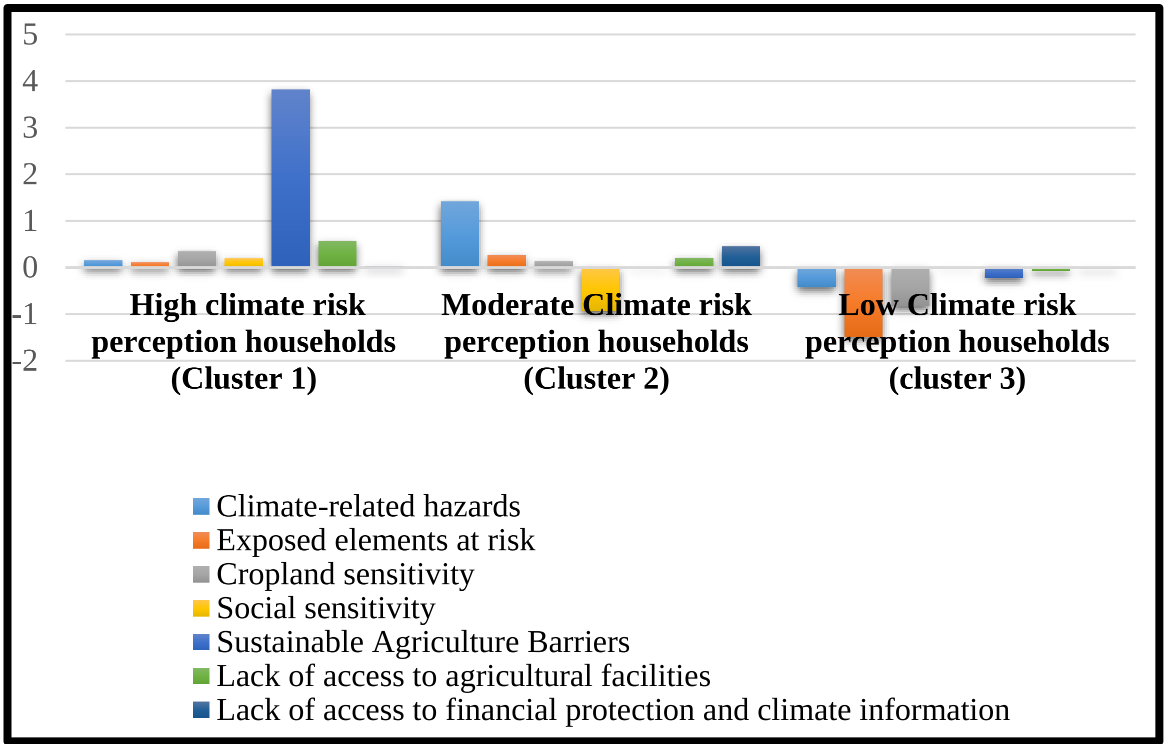

Figure 3.14. Cluster centers based on component/factor scores

access to agricultural facilities, and the highest cropland and social sensitivity. The majority of these households have cultivated medium land (67%), small (18%), or large (13%) with the majority having their household sizes between (6-10) (48%), (11-15) (41%), 79% of those households do not have non-farm income, but 75% are members of agricultural organizations (Figure 3.15).

Cluster 2 (moderate climate risk perception households) have the greatest perception of climate-related hazards and vulnerable elements, but the least access to financial protection and climate information (Figure 3.14). These households primarily had small (46%), medium (39%), and large (13%) cultivated land, with the majority of households falling into (1-5) (38%), (6-10) (36%), categories. Although 65% of these households have no non-farm income**,** 62% are members of agricultural organizations **(**Figure 3.15**).**

Households in Cluster 3 (those with low climate risk perception) have the lowest scores on all seven climate risk perception components (Figure 3.14).

They have the most marginal (43%) and small (39%) cultivated land, as well as the smallest range of household sizes (1-5) (76%), non-farm income (70%), and 94% are not members of agricultural organizations (Figure 3.15).

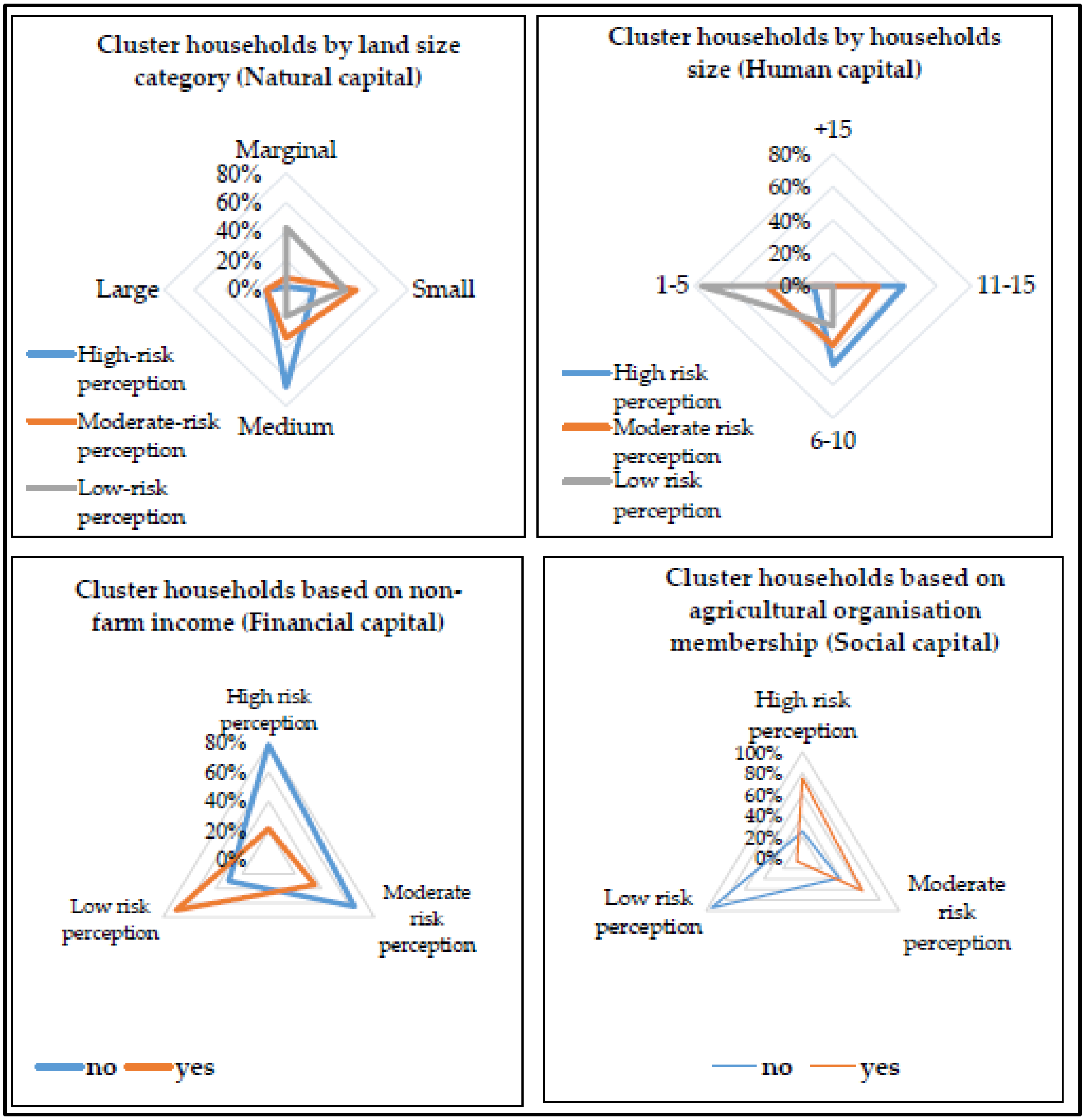

Figure 3.15. Cluster households' classification based on Natural, Human, Financial, and Social capital Note: Marginal (< 1ha); Small (1 ha-2.9ha); Medium (3ha -7ha); Large (Above 7ha)

These findings show that households with a large amount of cultivated land, large household size, and non-farm income perceive more climate change risks on their agroecosystem, and their perceptions increased as their perceived socio-ecological sensitivity, lack of adaptive capacity, and exposure increased. The greater their vulnerability and exposure to climate-related hazards, the greater their perceived climate change risks.

3.4. Discussion

The first step towards developing an effective risk management system is a proper perception of risk factors (Ndamani and Watanabe, 2017). Farmers' understanding and perceptions of climate risks are important because they can influence their management practices and provide a better guide for adaptation responses (Lebel et al., 2015; Lemma, 2016). Various studies (Niles and Mueller, 2016; Abid et al., 2016; Wolf and Moser, 2011) have shown that farmers' perceptions are important for understanding climate-related risks on agroecosystems because this body of knowledge is built on individual farmers' perspectives, beliefs systems, and interpretations of climate issues based on experience and local knowledge. In our study, both the qualitative results from the local stakeholders' workshop and the quantitative results from the household survey revealed that farmers, as well as local stakeholders, are aware of the change in climate parameters mainly in rainfall and temperature and the occurrence of their related extreme events. They perceived that the frequency and intensity of extreme weather events mainly droughts and floods have increased during the last two decades. Similarly, earlier studies carried out in the study area (e.g. Gadédjisso-Tossou, 2015; Sanou et al., 2018) reported that farmers perceived an increasing trend of temperature and changes in rainfall patterns marked by erratic rainfall and increase in extreme rainfall events in the Savanna region of Togo causing extreme events such as droughts and floods in the Savanna region of Togo. A study carried out by Kassie et al (2013) in Ethiopia revealed that small-holder farmers face several climate-related hazards, including highly variable rainfall and severe droughts, which can be devastating to their agroecosystem and livelihoods. According to (Gitz et al., 2016; Hussain et al., 2018), as the temperature increases and the rainfall pattern changes due to climate change, the likelihood of sudden disasters including floods and droughts will augment and intensify the risk of loss of rural income and livelihood for the most vulnerable populations. All of the previous findings supported the perceptions of local stakeholders and farmers in the study area, who believe that an increase in flood and drought events due to climate variability affect severely agroecosystems. Several climate impacts on agricultural land and production have been identified in the study area. The prominent impacts perceived were a decrease in agricultural income, a decline in crop production and yields, income, a decrease in soil fertility, a decrease in water availability, and increased soil erosion. These results are consistent with earlier studies on the impacts and risks of climate change on agriculture (Dahal et al., 2023; Ngoma, 2021; Arifah, et al., 2021; Nguyen-Thi-Lan et al., 2021; Idoko, 2016), which showed that because agriculture is so dependent on weather and climate, changes in their parameters can have a significant impact on agricultural production that affects farmers' livelihood.

In addition, several socio-ecological factors were identified as contributing to increased agroecosystem vulnerability. Among others, the perceived factors were loss of ecosystem services provided by land, strong dependency on agricultural income, unsustainable farming practices, lack of sufficient farm labor, lack of sufficient agriculture assets, lack of knowledge of sustainable cropland management strategies, lack of access to improved seeds, lack of access to irrigation, lack of access to financial safety nets and lack of access to climate information. Along the same line, the studies carried out by (Harvey et al., 2014; Thamaga-Chitja and Morojele, 2014; Ho et al., 2022) revealed that smallholder farmers are vulnerable to the effects of climate change due to low levels of technology, to high dependence on agriculture for their livelihoods; limited access to climate information and lack of other essential agricultural assets resulting in increased vulnerability and loss of livelihood.

Furthermore, when measuring farmers' perceptions of climate risk, the findings show that three major factors play a significant role in categorizing farmers as high, moderate, or low climate risk perceivers. Those factors are perceived socio-ecological sensitivity, lack of adaptive capacity, and exposure to climate-related hazards. This means that farmers with higher risk perception of climate change risks on agroecosystems had a higher perception of the vulnerability and exposure of their agroecosystem to climate hazards. This finding is consistent with the findings of (Shinbrot et al., 2019) in Chiapas, Mexico, who discovered that farmers with strong perceptions of climate hazards and their vulnerability to those hazards were more likely to appraise climate risk and adapt. Etongo et al. (2022) also found that understanding climate-related vulnerabilities and exposure is critical for understanding climate risk perception and improving agricultural practices to increase food production. According to Raghuvanshi and Ansari (2019), measuring farmers' perception of risks associated with climate change is of paramount importance and needs to be assessed so that appropriate adaptation measures can be implemented to mitigate productivity losses. This study demonstrated the importance of local knowledge in understanding the drivers of climate change risk in agriculture.

3.5. Summary

Using both observed climate records and perception-based approaches, our study assessed local-level climate change information as well as farmers' perceptions of climate change indicators such as temperature change, rainfall change, seasonality change, its impacts, and risk on agroecosystems in the Savanna region of Togo. This study found clear evidence of change in climate conditions in the study area, which is shared by the local farming communities. Five main changes were perceived by farmers in rainfall and temperature patterns. Among those changes, erratic rainfall, an increase in the duration of dry spells, an increase in extreme rainfall events, a shortening of the rainy season, and warmer temperatures were highly perceived as the most observable changes affecting their agriculture production and livelihood. Changes in rainfall and temperature were perceived to have serious implications for the occurrence of climate-related hazardous events such as droughts and floods, which are becoming more frequent and severe in the study area. Agroecosystems are impacted by the frequency and severity of drought and flood events. Three categories of climate risk perception levels have been distinguished among farmers; households with high-risk perception, households with moderate-risk perception, and households with low-risk perception. This categorization of farmers' households depends strongly on how they perceive their exposure, cropland sensitivity, socioeconomic sensitivity, and adaptive capacity to drought and flood events. This demonstrates that although farmers are aware of rainfall and temperature change, the perception of risks related to those changes on their agroecosystems is perceived differently among farmers depending on their personal experience and vulnerability[1]. The long-term negative effects of climate change on farmers' livelihoods could be severe without sustainable adaptation. Hence, the following chapter aims to identify and assess the effectiveness of main Ecosystem-based Adaptation practices developed by farmers to address climate change risks on agroecosystems in the Savanna region.

[1] This chapter's findings have been published in a scientific journal.
Perceptions of Climate Change Risk on Agriculture Livelihood in Savanna Region, Northern Togo. Climate 2023, 11, 86.https://doi.org/10.3390/cli11040086

CHAPTER 4: FARMERS' ASSESSMENT OF ECOSYSTEM-BASED ADAPTATION PRACTICES TO CLIMATE CHANGE RISKS IN THE AGRICULTURE SECTOR

4.1. Introduction

Climate-related extremes have affected the productivity of all agricultural sectors, with negative consequences for food security and livelihoods (Bezner et al., 2022). Farming communities in West African countries continue to rely on rain-fed agriculture, which renders their production activities increasingly vulnerable to climate variability and change (Sultan and Gaetani 2016, Zougmoré et al., 2016). Rain-fed agriculture constitutes the prime sector in Togo that governs the rural economy, given its contribution to gross domestic product (GDP), employment, and food supply. It contributes over 40% of GDP, supports two-thirds of the population, and accounts for more than 20% of export earnings (Republique Togolaise, 2023a). Climate is the most important factor governing food production and causes interannual variability in socioeconomic and environmental systems related to water resource availability (Koudahe et al., 2018; Djaman et al., 2016). Changes in rainfall patterns are characterized by large inter-annual fluctuations, an increase in the frequency of rainfall extremes, and prolonged droughts affecting long-term yield trends in West Africa (Salack et al., 2016, Sultan et al., 2019). For example, 1°C warming above the preindustrial climate has increased heat and rainfall extremes, and reduced yields by 10–20% for millet and 5–15% for sorghum in Western Africa (Sultan et al., 2019). Projected median maize yields will decrease by 9% as a result of 1.5 °C of global warming and by 41% at 4 °C, without adaptation compared to 2005 yield levels. Crop productivity in West Africa is expected to decline significantly over the next few decades because of increased climate variability and climate change, among other factors (Godfray et al., 2010; van Noordwijk et al., 2011; Vignola et al., 2015), posing major risks to farmers in poor communities who lack the financial, institutional, and technical capacity to adapt (Munang et al. 2014).

The productivity of agriculture as well as its contribution to the economy, food security, and poverty reduction, are dependent on ecosystem services such as soil fertility, freshwater delivery, pollination, and pest control (IFAD & UNEP, 2013). Withstanding the fact that increasing weather and climate extreme events can impair greatly the ecosystem functioning, it undermines the provision of numerous services and benefits drawn by the communities from the various ecosystems, hence exposing farmers to acute food and water insecurity, with the largest impacts observed in Africa (IPCC, 2022). Enhancing agricultural productivity, therefore, is critical for ensuring food and nutritional security for all, particularly for smallholder farmers. In the absence of sustainable adaptation strategies, the long-term negative consequences of climate change on the livelihood of smallholder farmers could be severe (Rao et al. 2016).

The rural communities in the Savanna region of northern Togo, rely heavily on agroecosystems for livelihood-supporting services and resources, which mobilizes nearly 90% of rural households (Munang et al., 2013; Komi et al., 2016). However, the region is one of the areas in Togo with high susceptibility to land degradation (e.g., soil erosion, loss of soil organic matter, and loss of biodiversity) due to the physical characteristics of its soils (low water retention capacity, fragile structure, a tendency to acidification), unsuitable human practices (e.g., deforestation, unsustainable agriculture practices), and the change in climatic conditions (Magamana et al., 2021). The region has recently been heavily impacted by climate change's effects, with a significant increase in the frequency and intensity of extreme events such as droughts, floods, erratic rain, and extreme temperatures, negatively affecting agriculture land and livelihood (Pilo et al., 2021; Gadédjisso-Tossou, 2015; Lare and Lamboni, 2015). The higher frequency of extreme climate events observed in the study area, combined with population growth, and associated increased demands for food and energy production, is leading to significant changes in the landscape—land, water resources, and vegetation cover, resulting in the degradation of agroecosystem and the reduction in ecosystem services supply (Badjana et al., 2015). Although local communities may experience short-term benefits from fulfilling food and energy demands, it is essential to acknowledge that they will inevitably incur substantial costs in food insecurity and population welfare insecurity in the long term.

Previous research studies conducted in various countries show that one effective method of supporting farmers in maintaining their farm-based livelihoods amidst the growing challenges of climate change and variability is by promoting farm management practices that utilize agrobiodiversity and ecosystem services, which offer valuable adaptation benefits. These benefits may result in greater resilience of agroecosystems to climate change, increased crop productivity and yield, and help to improve food security and rural livelihoods (Vignola, et al., 2015; Shah, et al., 2019; Ghanbari, et al., 2021; Parkoo, et al., 2022). Also, several international agreements highlighted that increasing trends in ecosystem degradation are increasing the vulnerability of communities to climate change and that Ecosystem-based Adaptation (EbA) strategies should be prioritized (Delbeke et al., 2019: UNISDR, 2015).

Ecosystem-based Adaptation (EbA) is one theoretical discourse that is drawing increasing attention, which acknowledges the importance of ecosystems in the adaptation process to improve societal resilience (Colls et al., 2009; Munang et al., 2014). EbA is defined as the use of biodiversity and ecosystem services to help people adapt to the adverse effects of climate change (CBD, 2009). Some examples of EbA approaches include management, conservation, and restoration of ecosystems that deliver services that can help reduce climate change exposure (Munang et al. 2013). EbA approaches are considered appropriate for African countries because of the many potentials such as flexibility, cost-effectiveness, and co-benefits (e.g., biodiversity conservation, enhanced habitat conditions, conservation of traditional knowledge, livelihood, and enhanced food security) (UNEP, 2018). In this regard, ecosystem-based adaptation practices such as sustainable land management practices, conservation agriculture practices, and integrated soil fertility management practices, have been introduced in the Savanna region through several projects from non-governmental organizations and local governments to develop an environmentally, economically, and socially sustainable farming system (Lare and Lamboni, 2015). However, knowledge about the existing EbA practices and their effectiveness in addressing climate-related impacts remains scarce. Understanding how smallholder farmers view and use EbA practices can show the benefits for their farmlands and livelihoods, leading to more sustainable agriculture and resilience in the face of climate change. There appears to be a gap in research regarding the use and effectiveness of agricultural ecosystem-based adaptation practices for climate change. Additionally, there seems to be little information available on the perceived co-benefits of these practices. Furthermore, there is not much evidence from the literature that this scope of analysis underlines the current research that has been carried out to fit the current socioeconomic context in the study area. Therefore, this study aims to identify the EbA practices, the effectiveness, and co-benefits of each EbA appropriate for farmers in the Savanna region to address climate risks. Then, this study addresses the following questions:

Q2.1. What are the main EbA practices in the agriculture sector to address climate change risks on agroecosystems in the Savanna region?

Q2.2. How do farmers perceive the effectiveness and the co-benefits of EbA practices in dealing with climate change risks in the Savanna region?

Q2.3. What are the significant Socioeconomic factors affecting farmers' assessment of EbA effectiveness?

From these questions, the following objectives have been derived :

OS2.1. To identify the main EbA practices in the agriculture sector to deal with climate-related risks in the Savanna region;

OS2.2. To assess farmers' perception of the effectiveness of EbA practices and their associated co-benefits in dealing with climate change risks in the Savanna region;

OS2.3. To analyze the socio-economic factors affecting farmers' perception of EbA effectiveness

From the objectives, three main hypotheses have been set up :

H2.1. Farmers in the Savanna region are implementing different types of EbA practices such as water and soil conservation practices, conservation agriculture practices, and integrated soil fertility management practices to increase the capacity of their agroecosystems to resist extreme weather events and to sustain agricultural livelihood and food security.

H2.2. Farmers in the Savanna region perceive EbA practices as effective in improving agricultural livelihoods while preserving agroecosystem health and are aware of the multiple co-benefits associated with these practices in buffering the impacts of climate change.

H2.3. Socio-economic factors such as land size, education, gender, and access to extension services among others may influence farmers' perception of EbA effectiveness.

4.2. Conceptual framework

In this study, we apply the framework proposed by Vignola et al. (2015) that is specific to smallholder farmers. Based on this framework, EbA is defined in agricultural systems as agricultural management practices, that use or take advantage of biodiversity or ecosystem services or processes (either at the plot, farm, or landscape level) to help increase the ability of crops or livestock to adapt to climate change and variability. According to Vignola et al. (2015), practices need to satisfy the three main dimensions and their underlying criteria to be considered as EbA practices that are suitable for smallholder farmers, namely: (1) ecosystem services provision; (2) adaptation benefits; and (3) livelihood and food security. The list of the underlying criteria for each dimension is presented in Table 4.1.

Table 4.1. Framework for Identifying EbA Agricultural Practices (based on Vignola et al. 2015)

Dimension 1: Ecosystem services provision	Dimension 2: Adaptation benefits	Dimension 3: Livelihood and food security
Criterion 1: Is based on the conservation, restoration, and sustainable management of biodiversity (e.g., genetic, species, and ecosystem diversity)	**Criterion 1:** Maintains or improves crop, animal, or farm productivity in the face of climate variability and climate change	**Criterion 1**: Increases livelihood and food security of smallholder households
		Criterion 2: Increases or diversifies income generation of smallholder households
Criterion 2: Is based on the conservation, restoration, and sustainable management of ecological functions and processes (e.g., nutrient cycling, soil formation, water infiltration, carbon sequestration)	**Criterion 2**: Enhances buffering capacities against extreme events (heavy rainfall, floods, drought, extremely high temperatures, strong winds, etc.)	**Criterion 3:** Takes advantage of local or traditional knowledge of smallholder farmers
		Criterion 4: Uses locally available and renewable inputs (e.g., using local materials from within the farm or landscape
	Criterion 3: Reduces crop pest and disease hazards due to climate change	**Criterion 5:** Requires implementation costs and labor affordable to smallholder farmers

If the practices meet at least one of the criteria in dimensions 1 and 2, then they are considered EbA practices. If the practices meet at least one criterion in dimension 3, then they are EbA practices suitable for smallholder farmers. This framework has been successfully applied to smallholder coffee farmers in Mesoamerica (Vignola et al. 2015), whereas Nanfuka et al. (2020a) used the same framework for characterizing EbA practices to drought for the smallholder cattle farmers in the central corridor of Uganda.

4.3. Methodology

4.3.1 Data collection

4.3.1.1. Focus Group Discussion

A list of EbA practices for climate-related risks in agriculture systems was initially established from the literature deemed appropriate for the study area **(**cf. Table 4.2**).** This list was used to discuss with key informants working in the field of sustainable and resilient agriculture (i.e., local NGOs, local public institutions, and farmers' organizations).

Table 4.2 List of agricultural EbA practices based on the literature

Agricultural EbA practices	**Brief description**	**Sources**
Intercropping	Intercropping is a practice that involves growing two or more crops on the same field at the same time.	Mfitumukiza et al., 2017; Nanfuka et al., 2020a
Mulching	The process of covering the open surface of the ground with a layer of external material.	Abdelmagied and Mpheshea, 2020; Vignola et al., 2015, Harvey et al., 2017a
Crop rotation	The practice of growing a variety of crops in the same area throughout several growing seasons.	Abdelmagied and Mpheshea, 2020; Vignola et al., 2015
Contour farming	Contour farming entails plowing the land along the contours of the field rather than in straight lines	Abdelmagied and Mpheshea, 2020; Harvey et al., 2017b
Terrace farming	Terrace farming is a sloped plane cut into successively receding flat surfaces or platforms that look like steps.	Abdelmagied and Mpheshea, 2020; Harvey et al., 2017b
Grass hedges	Planting lines of trees or shrubs along farm boundaries or the borders of home compounds, pastures, fields, or animal enclosures	Abdelmagied, and Mpheshea, 2020; Harvey et al., 2017b Mfitumukiza et al., 2017 ; Nanfuka al., 2020b,
Contour Stone bunds	Contour stone bunds are constructed with quarry rock or stones along the natural contour of the land to a height of 20-30 cm from the ground and spaced 20 to 50 m apart depending on the terrain's inclination.	Abdelmagied, and Mpheshea, 2020; Harvey et al., 2017b Mfitumukiza et al., 2017 ; Nanfuka al., 2020b
In-field water drainage channel	A structure that acts as a runoff collector and evacuator. The drainage channels are oriented towards streams, rivers, or retention basins and are implemented at the start of each season so that they can perform the function of evacuating excess water.	Easton et al., 2016; Ghane, 2018; Tolossa et al., 2020
Agroforestry	Agroforestry systems are land management practices in which trees and shrubs are grown alongside crops or livestock on the same plot of land.	Abdelmagied, and Mpheshea, 2020; Altieri and Koohafkan, 2008; Lin, 2007; Vignola et al., 2015
Integrated crop-livestock	Agricultural management systems in which land is rotated between crop, pasture, and livestock use over time and space.	Abdelmagied, and Mpheshea, 2020; Reddy, 2016; Sekaran et al., 2021; Vignola et al., 2015

During the focus group discussions (FGDs), the key informants were asked to select from the list the most common practices that they observed being utilized by smallholder farmers (at the farm level) as strategies to reduce climate-related risks. A total of seven FGDs were conducted; one in each of the seven districts in the study area. Each group was composed of five to ten people of mixed gender. The discussions were conducted in French as well as in local dialects namely, Moba and Tchokossi.

4.3.1.2. Household Survey

The information generated from the seven FGDs was used to develop the survey questionnaire. A total of eight farm management practices were considered agricultural EbA strategies used by farmers to respond to climate-related risks. The question topics include 1) household and livelihood characteristics; 2) the selected EbA practices implemented on the farm level; and 3) the perceived effectiveness of EbA practices using the framework. A 5-point Likert scale ranging from "No improvement" (1) to "Significant improvement" (4) was used to assess farmers' perceptions of the effectiveness of each EbA practice; whereas, a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5) was also used to assess farmers' perceptions of the benefits of EbA practices.

A pretest was conducted on the survey questionnaire with 60 farm households chosen at random in Sanfatoute and Borgou localities to ensure that the questions were clear and relevant. A total of 425 farm households were surveyed in fifteen localities (Table 3.1 in Chapter 3) following Cochran’s formula (equation1 in Chapter 3). The localities were purposefully chosen based on their agricultural importance and the severity of past climatic events (e.g., droughts and floods) impacts in terms of agricultural loss. The farm household was the unit of analysis in this study. The interviewees were the household heads (male or female) who had lived in the study area for at least 20 years before the survey and were at least 30 years old on the date of the survey.

To ensure the quality of the survey data, 10 interviewers were recruited based on their survey experience. They were familiar with the research area and spoke the local languages (Moba, Tchokossi) as well as French. They had gone through two intense training sessions, one before and one after the pretest on how to administer the questionnaires and collect accurate data. All interviews were conducted by common research principles and research ethics (Bogner et al., 2009). Before beginning any farm household interview, informal agreements were made by explaining the purpose and objectives of the study. During the data collection period, the researcher and interviewers were in the field together. Furthermore, supervision was ongoing, and daily meetings with interviewers were held to address any challenges encountered during the data collection process.

4.3.2. Data Analysis

Data analysis was conducted using the Statistical Package for Social Science (SPSS) version 26 and Microsoft Excel software. The frequency of each EbA practice was expressed as a percentage of the overall total of all frequencies.

Cronbach's alpha was used to assess the reliability of the items used in this study. Cronbach's alpha was typically calculated using the following formula:

$$\boldsymbol{Alpha = \frac{NC}{V + (N - 1) * C}} \quad \textbf{(8)}$$

Where N = the number of items, v = the average variance, and C = the average inter-item covariance.

In addition, the Spearman correlation coefficient, as calculated by Equation 3, is used to assess the strength of the relationship between items. Several researchers have commonly used the Spearman rank correlation coefficient for statistical analysis, particularly when the rank is used to analyze data. The Spearman rank correlation coefficient is a non-parametric estimate of the association between two series that uses ranks rather than real values (Kassem et al., 2020)

$$\boldsymbol{rs = 1 - \frac{6\sum d^2}{n(n^2 - 1)}} \quad \textbf{(9)}$$

where: rs: Spearman rank correlation coefficient, the higher the value of rs (approaching 1) indicates a strong association between the two sets of ranking.
d: difference in ranking, n: number of variables

In addition, the Weighted Average Index (WAI) was used to assess the effectiveness of the agricultural EbA practices. The effectiveness level of each of the EbAs was categorized based on the three dimensions i.e., ecosystem services provision, adaptation benefits to climate-related risks, and livelihood and food security improvement (Table 4.1). A weighted average (WA) is a type of average where each observation in the data set is multiplied by an assigned weight reflecting its importance before summing all data into a single average value (Ferdushi et al., 2019). WAI is estimated using the following formula as shown below:

$$WAI = \frac{\sum w_i X_i}{\sum w_i} \quad \textbf{(10)}$$

where $\mathbf{w_i}$ indicates the respective weights for the items, and $\mathbf{X_i}$ indicates the value of each item.

The EbA effectiveness analysis proceeded using first a rating scale to compute five effectiveness levels (EL) from the WAI values: Highly effective (HE) (3.49-4.28); Effective (E) (2.69-3.48); Moderately effective (ME) (1.89-2.68); Least effective (LE) (1.08-1.88); and not effective (NE) (1-1.07).

Furthermore, the Relative Importance Index (RII) analysis was used to rank the perceived EbAs' benefits. According to Rooshdi et al., (2018), the following formula is used to determine the relative importance index, as shown below:

$$RII = \frac{\sum W}{A * N} \quad \textbf{(11)}$$

where w is the weighting as assigned by each respondent on a scale of one to five with one implying the least and five the highest. A is the highest weight and N is the total number of the sample. According to Akadiri (2011), five important levels can be drawn from RII values: high (H) ($0.8 \leq RI \leq 1$); moderately high (H–M) ($0.6 \leq RI \leq 0.8$); moderate (M) ($0.4 \leq RI \leq 0.6$); moderately low (M-L) ($0.2 \leq RI \leq 0.4$); and low (L) ($0 \leq RI \leq 0.2$).

Moreover, a non-parametric approach Kruskall Wallis test was conducted to assess if the differences in the relative index values might be statistically significant across the categories of EbA dimension. The study tested the null hypothesis: the distribution of the relative index value of EbA benefits is the same across categories of EbA dimension.

Further analysis was made using a correspondence factor analysis (CFA) to assess the relative relationship between the perceived EbA's benefits and the most suitable EbA practices for smallholder farmers under each dimension of EbA; to this extent, a chi-square independence test between the two categorical variables (EbA practices and perceived EbA's benefits) was done setting α (Type I error) at 5 percent. For each dimension, the different perceptions of EbA's co-benefits and EbA practices were projected into a system of factorial axes resulting from the CFA.

The multiple regression model is employed to identify the influential factors of EbA practices effectiveness assessments by smallholder farmers EbA groups. Multiple Regression analysis is known as a set of approaches for analyzing the straight-line associations between two or more variables (Alexopoulos, 2010). The general equation of a multiple regression model is viewed as follows:

$$\mathbf{Yi = \beta 0 + \beta 1\ X1j + \beta 2\ X2j + \beta 3\ X3j + \ldots + \beta k\ Xkj + \varepsilon j} \qquad \mathbf{(12)}$$

Where Y is the dependent variable and X is the independent variable. The subscript j represents the observation (row) number. The β's are the unknown regression coefficients. The εj is the error (residual) of observation j.

Dependent variable

Farmers' perception of EbA effectiveness was represented by three dependent variables: Perceived ecosystem services provision, perceived adaptation benefits, perceived livelihood, and food security improvement indices. Those variables were obtained from the summation of all EbA practices considered.

Explanatory variables

Table 4.3 describes the socio-economic explanatory variables used in the regression models.

Table 4.3: Explanatory variables and measurement

Type of variables	Variable name	Measurement
Socio-economic explanatory variables	Food crop farming	Discrete, dummy takes the value of 1= Yes, 0= No
	Farm size	Continuous; Hectares
	Gender	Discrete, dummy takes the value of 1= male and 0 = female
	Age	Continuous ; years
	Education	Continuous ; years
	Farming Experience	Continuous, years
	Household Size	Continuous, People
	Land tenure	Discrete, dummy takes the value of 1= inherited and 0= Not inherited
	Access to extension service	Discrete, the dummy takes the value of 1=yes and 0=no
	Agricultural group membership	Discrete, the dummy takes the value of 1=yes and 0=no
	Labor availability (Number of family members working on the farm)	Continuous, people

4.4. Results

4.4.1. EbA Practices in the Agriculture Sector

A total of eight practices were reported as being commonly practiced by the respondents to deal with climate-related risks **(**Figure. 4.1). These EbA practices can be categorized into the following three groups: **(1)** conservation agriculture practices (i.e., conservation tillage mulching, crop rotation, and intercropping); **(2)** soil and water conservation practices (i.e., grass hedge/stone bunds and in-field water drainage channel); and **(3)** integrated soil fertility management practices (i.e., agroforestry and integrated crop-livestock). Many farmers were engaged in agroforestry (85%), crop rotation (77%), in-field water drainage channel (74%), grass hedge /stone bunds practices (69%), and intercropping (61%). Agroforestry is the most dominant among the reported practices and mulching is the least known practice. These results revealed that farmers used a combination of different EbA practices to buffer climate change risks.

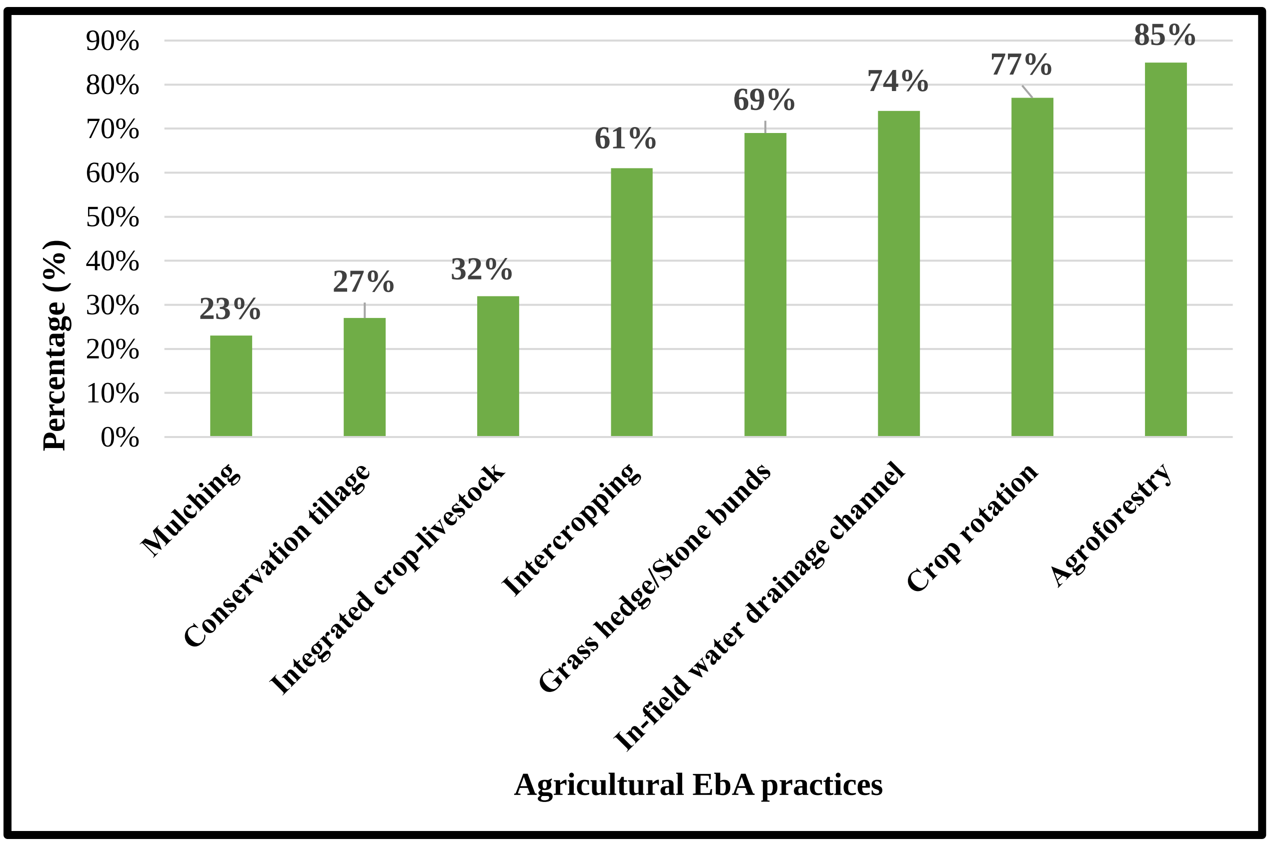

Figure 4. 1. EbA practices by agricultural farmers (n =425)

Regarding locality level, the respondents across the localities used a minimum range of 1 to 3 and a maximum range of 4 to 7 EbA practices per farm (Table 4.4). Mogou locality has the highest minimum (3) and maximum (7) EbA practices per farm than the rest.

Table 4.4. Variation in the adoption of EbA practices across the districts.

Localities	A minimum of EbA implemented	Maximum of EbA implemented	Average EbA implemented
Barkoissi	1	4	2.5
Bologou	2	5	3.5
Borgou	1	5	3
Kantindi	1	4	2.5
Kourientre	2	4	3
Mandouri	1	5	3
Mango	1	5	3
Mogou	3	7	5
Namoudjoga	1	5	3
Ogaro	2	5	3.5
Pligou	1	4	2.5
Sadori	2	5	3.5
Sanfatoute	1	5	3
Tambigou	1	4	2.5
Timbou	1	6	3.5

4.4.2. Reliability and Correlation Analysis

The Reliability analysis was assessed using Cronbach's alpha. It is the measure of the internal consistency of the constructs in the study. A construct is reliable if the Alpha (**α**) value is greater than 0.70 (Hair et al, 2010). The reliability test (Table 4.5**)** showed that the values of Cronbach's alpha for each component of EbA practices effectiveness and EbA practices benefits were found reliable.

The Spearman correlation coefficient was used to measure the correlation between EbA practices and EbA dimensions in the study area. The findings show a positive correlation between each practice and each category of EbA dimension based on Spearman test analysis **(**see Appendix 5).

Table 4.5. Cronbach's alpha test of EbA practices and EbA dimension

Components	No of items	Alpha
EbA practices		
Agroforestry	3	0.91
Conservation tillage	3	0.77
Crop rotation	3	0.86
In-field water drainage channel	3	0.72
Integrated crop-livestock	3	0.74
Intercropping	3	0.75
Grass hedge/ stone bund	3	0.82
Mulching	3	0.71
EbA dimensions		
Ecosystem services provision	6	0.92
Adaptation benefits	3	0.76
Livelihood and food security improvement	5	0.87

4.4.3. Perceived Effectiveness of EbA Practices

Table 4.6 summarizes the perceived effectiveness of identified EbA practices about the framework's three dimensions: (1) ecosystem service provision; (2) adaptation benefits; and (3) livelihood and food security improvement.

Table 4.6. Perceived effectiveness of EbA practices according to the framework's dimensions

EbA practices	(1) Ecosystem services provision		(2) Adaptation benefits		(3) Livelihood and food security improvement	
	WAI (1)	Effectiveness Level	WAI (2)	Effectiveness Level	WAI (3)	Effectiveness Level
Agroforestry	3.69	HE	3.84	HE	3.80	HE
Conservation tillage	2.48	ME	1.88	LE	2.46	ME
Crop rotation	3.36	E	3.34	E	3.16	E
In-field water drainage channel	3.05	E	2.98	E	3.11	E
Integrated crop-livestock	1.88	LE	2.42	ME	1.85	LE
Intercropping	2.59	ME	2.16	ME	3.10	E
Grass hedge/ stone bund	3.50	HE	3.51	HE	3.22	E
Mulching	1.87	LE	1.80	LE	1.84	LE

***Legend**: Highly effective (HE) (3.49-4.28); Effective (E) (2.69-3.48); Moderately effective (ME) (1.89-2.68); Least effective (LE) (1.08-1.88); and not effective (NE) (1-1.08).*

Agroforestry is perceived by the respondents as the most effective (HE) EbA practice for enhancing all the dimensions. Grass hedge/stone bund is perceived as most effective (HE) in terms of dimensions 1 and 2 and effective (E) in dimension 3. Both crop rotation and in-field water drainage channels were perceived as effective (E) in all dimensions. In contrast, mulching practice is perceived as the least effective at improving the three dimensions. These results suggest that agroforestry, grass hedge/stone bunds, crop rotation, and in-field water drainage channels can be considered the most suitable EbA practices for smallholder farmers in the study area. At the same time, those practices were the most applied practices by the smallholder farmers in the study area (Figure 4.1).

4.4.4. Perceived Benefits of Agricultural EbA Practices

The relative importance values of each benefit as perceived by the respondents are presented in Table 4.7.

Table 4.7. Ranking of the EbA practices based on the associated benefits

EbA Dimension	Perceived EbA benefits	Relative Index	Ranking	Importance level
(1) Ecosystem services provision	• Soil fertility improvement	0.91	1	H
	• Improvement of water infiltration and erosion regulation	0.89	2	H
	• Runoff regulation	0.88	3	H
	• Agrobiodiversity conservation	0.85	4	H
	• Nutrient regulation	0.83	5	H
	• Improvement of pollination	0.36	6	M-L
(2) Adaptation benefits	• Improving crop productivity	0.88	1	H
	• Reduction of climate impacts on crop and farming systems	0.85	2	H
	• Reduction of crop pests and disease incidence	0.64	3	H-M
(3) Livelihood and food security improvement	• Improvement of local income	0.87	1	H
	• Improvement of food security	0.86	2	H
	• Use of locally available and renewable inputs	0.83	3	H
	• Requires implementation costs and labor affordable to smallholder farmers	0.83	4	H
	• Take advantage of traditional knowledge	0.82	5	H

***Legend**: High (H), high medium(H–M), medium (M), medium-low (M-L), and low (L)*

The Overall RII analysis shows that for dimension 1: Ecosystem services provisions, (Soil fertility improvement) are the most perceived benefit with RII = 0.91, followed by (water infiltration and erosion regulation) with RII = 0.89, the third most perceived benefit (runoff regulation) with RII= 0.88 and the last one is (improvement of pollination) with RII= 0.36. For dimension 2: Adaptation benefits, (Improving crop productivity) rank first with RII = 0.88, followed by (reduction of climate-related risks on crop and farming systems) with RII = 0.85, and last (reduction of crop pests and disease incidence) with RII = 0.64. The highest rank for dimension 3: Livelihood and food security is (improvement of local income) with RII = 0.87, followed by (improvement of food security) with RII = 0.86, and the lowest is (use traditional knowledge) with RII = 0.82.

Furthermore, the independent-samples Kruskal-Wallis Test was used to determine whether the differences in index value across the three EbA dimension categories were statistically significant or not, with the null hypothesis tested being: that the mean ranks of the categories are the same. The summary of the Kruskal-Wallis Test result is presented in Table 4.8. The results show that the P-value= 0.648 is greater than the significance level of 0.05. Then, the null hypothesis is retained. The distribution of the relative index of benefits is the same across categories of the EbA dimension. These findings indicate that farmers in the study area perceived all of the EbA benefits under the three EbA dimension categories as important benefits gained from the implementation of EbA practices necessary for agroecosystem resilience, resisting climate change impacts, and improving livelihoods and food security.

Table 4.8: Independent-Samples Kruskal-Wallis Test Summary

Test Statistics [a,b]	**The relative index of benefit**
Kruskal-Wallis H	.867
df	2
Asymp. Sig. (2-sided test)	.648

a. Kruskal Wallis Test
b. Grouping Variable: EbA dimension

4.4.5. Relationships Between Perceived Effectiveness and Perceived Benefits of EbA Practices

The CFA results show that the most effective EbA practices and their perceived benefits are statistically associated (p-value = 0.000) under all three dimensions. The chi-square test results showed that there was a significant relationship between the EbA practices and the perceived EbA benefits in all three dimensions. Significant relationships were observed between agroforestry and crop rotation; between intercropping and crop rotation; and between grass hedge/stone bunds and in-field water drainage channels.

For dimension 1: ecosystem service provision (Figure. 4.2), axis 1 explains 82 percent of the information related to perceptions of EbA provisions based on various EbA practices, whereas axis 2 explains 16 percent, suggesting that the correspondence analysis of the two axes explains 98 percent of the information. There are three key relationships observed under this dimension: (1) in the lower half of the plot, crop rotation and agroforestry are closely associated and perceived to relate to nutrient regulation, soil improvement, and agrobiodiversity conservation; (2) at the left side of the lower half of the plot, in-field water drainage channel is perceived distinctively to other EbAs and closely relate to runoff regulation; whereas, (3) on the upper half, grass hedge/ stone bund is perceived distinctively to other EbAs and closely related to water infiltration and erosion.

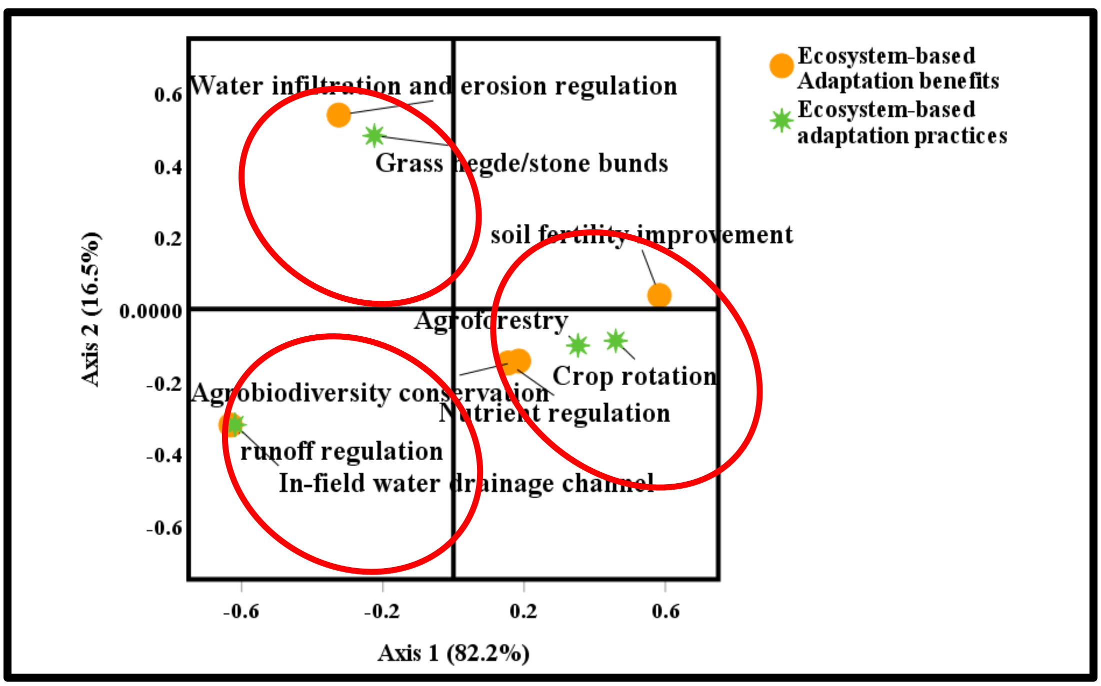

Figure 4.2. Projection in a system of axes of EbA benefits and effective EbA practices (Dimension 1: ecosystem services provision)

For dimension 2: adaptation benefits (Figure. 4.3), axis 1 accounted for 92 percent of the information about perceptions of EbA benefits based on various EbA practices, whereas, axis 2 accounted for 8 percent, suggesting that the correspondence analysis of the two axes accounts for

100 percent of the information. In figure. 4.3, the EbA practices such as grass hedge/stone bunds and in-field water drainage are perceived distinctly from agroforestry and crop rotation. In terms of associated ecosystem services, grass hedge/stone bunds and in-field water drainage are perceived as closely related to reducing climate risks on crop and farming systems; agroforestry and crop rotation are perceived to relate to improving crop productivity and reducing crop pest and disease incidence, respectively.

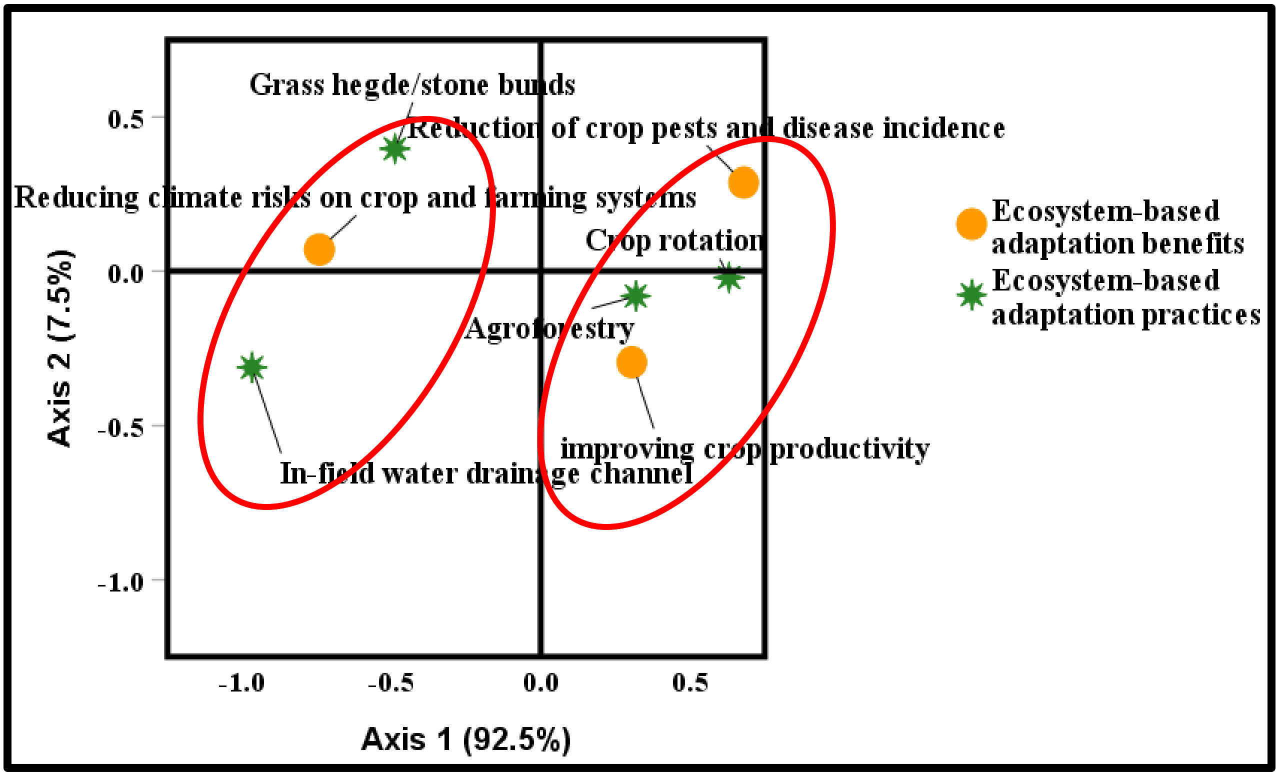

Figure 4.3. Projection in a system of axes of EbA benefits and effective EbA practices (Dimension 2: Adaptation benefits)

For dimension 3: livelihood and food security improvement (Figure 4.4), axis 1 explains 97 percent of the information about perceptions of EbA benefits based on various EbA practices, whereas axis 2 explains 2.6 percent, implying that the correspondence analysis of the two axes explains almost 100 percent of the information. On the lower half of the plot on the right side, crop rotation and intercropping are perceived as related to food security improvement and affordable implementation cost and labor. On the left side of the plot, grass hedge/stone bunds and in-field water drainage channel are associated with each other and perceived to relate to the use of locally available and low-cost materials; and taking advantage of traditional knowledge. Agroforestry is perceived to relate to local income improvement.

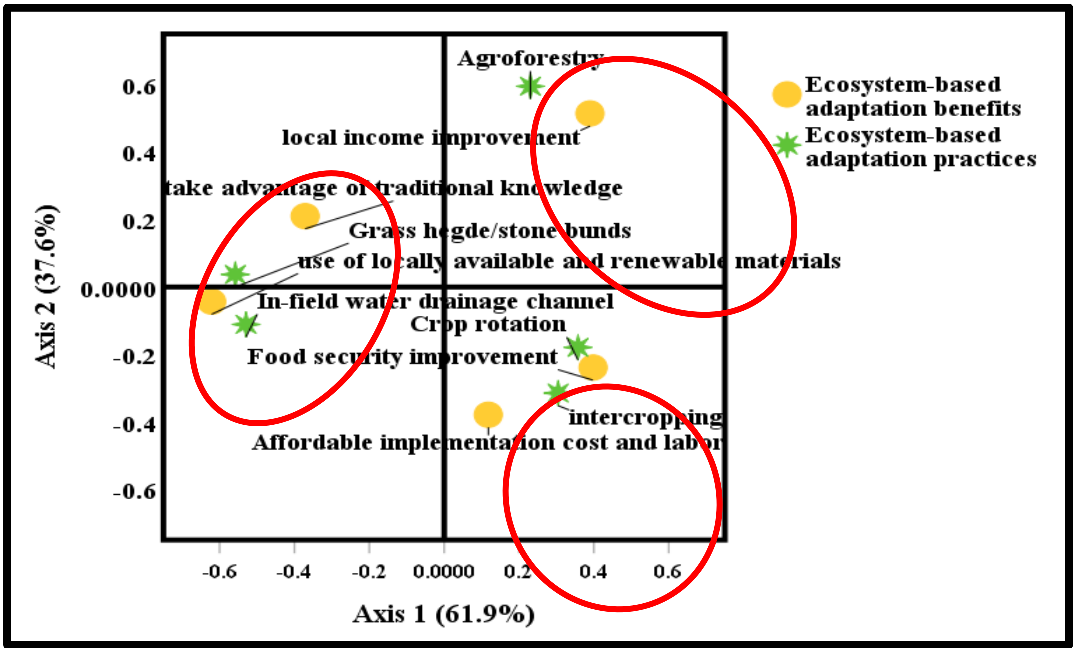

Figure 4.4. Projection in a system of axes of EbA benefits and effective EbA practices (Dimension 3: Livelihood and food security improvement)

Based on Figures 4.2; 4.3; and 4.4**,** agroforestry is perceived as the most effective EbA practice in the study area for improving a wide range of co-benefits such as soil fertility and nutrient regulation, agrobiodiversity conservation, crop productivity, and local income. Crop rotation is perceived as effective for improving agroecosystem functions, agrobiodiversity conservation, food security, and reducing crop pest and disease incidence. Both grass hedge/stone bunds and in-field water drainage channels are perceived to improve water infiltration, erosion regulation, and runoff control. Intercropping is perceived to improve crop productivity and food security.

4.4.6. Typologies of household implementing the perceived effective EbA practices

The spider web diagrams (Figures 4.5 to 4.8) depict the use of effective EbA practices based on livelihood indicators (human, social, financial, and natural capital). Figure 4.5 shows the use of effective EbA based on human capital indicators (gender, age, and labor availability).

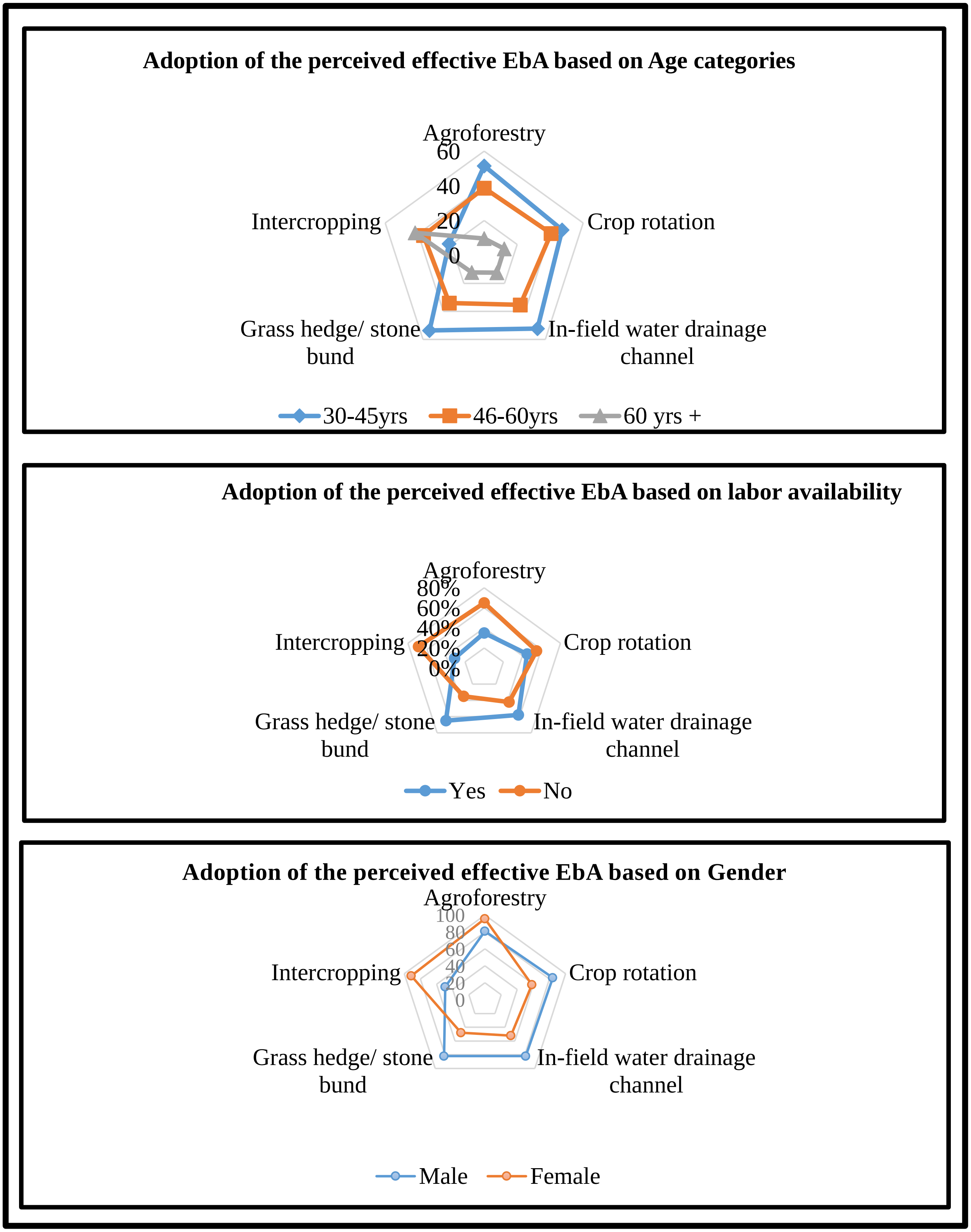

Figure 4.5. Farmer use of the perceived effective EbA based on human capital

The results revealed that females prioritized agroforestry and multi-cropping while men prioritized crop rotation, grass hedges/stone bunds, and in-field water drainage channels. Also, among farmers who implemented agroforestry, grass hedge/stone bunds, in-field water drainage channels, and crop rotation the majority are under 30-60 years of age while intercropping is being prioritized by those who are over 60 years of age. The majority of farmers who have a sufficient labor force prioritized the adoption of grass hedge/stone bunds and in-field water drainage channels while those who do not have a sufficient labor force preferred intercropping, crop rotation, and agroforestry.

Figure 4.6 shows that the majority of farmers who implemented the perceived effective EbA practices are members of an agricultural organization (social capital). They rely on agriculture for a moderate to high proportion of their income (Figure 4.7) (Financial capital) and have in majority medium to small size of land (figure 4.8) (Natural capital).

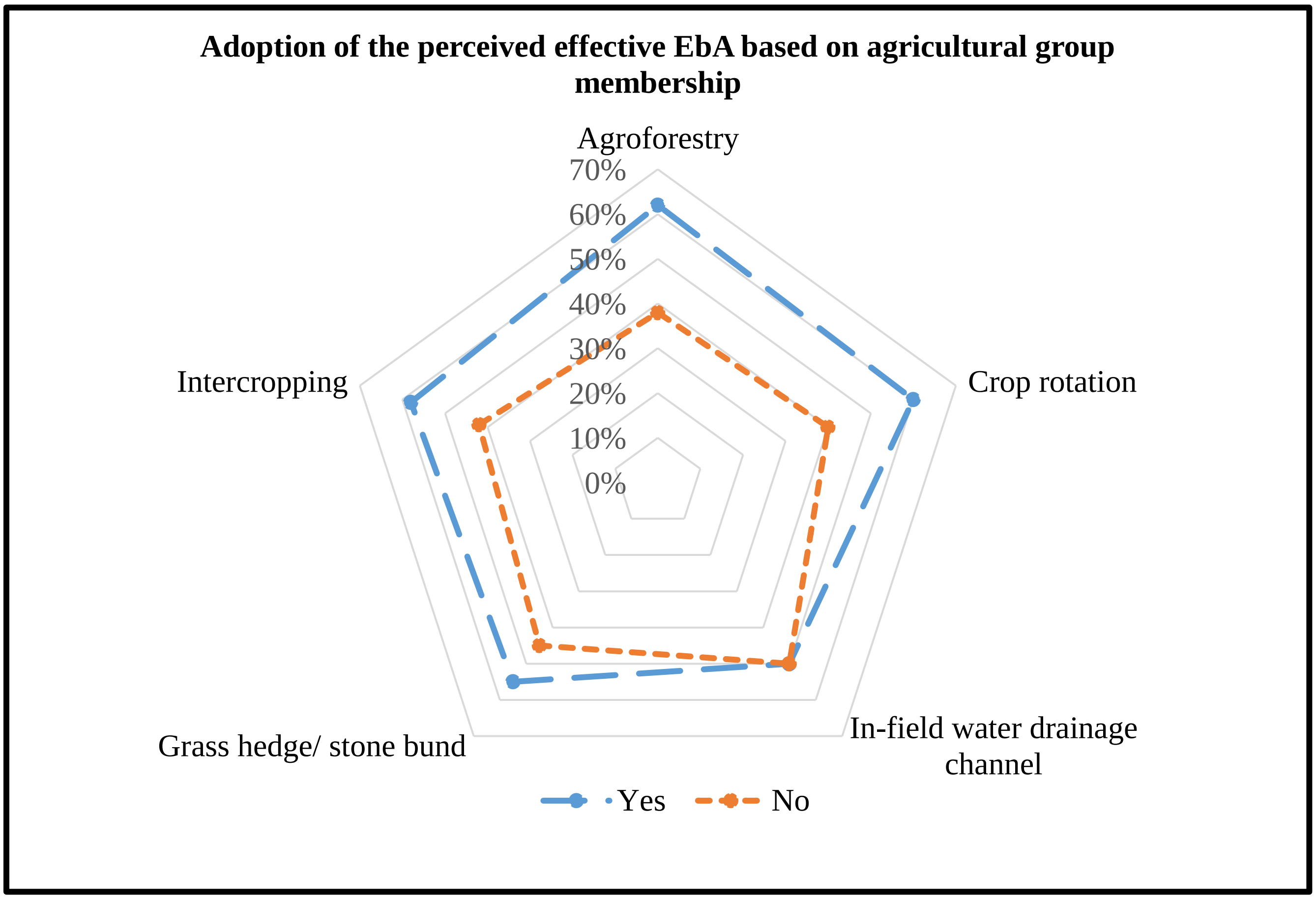

Figure 4.6. Farmer use of the perceived effective EbA based on social capital

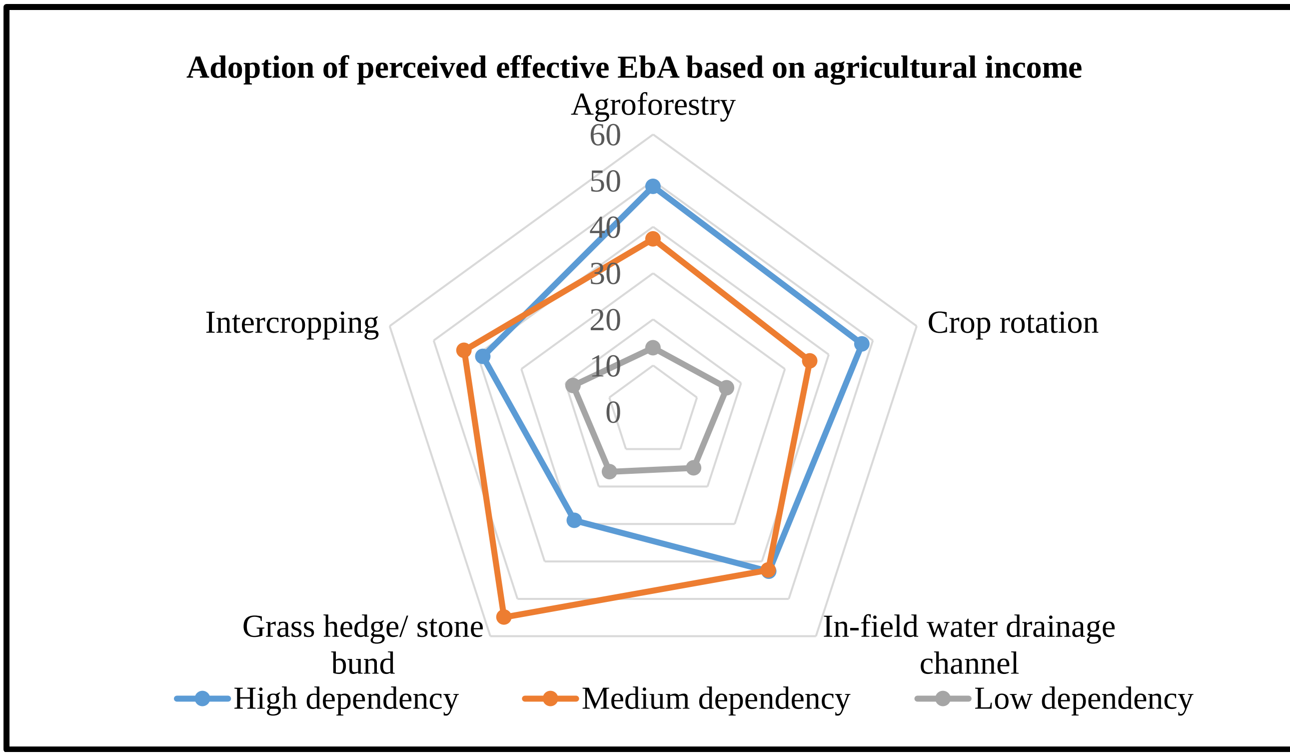

Figure 4.7. Farmer use of the perceived effective EbA based on financial capital
Note: High dependency (75-100%); Medium dependency (50-75%); low dependency (below 50%)

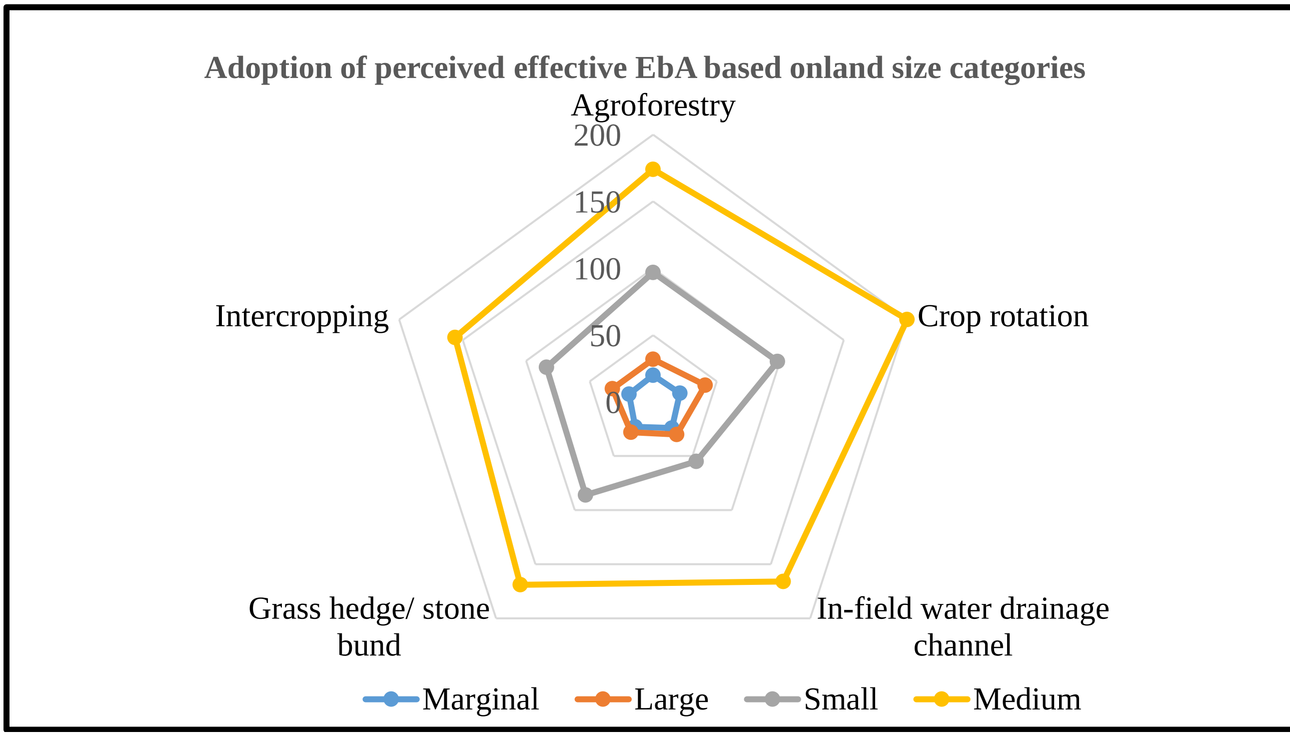

Figure 4.8. Farmer use of the perceived effective EbA based on Natural Capital
Note: Marginal (< 1ha); Small (1 ha-2.9ha); Medium (3ha -7ha); Large (Above 7ha)

4.4.7. Factors Influencing Farmers' Perceptions of the Effectiveness of EbA Practices

This section explains the influences of important factors on farmers' assessment of EbA effectiveness. The three dependent variables (i.e.) were in the multiple regression models with the explanatory variables in Table 3.3. The reliability test showed that the values of Cronbach's alpha for perceived ecosystem services provision perceived adaptation benefits, and perceived livelihood and food security improvement were quite good at .767, .73.3, and .643 respectively. All the values are greater than 0.5 as we use less than 10 items related to the five most suitable EbA practices. Table 4.9 shows the R square, adjusted R square, and F test. According to the R squares for all models, statistically significant explanatory variables can explain approximately 32.6% to 33.3% of the variation in farmers' assessments of EbA practices' effectiveness. All models were highly significant, with p-values of 0.000. There were no issues with multi-collinearity because the variance inflation factor (VIF) for all explanatory variables was less than 10. The residuals' normality, linearity, and homoscedasticity assumptions were also fulfilled.

Table 4.9. The three models summarize

Dependent variables	R square	Adjusted R square	F test, p-value
Perceived ecosystem services provision	0.329	0.212	.000
Perceived Adaptation benefits	0.333	0.215	.000
Perceived livelihood and food security improvement	0.326	0.210	.000

Table 4.10 shows the regression coefficients for the three regression models. In all three models, major agricultural farming (food crop framing), farm size, agricultural group membership, education status, and extension services were the most significant factors at 1%, 5%, and 10%.

According to Model 1 **(Table 4.10),** farm size, agricultural group membership, education status, and extension services were less likely to influence perceptions of EbA improving ecosystem services provision than perceptions of EbA improving adaptation benefits, livelihood, and food security, whereas major agricultural farming (food crop farming) was more likely to influence perceptions of EbA improving ecosystem services provision than perceptions of EbA improving adaptation benefits, livelihood, and food security.

Table 4.10. Multiple regression results

Explanatory variables	Unstandardized coefficients in 3 regression models					
	Model 1 Perceived ecosystem services provision improvement		**Model 2** Perceived Adaptation benefits improvement		**Model 3** Perceived livelihood and food security improvement	
	B	**p-value**	**B**	**p-value**	**B**	**p-value**
(Constant)	3.921***	0.000	2.704***	0.000	3.315***	0.000
Major agricultural farming	0.112*	0.052	0.701*	0.072	0.317**	0.048
Farm size	0.006**	0.036	0.776**	0.002	0.630**	0.002
Gender	0.016	0.682	-0.074	0.391	0.014	0.767
Age	-0.042	0.285	0.028	0.746	0.093	0.056
Agricultural Group membership	0.007*	0.062	0.025**	0.002	0.954***	0.000
Education status	0.075**	0.028	0.284***	0.000	0.139***	0.001
Land tenure	-0.027	0.512	-0.145*	0.098	0.259*	0.056
Extension services	0.129*	0.052	0.929**	0.007	0.106**	0.011
Labor availability	0.007	0.226	0.021	0.115	0.139**	0.011
Farming experience	-0.003**	0.038	.002	.493	-.004**	0.019
Household Size	0.057*	0.090	-.118	.106	0.044	0.284

According to Model 2 **(**Table 4.10**)**, education status, and extension services were more likely to influence perceptions of EbA improving adaptation benefits than perceived ecosystem services provision and perceived livelihood and food security improvement. Major agricultural farming, on the other hand, was less likely to influence the perception of EbA improving adaptation benefits for the same. Farm size and agricultural group membership were more likely to influence perceived adaptation benefit improvement than perceived ecosystem services provision and less likely to influence perceived livelihood and food security improvement.

Model 3 (Table 4.10) found that major agricultural farming and agricultural group membership were more likely to influence perceptions of EbA improving livelihood and food security than adaptation benefit, ecosystem resilience, and service provision. When compared to ecosystem services provision, education status, and extension services were more likely to influence EbA to improve livelihood and food security and less likely to influence adaptation benefit improvement.

4.5. Discussion

In agricultural systems, EbA is seen as the adoption of agricultural management practices that help increase the ability of crops or livestock to adapt to climate variability through the delivery of multiple co-benefits that are appreciated as ecosystem services, adaptation benefits, and livelihood and food security improvement (Munang et al., 2013; Vignola et 2015; Scarano, 2017). In the study area, farmers are implementing EbA practices on their farms to deal with the impacts of climate change. The most common EbA practices implemented by smallholder farmers are agroforestry, grass hedge/stone bunds, crop rotation, in-field water drainage channels, and intercropping. Although several studies have claimed the lack of understanding of the multiple co-benefits and the effectiveness of EbA practices in responding to the impacts of climate change as major barriers to EbA implementation (Munroe et al. 2011; Pramova et al. 2012; Berry et al. 2016; Wolf et al. 2020), our findings show that smallholder farmers in the study area are greatly aware of the multiple co-benefits and effectiveness of EbA practices. Several of the EbA practices have been previously described in other studies for maintaining local genetic diversity, organic soil management, water conservation, and harvesting, and general enhancement of agrobiodiversity, enhancement of the regulation of weeds, diseases, and insect pests, while increasing pollination services, maintaining soil fertility and crop production (Altieri et al., 2015; Damene et al. 2020; Liere et al., 2017; Melece and Shena, 2020; Pittelkow et al., 2015).

The adoption of agroforestry by smallholder farmers is not new in the study area; consequently, the widespread use of this practice is due to increasing land degradation caused by climate-related risks that threaten smallholder farmers' agricultural production and livelihood: Thus, they purposefully incorporate trees into their various cropping systems to provide a variety of co-benefits and services. It is believed that the presence of trees on their farm improves agroecosystem functions, agrobiodiversity, and crop productivity, as well as increasing income (Aleza et al.2015; Aleza et al. 2018; Kuya et al. 2020). This finding is in line with the results of a study carried out in the Arasbaran biosphere reserve of Iran where a vast majority of farmers were involved in agroforestry for an additional source of income and its effectiveness in adapting to climate change (Ghanbari et al, 2021). Other studies showed that agroforestry can prevent agroecosystem degradation, improve agricultural productivity, and support healthy soil and healthy ecosystems while providing stable incomes and other co-benefits to human well-being (Debaeke et al., 2017; Castle et al., 2022).

In the study area, crop rotation practice is one of the most used practices aiming at replenishing soil in nutrients as a means to alleviate fertilizer constraints, and weed and pest control. The respondents believe that crop rotation improves agroecosystem function by managing soil fertility, ensuring integrated management of weeds, diseases, and pests, and improving agrobiodiversity, crop productivity, and food security. Similar findings have been recorded by Thierfelder et al., 2013; Kollas et al., 2015; and Shah et al., 2019. Besides the aforementioned findings, these studies also showed that crop rotation can increase organic matter in the soil, maintain long-term soil fertility, aid in weed control, improve crop productivity, soil moisture, water infiltration, and soil carbon

Regarding intercropping practice, smallholder farmers prefer it because of limited land and access to commercial fertilizers. They primarily combine pulse crops and cereals (e.g., maize, sorghum, millet, beans, groundnut). Such crop associations not only maintain crop productivity and soil moisture but also reduce the risk of soil erosion. When cereal is combined with pulse crops, it also helps to conserve agrobiodiversity, manage soil fertility, and weed control. These observations are consistent with the findings of Sharma et al. (2017) and Senyolo et al. (2018) that intercropping is a useful strategy for increasing farmer production and income while also improving water use efficiency, land fertility, and reducing runoff and soil loss:

Concerning, soil and water conservation techniques such as grass hedge/stone bunds and in-field water drainage channels are used by smallholder farmers to stop or trap water runoff and reduce soil erosion in the study area, where grassed lines are planted at the edges of plots. Also, a stone bund made up of blocks of rubble or stones (pebbles) is arranged in one or more rows along a contour line. In addition, in the field water drainage channels are made and act as runoff collectors and evacuators. Smallholder farmers use grassed lines, stone bunds as well in-field drainage channels as devices that help to reduce crop vulnerability to flooding by improving agroecosystem function through water infiltration, soil erosion, runoff control, and maintaining soil moisture. Those practices were also seen to enhance the buffering capacities of agroecosystems against extreme events and increase crop productivity, livelihood, and food security. These observations are consistent with the findings (Kanito, 2020) that grass hedges, stone bunds, and in-field drainage channels help to reduce runoff, halt erosion, increase infiltration and soil moisture, and are also considered as insurance to sustain and boost soil fertility and land productivity.

Mulching and integrated crop-livestock are the least farm management practices utilized by smallholder farmers and are perceived as the least effective. This observation could be attributed to the reasons that crop residues are used mainly for cooking purposes (instead of mulching) whereas livestock farming is primarily based on poultry farming. Studies by Harvey et al. (2017a) and Nanfuka et al. (2020a) reported that mulching is among the rarely used EbA practices despite its promotion among farmers.

Assessing the effectiveness of EbA measures is critical to better understanding and deploying EbA as well as maximizing its benefits while minimizing its limitations (UNEP, 2019). Based on our study, smallholder farmers practicing more EbA strategies (such as in the locality of Mogou) have higher chances to adapt to climate change because of the wide range of co-benefits these strategies provide than those farmers employing one strategy or almost none. Using the framework, we can identify the best combination of EbA practices that meet all criteria needed by smallholder farmers such as food security, adaptation benefits, and ecosystem services provision.

Capturing the perceptions is a useful way to assess EbA effectiveness in the absence of available scientific or quantitative data relating to social-ecological effectiveness criteria (Doswald et al. 2014; Seddon et al. 2016; Ojea 2015; Reid et al., 2019). In comparison with the other frameworks (Munroe et al. 2011; Doswald et al. 2014; Reid & Alam, 2014; Bertram et al. 2017; Reid et al. 2018) which are useful for assessing the effectiveness of EbA projects or interventions at national to the community level, the framework provided by Vignola et al (2015), used in this study, is simple to connect the EbA agricultural practices about providing ecosystem services (provisioning services, regulating and supporting services), the desired adaptation benefits and co-benefits related to their livelihood improvement at smallholder farmer level. However, the respondents may lack consistency in understanding the dimensions and criteria used for the assessment and their perception is likely to be limited.

4.6. Summary

Our study identified the ecosystem-based adaptation (EbA) practices in the study area. Based on farmers' perceptions, it assessed their effectiveness in reducing their vulnerability to climate-related risks, including the co-benefits and suitability in the Savanna region, Togo. Eight agricultural practices were identified in the study area. Among the eight practices, five practices were mainly used and perceived as the most effective at reducing vulnerability to climate-related risks while at the same time improving agroecosystem services provision, adaptation co-benefits, and livelihood and food security. Those practices are agroforestry, crop rotation, intercropping, grass hedge/stone bunds, and in-filed rain-water drainage channels. The majority of farmers who use those practices are between the ages of 30 and 60, are members of agricultural organizations, rely on agriculture for a moderate to high portion of their income, and have small to medium-sized plots of land. Farmers perceived wide socioecological co-benefits gained from implementing those EbA practices. The most critical co-benefits gained from the combination of effective practices include soil fertility improvement, nutrient regulation, water infiltration and erosion control, runoff control, agrobiodiversity conservation, reduction in extreme events impacts on crop and farming systems, reduction in pest and crop disease incidence, an increase in crop productivity, and an increase in food security and local income. Implementing those practices also used locally available and low-cost materials and traditional knowledge. This shows the awareness and the good understanding of farmers in the study area on the co-benefits and the effectiveness of some agricultural EbA practices in reducing vulnerability to climate-related risks. The study reveals also that farmers' perception of EbA effectiveness is significantly influenced by food crop framing, farm size, agricultural group membership, education status, and extension services.

These EbA practices deserve the major attention of public programs, donor agencies, and government policies of climate change adaptation and poverty alleviation, especially in the Savana region. Some EbA practices were used by a very limited number of farmers such as conservation tillage, integrated crop-livestock, and mulching in the study districts. As a result, EbA practices can help to manage climate risks on a large scale in the study area[2]. There is still a need for additional knowledge to figure out the decision-making process of farmers towards the implementation of EbA to effectively address climate change risks on agroecosystems. Recall that farmers seemed aware of rainfall and temperature change but their perception of risks related to those changes on their agroecosystems is perceived differently among farmers depending on their personal experience and vulnerability which are cognitive factors by essence. The following chapter aims to combine cognitive, psycho-social, and socioeconomic factors to model their influence on farmers' decisions toward the adoption of EbA to reduce climate change risks.

[2] The results of this chapter have been pubished in scientific Journal
Ecosystem-Based Adaptation Practices of Smallholder Farmers in the Oti Basin, Togo: Probing Their Effectiveness and Co-Benefits. Ecologies 2023, 4, 535–551. https://doi.org/10.3390/ecologies4030035

CHAPTER 5: MODELLING FARMERS' ADOPTION DECISIONS OF ECOSYSTEM-BASED ADAPTATION PRACTICES TO REDUCE CLIMATE CHANGE RISKS ON AGROECOSYSTEMS

5.1. Introduction

Agriculture is critical to West African livelihoods. It employs 60% of the region's workforce and accounts for 35% of its GDP (Jalloh et al., 2013). Climate change threatens this vital economic activity. Various scholars have investigated how climate change has impacted agriculture in the West African region, concluding that rising temperatures and rainfall anomalies have increased the occurrence and intensity of extreme events over the last decade, affecting natural resource availability, biodiversity, and agricultural productivity and yields, undermining food security in the region (Sultan and Gaetani, 2016; Tarchiani et al., 2017; Sorgho et al., 2020; Gil, 2022). This situation is likely to become more desperate and threaten the survival of the majority of poor farmers as global warming continues(Jalloh et al., 2013).

Togo, like other countries in the West Africa region, is currently experiencing climate disruption, which includes irregular rainy season onset, overall shortening of the rainy season, and unevenly distributed rainfall throughout the year. These changes are significantly harming agricultural land impacting negatively the supply of ecosystem services thereby rendering agricultural productivity, livelihood, and hence food security, especially in the Savanna region with the majority of the rural population depending on agriculture for their livelihoods and have a lower capacity to adapt (MERF, 2022).

Existing studies in the Savanna region of Togo on climate change adaptation emphasized the importance of ecosystem-based adaptation practices to improve agricultural land resilience and boost crop productivity in the climate change context (Pilo et al., 2021; Gadédjisso-Tossou, 2015; Lare and Lamboni, 2015). Ecosystem-based adaptation (EbA) practices a concept that employs both ecosystem services and biodiversity as integral components of adaptation strategy, are now widely acknowledged to be effective in reducing climate risks while also giving a better ability to communities to adapt to climate change over time (Montes de Oca Munguia et al., 2021; Foguesatto et al, 2020). In the agriculture sector, EbA works to protect and restore the natural resource base, with the overall goal of maintaining and improving agroecosystem services and biodiversity for food and agriculture, allowing farmers' communities to adapt to the effects of climate change and maintain long-term food security (Abdelmagied, and Mpheshea, 2020). These include Conservation Agriculture (CA) practices, like mulching, conservation tillage, crop rotation, and intercropping, and others; Soil and Water Conservation practices (SWC) like grass hedges, stone bunds, in-field water drainage channels; water harvesting, contour farming, terracing and others; Integrated Soil Fertility Management (ISFM) practices like manuring and composting, agroforestry integrated crop-livestock among others (Kissi et al., 2023b; Nanfuka et al., 2020a; Kurgat et al., 2020; Abdelmagied, and Mpheshea, 2020; Harvey et al., 2017a Vignola et al., 2015).

Due to the non-wide use of EbA practices to address climate change and its associated risks in the savanna region (Munang et al. 2013), there is a need to investigate the determinants of EbA adoption decisions among farmers. There is little research (Adji et al., 2022; Pilo et al., 2021; Abalo-Esso et al., 2021; Djiwagui et al., 2017; Gadédjisso-Tossou, 2015) on farmers' adoption of EbA practices in the study area and they have generally focused on the socioeconomic factors influencing farmers' adoption of EbA Practices for climate change adaptation. Several studies (Rosário et al., 2022; Foguesatto et al., 2020; Dessart et al., 2019; Morais et al., 2017; Keshavarz and Karami 2014; Karali et al., 2011; Vignola et al., 2010; Knowler & Bradshaw, 2007; Sambodo, 2007; Bayard and Jolly, 2007) suggested the inclusion of sociopsychological constructs as well as cognitive variables in the modeling of the farmer's decision to adopt or not adopt agricultural technologies. However, as far as we are aware, no studies have been conducted to analyze how this integration of sociopsychological and cognitive constructs in modeling has been carried out in the study area. This study adopts an integrative approach, examining how the combination of psycho-social factors, cognitive factors, and socioeconomic factors, influence farmers' decision toward the adoption of EbA for climate change adaptation. The study was specifically designed to answer the following questions: How does the combination of psycho-social, cognitive, and socioeconomic factors influence farmers' decisions toward the adoption of EbA to reduce climate change risks?

From this main question, the following objective has been formulated:

OS3.1. To integrate socio-psychological, cognitive, and socio-economic factors in modeling farmers' EbA adoption decisions for climate change adaptation in the Savanna region.

Based on this objective, the following hypothesis has been established:

H.3. A combination of socio-psychological, cognitive, and socioeconomic variables explains significant differences among farmers' EbA adoption groups.

5.2. Decision-Making Model

The study relies on the Theory of Planned Behavior (Ajzen, 1991), and the conservation decision model developed by Vignola et al., (2010) to model farmers' decisions about EbA adoption. Because of its strong predictive power, various studies integrated the theory of planned behavior factors into the decision-making process of farmers regarding sustainable land management practices (Jacob & Valois, 2021; Kasargodu Anebagilu et al., 2021; Pouladi et al., 2019; Mutyasira et al., 2018). Figure 5.1 below depicts how the theory's three independent constructs lead to intention and behavior. To lead to intention and behavior, attitudes, subjective norms, and perceived behavioral control must all interact.

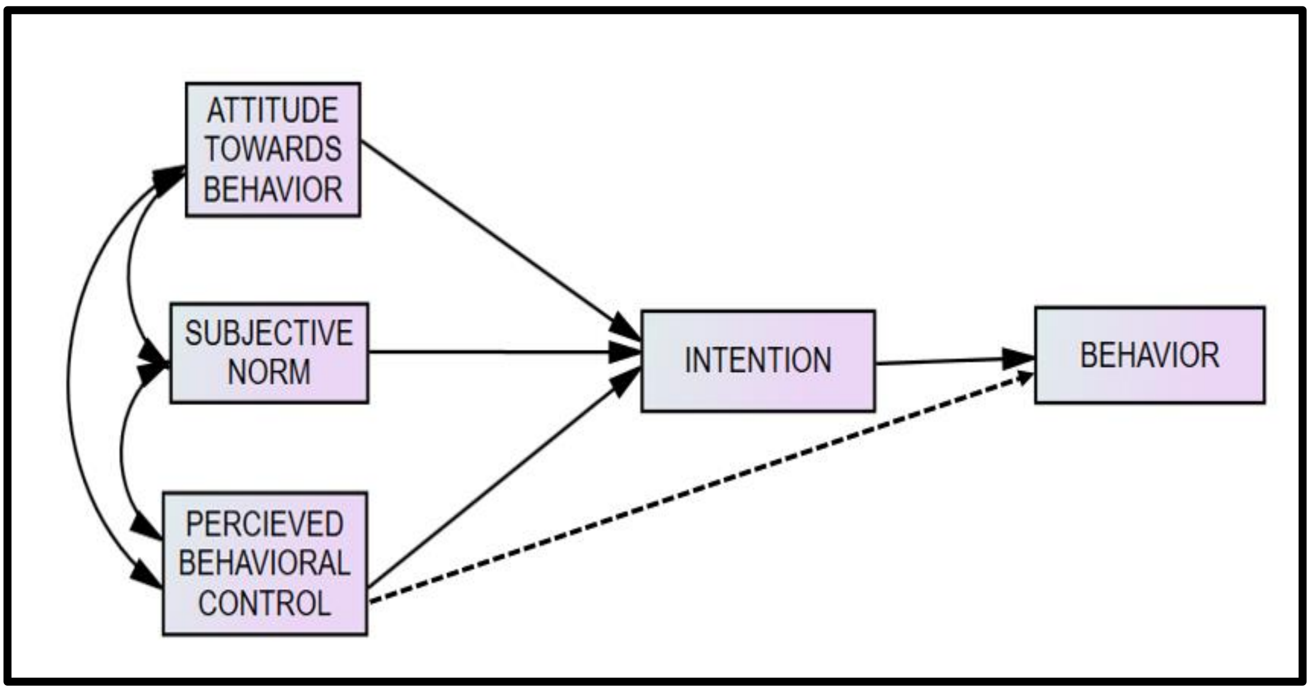

Figure 5.1. Schematic representation of the Theory of Planned Behavior (Ajzen,1991)

A positive attitude, favorable social norms, and a high level of perceived behavioral control are the best predictors of behavioral intention formation, and, the TPB Model's ability to predict behavior is determined by the degree of behavioral intention and the direct effect of perceived behavioral control (Beck & Ajzen, 1991). The behavioral factors are included as independent variables along with cognitive factors and a set of socio-economic variables in the conservation decision model developed by Vignola et al., (2010) (equation 13) to model farmers' decisions toward EbA adoption.

$$\textbf{EbAD = f (BF, RP EbAV, SE)} \qquad \textbf{(13)}$$

where EbA decisions (EbAD) depend on four types of independent factors such as behavioral factors (BF), risk perception factors (RP), EbA value factors (EbAV), and a set of socioeconomic characteristics (SE).

The behavioral factors (TPB constructs) as well as the cognitive factors (Risk perception and EbA value) are latent variables, and thus cannot be observed or measured directly. Instead, a set of measures is used to act as indicators for the underlying latent variables (Table 5.1).

Table 5.1: Items to measure the behavioral and cognitive variables

TPB Behavioral and Cognitive variables	Items
	Attitude (ATT):
Behavioral Factors	I think that the implementation of EbA practices to adapt to climate change is effective at improving cropland resilience
	I think that the implementation of EbA practices to adapt to climate change is effective at enhancing adaptation benefits
	I think that the implementation of EbA practices to adapt to climate change is effective at increasing farmers' livelihood and food security
	I believe that the implementation of EbA is a wise idea to deal with climate change impacts on cropland and farmers 'livelihoods.
	Subjective Norm (SN)
	My family members and relatives encourage me to implement EbA practices on my farm to adapt to climate risks.
	My friends and neighbors encouraged me to implement EbA practices on my farm to adapt to climate risks
	I care about what people who are important to me encourage me to do on my farm to adapt to climate risks
	Perceived behavioral control (PBC)
	I have the technical knowledge to implement EbA practices on my farm.
	I can easily implement EbA practices on my farm, if I want.
	I have the necessary resources for the implementation of EbA practices on my farm.
	Intention (INT)
	I intend to continue or adopt EbA practices on my farm

TPB Behavioral and Cognitive variables	Items
	I am willing to continue or adopt EbA practices on my farm with or without financial assistance from NGOs or government subsidies
	I am not willing to engage in EbA practices
	Behavior (BEH) in the next 5 years
	I decided to engage in conservation agriculture practices on my farmland to adapt to climate risks
	I decided to engage in soil and water conservation practices on my farmland to adapt to climate risks
	I decided to engage in integrated soil fertility management practices on my farmland to adapt to climate risks in the next years
Risk perception (RP)	**Perceived climate-related hazards (H)**
	I think the duration of dry spells is increasing
	I think that the rainfall becomes uneven
	I think that the rainfall extreme events are increasing
	I think the rainy season becomes shorter
	I think that the temperature is increasing
	I think that drought events become more frequent and severe
	I think that flood events become more frequent and severe
	Perceived Exposition (E)
	I think that farmers have become more exposed to drought and flood events
	I think that croplands have become more exposed to drought and flood events
	Perceived Vulnerability (V)
	I think that the loss of ecosystem services provided by cropland for farming increases the vulnerability of cropland to drought and flood events
	I think that unsustainable farming practices increase the vulnerability of cropland to drought and flood events
	I think that farmers' strong dependency on agricultural income increases their vulnerability to drought and flood events
	I think that the lack of access to improved seeds increases the vulnerability of farmers to drought and flood events
	I think that the lack of access to agricultural assets increases the vulnerability of farmers to drought and flood impacts
	I think that lack of irrigation infrastructure increases the vulnerability of farmers to drought and flood events
	I think that the lack of access to a financial safety net increases the vulnerability of farmers to drought and flood events
	I think that lack of access to climate information increases the vulnerability of farmers to drought and flood events
EbA Value (EbAV)	**EbA affordability (Eba_aff)**
	I think the cost incurred at the beginning of implementing EbA practices is affordable

TPB Behavioral and Cognitive variables	Items
	I think the cost of inputs needed for EbA practices implementation are locally available and affordable
	I think the cost related to labor needed for EbA practices implementation is affordable
	EbA benefits (Ebabenef)
	EbA implementation improves soil fertility
	EbA implementation improves runoff and erosion regulation
	EbA implementation improves crop productivity
	EbA implementation reduces climate impacts on farming systems
	EbA implementation improves local income
	EbA implementation improves food security

All variables are measured on a Likert scale of 1 (strongly disagree) to 5 (strongly agree)

5.3. Behavioral Hypotheses Development

5.3.1. Relationship Between TPB's Constructs

The first construct, **attitude towards the behavior**, represents the degree to which a person evaluates a behavior favorably or unfavorably. It is made of an affective attitude which is related to whether the behavior is enjoyable or not and the instrumental attitude which is related to whether the behavior is beneficial or harmful (Ajzen,1991). The second construct, **subjective norm**, refers to an individual's perception of social pressure to engage in a particular behavior. It consists of beliefs about social expectations as well as the motivation to meet those expectations (Ajzen, 1991). In other words, because people are context-dependent, others' opinions matter in shaping an individual's intention to use new technologies (Shah, 1998; Venkatesh & Davis, 2000). Finally, **perceived behavioral control (PBC)** refers to a person's perception of his/her capability to perform the behavior. It increases when people believe they have more resources and confidence (Ajzen, 1985; Hartwick & Barki, 1994; Lee & Kozar, 2005). As a general rule, the more favorable the attitude toward the behavior and subjective norm, as well as the greater the perceived behavioral control, the stronger an individual's intention to perform the under-consideration behavior. It is expected that the relative importance of attitude, subjective norm, and perceived behavioral control in predicting intention will vary across behaviors and situations.

A previous study dealing with TPB farmer's conservation behavior has demonstrated that Attitudes, Subjective Norms, and Perceived Behavioral Control play key roles in shaping the Intention to engage in sustainable agriculture management behaviors (Coulibaly et al., 2021;

Nguyen & Drakou, 2021; Kasargodu et al., 2021; Bonke & Musshoff, 2020; Waseem et al., 2020; Akyüz & Theuvsen, 2020; Mutyasira et al., 2018).

In addition, according to the theory of planned behavior, behavior performance is a joint function of intentions and perceived behavioral control (Ajzen, 1991). The relative importance of intentions and perceived behavioral control in behavior prediction is expected to vary across situations and behaviors (Ajzen, 1991). Evidence concerning the relationship between intentions and behavior as well as perceived behavioral control and behavior has been found concerning many different types of behaviors (Ajzen, 1991; Pouladi et al., 2019; Kasargodu et al., 2021). Hence, the first set of hypotheses **(H1)** is investigated to validate the evidence regarding the relationship between TPB constructs. The study hypothesized that:

H1a: Farmers' attitude toward EbA practices positively influences their intention to implement EbA practices at their farm level.

H1b: Farmers' Subjective norms are directly and positively associated with individuals' Intention to implement EbA practices at their farm level.

H1c: There is a positive relationship between farmers' perceived behavioral control and
and their intention to implement EbA practices at their farm level.

H1d: Farmers' intention towards the implementation of EbA positively influences their behavior to implement EbA practices at their farm level.

H1e: Farmers 'perceived behavioral control toward EbA practices positively influences their behavior to implement EbA practices at their farm level.

5.3.2. Mediating Role of Intention in the Theory of Planned Behavior

According to the TPB, attitudes toward the behavior, as well as subjective norms and perceived behavioral control, influence behavior indirectly through intention (Ajzen, 1991). Several studies have shown evidence of the mediating role of intention in predicting the different types of behavior (Mafabi et al., 2017; Tan et al., 2016; Lim et al., 2015; Kusumawati et al., 2014). For these reasons, the second set of hypotheses is being examined to understand the impact of farmers' intention as a mediator in the relationship between attitude, subjective norm, perceived behavioral control, and EbA implementation behavior. It is hypothesized that:

H2a: Farmers' intention towards EbA practices mediates the relationship between Farmers 'attitude towards EbA practices and Farmers' behavior in implementing EbA practices at their farm level.

H2b: Farmers' intention towards EbA practices mediates the relationship between Farmers 'subjective norm towards EbA practices and Farmers' behavior in implementing EbA practices at their farm level.

H2c: Farmers' intention towards EbA practices mediates the relationship between Farmers 'perceived behavioral control towards EbA practices and Farmers' behavior in implementing EbA practices at their farm level.

5.3.3. Moderating Role of Perceived Behavioral Control in the Theory of Planned Behavior

From a theoretical perspective, perceived behavioral control is expected to moderate the effects of attitude toward the behavior and of subjective norm on intention, and the effect of intention on behavior (Ajzen, 1985, 2002; La Barbera & Ajzen, 2020). In other words, individuals are more likely to act on their behavioral intentions and report intentions that are aligned with their attitudes and subjective norms when their perceived behavioral control (PBC) is high (Hagger et al., 2022). Several researchers (Conner & McMillan, 1999; Hukkelberg et al., 2014; Kothe & Mullan, 2015; Yzer & van den Putte, 2014; La Barbera & Ajzen, 2020)) have reported a positive significant interaction between Attitude and Perceived Behavioral Control in the prediction of intention. Regarding the interaction between subjective norm and perceived behavioral control in the prediction of intention, inconsistent empirical findings have been found (Hagger et al., 2022; La Barbera & Ajzen, 2020). Of the few studies that tested this interaction, some found a non-significant effect of Perceived Behavioral Control on the prediction of intention from Subjective Norm (Hagger et al., 2022; Earle et al.,2020; Kothe & Mullan, 2015; Umeh & Patel, 2004); However, La Barbera & Ajzen (2020) and Castanier et al (2013) showed a significant negative effect of the interaction between Subjective Norm and Perceived Behavioral Control in the prediction of intention, indicating that the prediction of intention from Subjective Norm was weaker when Perceived Behavioral Control was high versus low. According to the findings of these studies, the more people felt in control of their behavior, the less they were influenced by peer pressure in forming their intentions. Hill et al. (1996) concluded in his study that the influence of subjective norms may be especially important for novel behaviors that are difficult to control.

Furthermore, consistent empirical findings have been found regarding the moderation effect of perceived behavioral control on the intention-behavior relation (Hagger et al., 2022); La Barbera & Ajzen, 2021; Yang-Wallentin et al., 2004; Notani, 1998). These studies revealed that the more an individual has actual control over his or her behavior, the more likely they are to carry out their intention. In other words, individuals with higher levels of Perceived Behavioral Control are more likely to try harder to perform the target behavior than those with lower levels of Perceived Behavioral Control. Taken together all these considerations from the previous studies, the third set of hypotheses are examined to find out the impact of the interaction between perceived behavioral control and attitude, subjective norm on the intention prediction as well as the impact of the interaction between intention and perceived behavioral control on the prediction of farmers' behavior towards the implementation of EbA practices. Hence the study hypothesized that:

H3a: interaction between Attitude and Perceived Behavioral Control has a positive significant effect on the prediction of farmers 'intention.

H3b: interaction between Subjective norm and Perceived Behavioral Control has a negative significant effect on the prediction of intention.

H3c: interaction between intention and Perceived Behavioral Control has a positive significant effect on the prediction of behavior.

5.4. Data Collection

A survey approach was conducted in fifteen localities (see Table 3.1 in Chapter 3) to determine influencing factors on farmers' decision-making toward the adoption of EbA practices. The research instrument was a fixed-response questionnaire that includes socio-economic variables (Age, education, household income, farm labor, and farmland size), and a list of statements based on the theory of planned behavior constructs and the adopted decision model variables. This list of the statements was used to elicit information on farmers' attitudes toward EbAs, the perceived social pressure to adopt EbAs, Perceived Behavioral Control overuse of EbAs, their overall intentions to adopt EbAs on their farms as well as the perceived climate change risk components (hazard, exposure, and vulnerability) and perceived EbA value (EbA affordability and EbA benefits). Eligible interviewees were the head (male or female) of an agricultural household in the survey area who had lived there for at least 20 years and were at least 30 years old when the survey data was collected. Following Cochran's formula, (Equation 1 in Chapter 3) 425 farm households were surveyed.

5.5. Modelling procedure

5.5.1. Structural Equation Modelling (SEM)

In the first stage of the modeling process, structural equation modeling particularly, the covariance-based approach is used to test the hypotheses established for the behavioral factors based on the theory of planned behavior. The covariance-based approach to SEM is the most reliable for theory testing and evaluating the structure of a given model as well as its relationships. The two-step modeling approach of structural equation modeling recommended by Anderson and Gerbing (1988) and McDonald and Ho (2002): the measurement model and the structural model analyses (Hair et al., 2006; Barroso et al., 2010) have been used. Thus, the structural equation model is made up of an outer sub-model that specifies the relationships between the latent variables and their observed indicators, followed by an inner sub-model that evaluates the relationship between the dependent and independent latent variables, as well as their respective path coefficients (Wong, 2013). SEM has an advantage over other techniques in that it can evaluate multiple dependent variables at the same time while accounting for measurement error in each variable (Collier, 2020).

5.5.1.1 Measurement Model Analysis

The measurement model connects observed variables to their associated constructs to examine whether the theoretical constructs are correctly measured by the manifest variables (indicators), In SEM, the measurement model analysis is done through confirmatory factor analysis (CFA). Confirmatory factor analysis (CFA) is a statistical technique that analyzes how well indicators measure the unobserved constructs and if the unobserved constructs are uniquely different from one another (Henson and Roberts, 2006; Collier, 2020) concerning the model fit indices, the reliability, and validity of the indicators for each construct.

- **Evaluation of Model Fit**

In structural equation modeling, the evaluation of model fit requires considering multiple criteria and evaluating model fit based on various measures simultaneously (Schermelleh-Engel et al, 2003). To evaluate the adequacy of our model, the study used the Maximum Likelihood (ML) fitting function for structural equation models. The ML estimator assumes that the variables in the model are multivariate normal (Schermelleh-Engel et al, 2003). The model fit tests have been assessed firstly with the chi-square goodness of fit test. Jöreskog and Sörbom (1993) proposed using chi-square as a descriptive goodness-of-fit index rather than a formal test statistic. They proposed that the magnitude of chi-square be compared to the expected value of the sample distribution, i.e., the number of degrees of freedom, using the formula $E(\chi 2) = df$. For a good model fit, the ratio chi-square/df between 2 and 3 is indicative of a "good" or "acceptable" data-model fit, with the p-value associated with the chi-square value that should be larger than .05. However, according to Bollen (1989), this procedure does not address the issue of sample size dependence. Secondly, the descriptive goodness-of-fit measures have been assessed to determine the degree to which the structural equation model fits the empirical data. Two main classes of measures were used i.e., measures based on model comparisons and measures of overall model fit. The descriptive measures based on model comparison used are the comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker–Lewis's index (TLI); and the descriptive measures of overall model fit used are Root Mean Squared Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). These indices are based on the difference between the sample covariance matrix and the model-implied covariance matrix (Schermelleh-Engel et al, 2003). According to (Hu & Bentler, 1998, 1999) the model fit indices (CFI, TLI, IFI) should be greater than or equal to .95 to have an acceptable fit. Hu & Bentler (1999) define RMSEA values less than or equal to .06 as a good fit, values between .05 and .08 as an adequate fit, and values between .08 and .10 as a mediocre fit, whereas values greater than .10 are not acceptable. According to Hu and Bentler (1999), a rule of thumb for SRMR should be less than .08 for a good fit, whereas values greater than .10 may be interpreted as not acceptable model fit indices.

- **Assessment of Normality, Reliability, and Validity of Indicators and Constructs**

In the CFA analysis, after the fitness indexes have been achieved, the study examined the normality, reliability, and validity assessment for the data before proceeding to model the structural model. The normality assessment is made by assessing the measure of skewness and Kurtosis for every item. The data is considered to be normally distributed if the skew values range between −2 and +2 and the kurtosis, ranges between −10 to +10 (Collier, 2020). The statistical estimates of the direct effects between the constructs and their indicators called "factor loadings" are examined to show how well the indicators represent their underlying constructs. The factor loading ranges from

0 to 1 scale and the factor loading should be greater than 0.50 (Bagozzi and Yi, 1988, Hair et al., 2006, Marticotte and Arcand, 2017), for the indicator to explain the construct. Secondly, the CFA is accomplished by examining two elements of factorial validity: convergent and discriminant validity of measures (Churchill, 1979; Gerbing & Anderson, 1988). The convergent validity tests whether indicators will converge to measure a single concept, whereas discriminant validity tests to see if a construct is unrelated or distinguished from other constructs (Collier, 2020). Fornell and Larcker's method was used to assess convergent validity. Fornell and Larcker (1981) stated that calculating the Average Variance Extracted (AVE) for each construct is necessary to assess convergent validity. To indicate that the indicators have convergent validity on the construct, the AVE number must be greater than .50. After assessing convergent validity, the discriminant validity of the constructs has been assessed using the Fornell and Larcker criterion and Heterotrait-Monotrait (HTMT) Ratio. According to the Fornell and Larcker criterion, discriminant validity is established when the square root of AVE for a construct is greater than its correlation with the other constructs in the study. However, the Fornell and Larcker criterion has recently been criticized and a new method to assess the discriminant validity that is HTMT ratio is increasingly utilized. The HTMT method examines the correlations of indicators across constructs to the correlations of indicators within a construct. According to (Kline, 2011; Henseler et al., 2015,), if an HTMT value is under .85, this indicates that discriminant validity is established.

5.5.1.2. Structural Model Analysis

The structural model's focus is on examining the relationships between constructs. The study looked at how independent constructs influence dependent constructs. More specifically, we tested three hierarchical TPB models: the first tested the hypothesized paths between TPB constructs.

The suggested equation for intention by TPB has been shown in equation (14)

$$\mathbf{INT = \beta 1ATT + \beta 2SN + \beta 3PBC + \varepsilon} \tag{14}$$

where the β s are empirically estimated derived weights or coefficients for each parameter depicting the relative importance of each of the three constructs and ε is the error term.

The suggested equation for behavior is expressed in equation (15) below

$$\mathbf{BEH = W1INT + W2PBC} \quad \textbf{(15)}$$

where BEH is the target behavior, INT is the intention, PBC is perceived behavioral control, and $\mathbf{W_1}$ and $\mathbf{W_2}$ regression weights (Fishbein & Ajzen, 1975; Conner & Sparks, 2005)

The second model included the mediation role of intention in the relationship between attitude, subjective norm, perceived behavioral control, and behavior. To test the type of mediation effect of farmers 'intention toward EbA practices, the study used a bootstrap technique of 5000 to determine the significance of the direct effect, the indirect effect, and the total effect between constructs. According to Collier (2020), a bootstrap technique treats the data sample like a pseudo-population, and then uses a random sample with replacement to determine whether the indirect effect is within a confidence interval.

The third model looked at the moderating effect of perceived behavioral control in the relationship between attitude, subjective norm, and intention, as well as intention and behavior. The study used the "interaction term" method to assess this moderation effect. According to Collier (2020), an interaction term is formed by combining the independent variable and the moderator. This interaction term will then indicate whether the presence of the moderator has a significant impact on the relationship between the independent variable and the dependent variable.

5.5.2. Modelling of Farmers' Decision-Making Toward EBA Adoption

To measure farmers' EbA Decisions, the common EbA practices in agriculture systems adopted by farmers at the farm level to adapt to climate-related risks in the study area were used **(**See Chapter 4**)**. These EbA practices include agroforestry, intercropping, grass hedge/stone bunds, in-field water drainage channels, integrated crop-livestock, conservation tillage, and mulching. A binary variable for each practice has been constructed. The dependent categorical variable of EbA Adoption was then created for each farmer i. EbAD(i) = 1 for low adoption, EbAD(i)=2 for medium adoption, and EbAD(i) = 3 for high adoption. We computed the EbA score:

$$\mathbf{EbAS(i) = P(i)/T} \quad \textbf{(15)}$$

where EbAS(i) is the EbA score by the farmer i, P(i) is the total number of practices adopted by the farmer i and T is the total number of practices identified.

The EbA score variable was used to define: EbAD(i) by: EbAD(1) if $EbAS(i) < 0.5$; EbAD(2) if $0.5 \leq EbAS(i) \leq 0.75$; EbAD(3) if $0.75 < EbAS(i)$.

Furthermore, the behavioral factors and the cognitive factors indices were created and were ultimately used together with socioeconomic variables, to model farmers' decision-making toward EbA adoption. The items under each variable (see Table 5.1) were summated to obtain intention, perceived behavioral control, perceived climate-related hazards, perceived exposed element at risk, perceived vulnerability, EbA Affordability, and EbA benefits indices. The reliability test (Cronbach's alpha) has been performed for each variable before summating the items.

Afterward, Discriminant analysis was conducted, using EbAD(i) as the dependent variable, to predict farmers' EbA-adoption groups and how well the predictor variables separate the groups. The proposed empirical model for the Discriminant Function takes the form of equation (16):

$$\mathbf{Di = + \alpha 1PBC\ \alpha 2INT + \alpha 3Haz + \alpha 4\ Exp + \alpha 5Vul + \alpha 6EbAaff + \alpha 7EbAbenef + \alpha 8Income + \alpha 9labor + \alpha 10Landsiz + \alpha 11AGE + \alpha 12EDUC \ldots\ldots\ldots\ldots (16)}$$

Where Di is the predicted score (discriminant score); and α is the discriminant coefficient.

The study hypothesizes that:

Ho (the null hypothesis): A combination of behavioral, cognitive, and socioeconomic variables explains significant differences among farmers' EbA adoption groups.

The null hypothesis was tested with a pairwise ANOVA to compare groups' mean scores on behavioral, cognitive, and socioeconomic variables.

In addition, the assumptions of normality, homogeneity, and collinearity for the predictor variables were tested.

The data were analyzed through several statistical techniques using the Statistical Package for the Social Sciences (SPSS) version 26 and the Analysis of a Moment Structures (AMOS) version 26.

5.6. Results

5.6.1. Psycho-Social Factors Influencing Farmers' Behavior Toward EbA Decision

5.6.1.1. Evaluation of Model Fit

Following the two-step approach of Anderson and Gerbing (1988), confirmatory factor analysis (CFA) was performed to assess the reliability and validity of the measurements or items and constructs used. Confirmatory factor analysis was employed to examine whether measures of a factor were consistent with the nature of that factor or not (Henson and Roberts, 2006). The confirmatory measurement model was tested by AMOS software (V26). As shown in **Table 5.2**, several commonly used fit indices (Chi-square/df; CFI; TLI; IFI; RMSEA, SRMR) were employed to assess the overall model fit (Schreiber, 2008). The five factors of the TPB model (Attitude, Subjective norm, perceived behavioral control, intention, and behavior) yielded a good fit for the data as all the fit indices outlined above fall within the excellent cut-off criteria according to Hu and Bentler (1999) **(Table 5.2)**: $\chi 2/df = 2.167$; CFI = 0.963; TLI = 0.952; IFI = 0.963; RMSEA = 0.052; SRMR = 0.049.

Table 5.2. Model fit indices results of the TPB model

Fit Indices	Threshold	Obtained value
Chi-square	--	203, 116
df	--	94,00
Chi-square /df	Between 1 and 3	2.167
CFI	>0.95	0.963
TLI	>0.95	0.952
IFI	>0.95	0.963
RMSEA	<0.06	0.052
SRMR	<0.08	0.049

***CFI**: Comparative Fit Index; **IFI**: Incremental Fit Index; **TLI**: Turcker-lewis Index; **RMSEA**: Root Mean Square Error of Approximation.; **SRMR**: Standardized Root Mean Square Residual*

5.6.1.2. Measurements and Construct Normality, Reliability, and Validity

The measurement models were tested for indicator normality (skewness and kurtosis), reliability (factor loadings), construct reliability (composite reliability), convergent validity analysis (average variance extracted or AVE), and discriminant validity (square root of AVE and loadings and cross-loadings analysis). For this study, an item-trimming process was undertaken for the research model. Measures with very low loadings were removed one at a time until most measures achieved reasonable loadings and a significant t-value at the 0.05 level. Out of a total of 20 measures used, 4 measures were deleted. Based on the results presented in Table 5.3, we can see that both the skew and kurtosis are in an acceptable range to be considered normal. The skew values range between −2 and +2 and the kurtosis, ranges between −10 to +10 (Collier, 2020).

The measurement models were tested for data indicator reliability (factor loadings), construct reliability (composite reliability), convergent validity analysis (average variance extracted or AVE), and discriminant validity (square root of AVE and loadings and cross-loadings analysis). Figure 5.2 illustrates the factor loadings of all the measurement items for each construct. A cut-off point of 0.5 was set for the factor loadings subject to these measures achieving significant t-values of at least 0.05 as prescribed by (Bagozzi and Yi, 1988, Hair et al., 2006, and Marticotte and Arcand, 2017). All the factor loading except for SN1 is greater than 0.5, with all achieving significant t-values ($p<0.001$) satisfying the requirements for acceptability (Hair et al., 2006). The observed indicators are then strongly related to their associated latent variable or construct except for SN1 which has been removed from the analysis.

Table 5.3. Normality and Factor loading of the measurement items, mean, and standard division.

Constructs and measurement items	Skew	Kurtosis	t-value (significance)
ATTITUDE (ATT): Mean (3.61); Standard Deviation (0.90)			
ATT1: I think that the implementation of EbA practices to adapt to climate change is effective at improving cropland resilience.	1.753	1.350	Fixed
ATT2: I think that the implementation of EbA practices to adapt to climate change is effective at enhancing adaptation benefits	1.570	0.754	10.029***
ATT3: I think that the implementation of EbA practices to adapt to climate change is effective at increasing farmers’ livelihood and food security.	1.308	0.609	10.228***
ATT4: I believe that the implementation of EbA is a wise idea to deal with climate change impacts on cropland and farmers ‘livelihoods.	1.600	1.013	9.643***

Table 5.3. **Cont'**

SUBJECTIVE NORM (SN): Mean (3.72); Standard Deviation (0.38)				
SN1: My family members and relatives encourage me to implement EbA practices on my farm to adopt to climate risks.	1.511	0.571		Fixed
SN2: My friends and neighbors encouraged me to implement EbA practices on my farm to adopt to climate risks.	1.425	0.186		12.308***
SN3: I care about what people who are important to me to encourage me to do on my farm to adapt to climate risks.	1.467	0.548		12.789***
PERCEIVED BEHAVIORAL CONTROL (PBC): Mean (2.98); Standard Deviation (0.67)				
PBC1: I have the technical knowledge to implement EbA practices on my farm.	0.860	- 0.492	0.817	Fixed
PBC2: I can easily implement EbA practices on my farm if I want.	-0.044	-1.826	0.815	5,415***
PBC3: I have the necessary resources for the implementation of EbA practices on my farm.	0.516	-1.634	0.732	5,574***
INTENTION (INT): Mean (4.07); Standard Deviation (0.52)				
INT1: I intend to continue or adopt EbA practices on my farmland	1.299	-0.151	0.769	Fixed
INT2: I am willing to continue or adopt EbA practices on my farm with or without financial assistance from NGOs or government subsidies.	1.389	0.052	0.859	17.908***
INT3: I am willing to engage in EbA practices because of its benefit to farmland and farmers' livelihoods	1.242	-0.326	0.866	18,012***
BEHAVIOR (BEH): Mean (2.25); Standard Deviation (1.52)				
BEH1: I decide to engage in conservation agriculture practices on my farmland to adapt to climate risks in the next years	0.603	-1.571	0.904	Fixed
BEH2: I decide to engage in soil and water conservation practices on my farmland to adapt to climate risks in the next years	0.768	-1.366	0.844	21.114***
BEH3: I decide to engage in integrated soil fertility management practices on my farmland to adapt to climate risks in the next years	0.603	-1.571	0.754	18.212***

Note: Respondents were asked to rate their agreement on all measurement items using a 1–5 scale (1) Strongly disagree to (5) strongly agree

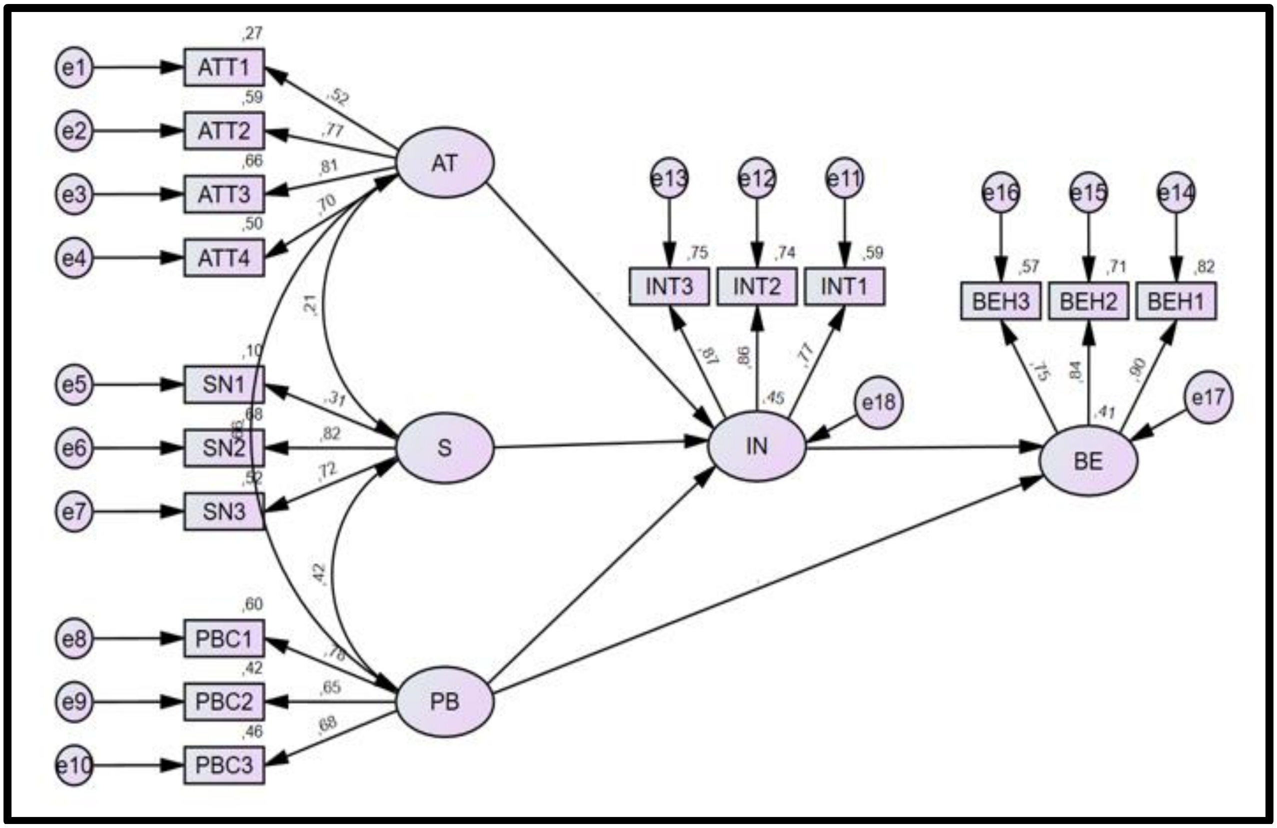

Figure 5.2. The factor loadings of all the measurement indicators for each construct

Taken together, the findings indicate that the proposed model and the data were a good fit. The loadings of all indicators except SN1 in the final trimmed model were examined to assess the reliability of the constructs.

The Construct Reliability was assessed using Cronbach's Alpha and composite Reliability. Cronbach's Alpha is the degree to which responses are consistent across the items within a construct. As presented in Table 5.4. Cronbach's Alpha ranges from 0.74 to 0.87 among the five factors exceeding the required limit of 0.70 (Hair et al., 2010). The composite reliabilities ranged from 0.80 to 0.87, exceeding the prescribed criterion of 0.70 suggested by Hair et al. (2010). Hence construct reliability was established for each construct in the study.

To evaluate the construct validity, the convergent and discriminant validities were each examined (Fornell and Larcker, 1981). The convergent validity of each construct was estimated using the Average Variance Extracted (AVE). These were all found to be above the threshold value of 0.5 (Fornell and Larcker, 1981; Hair et al., 2010; Khan et al., 2016) for all the constructs. Therefore, the constructs used for the present study have the required convergent validity (Table 5.4).

Table 5.4: Constructs Validity and reliability results

Constructs	Cronbach's Alpha	Composite Reliability	AVE
Attitude	0.78	0.80	0.58
Subjective norms	0.74	0.81	0.59
Perceived behavioral control	0.74	0.83	0.62
Intention	0.87	0.87	0.69
Behavior	0.86	0.87	0.70

The discriminant validity is entirely established using the Fornell and Larcker criterion and HTMT ratio. As presented in Table 5.5a, it emerged that all the squared AVE values were greater than each inter-construct correlation supporting the Fornell and Larcker criterion (Fornell and Larcker, 1981).

Table 5.5a: Discriminant validity of the measures based on Fornell and Larcker criterion

	Attitude	Subjective norms	Perceived behavioral control	Intention	Behavior
Attitude	***0.761***				
Subjective norms	0.660***	***0.769***			
Perceived behavioral control	0.608**	0.613***	***0.789***		
Intention	0.616***	0.657***	0.527**	***0.832***	
Behavior	0.612***	0.615***	0.584***	0.536***	***0.836***

Notes: Squared Average variances extracted (AVE) are on the diagonal (in Bold and italics); correlations are off-diagonal. ** P< 0.01; *** P<0.001

When assessing the discriminant validity using the HTMT ratio, as presented in Table 5.5b, all ratios were less than the required limit of 0.85 (Henseler et al., 2015). Hence satisfying the criteria for discriminant validity. Collectively, the results presented above provide support for the overall quality of the final measures used in this study. The statistics suggest that the component measures are normally distributed, reliable, internally consistent, and have convergent and discriminant validity. The measurement models are therefore acceptable for further analysis, and the next section presents the results of the analysis of the structural models.

Table 5.5b: Discriminant validity of the measures based on the HTMT ratio

	Attitude	Subjective Norm	Perceived behavioral control	Intention	Behavior
Attitude					
Subjective Norm	0.681				
Perceived behavioral control	0232	0.444			
Intention	0.538	0.660	0.266		
Behavior	0.436	0.598	0.391	0.548	

5.6.1.3. Structural Model Analysis and Behavioral Hypotheses Testing

After validating the measurement models, SEM was used to investigate the causal relationships between the predictor and outcome variables that are hypothesized in the Theory of Planned Behavior framework. This was done through the estimation of separate structural models in Amos 26 to test the direct, mediating relationship and the moderation effect. Overall, the fit indices for the structural model fell within the acceptable range with CMIN/df = 2.124; IFI= 0.963; TLI= 0.954; CFI= 0.963; RMSEA= 0.034 and SRMR = 0.040 (Schreiber, 2008).

The estimates for the test of direct relationships are presented in Table 5.6 and graphically depicted in Figure 5.3**.** These capture the findings of the tests for H1a through to H1e. As can be observed from Table 5.6, all the hypotheses were supported (H1a, H1b, H1c, H1d), except for one (H1e). The attitude was found to have a significant positive effect on intention (β= 0.31, t= 4.97, p<0.001) as well and perceived behavioral control to have a significant positive effect on Intention (β= 0.45, t= 8.56, p<0.001). Nevertheless, the relationship between subjective norm and intention was found to be insignificant (β= 0.03, t= 0.52, p = 0.60 > 0.05).

Table 5.6: Direct path analysis

Hypotheses	**Path description**	**β**	**t-value**	**Results**
H1a	Attitude --> intention	0.31	4.97***	Supported
H1b	Subjective norm -->intention	0.03	0.52 (0.60)	Not supported
H1c	Perceived behavioral control-->intention	0.45	8.56***	Supported
H1d	Intention -->behavior	0.44	7.24***	Supported
H1e	Perceived behavioral control -->behavior	0.51	4.40***	Supported

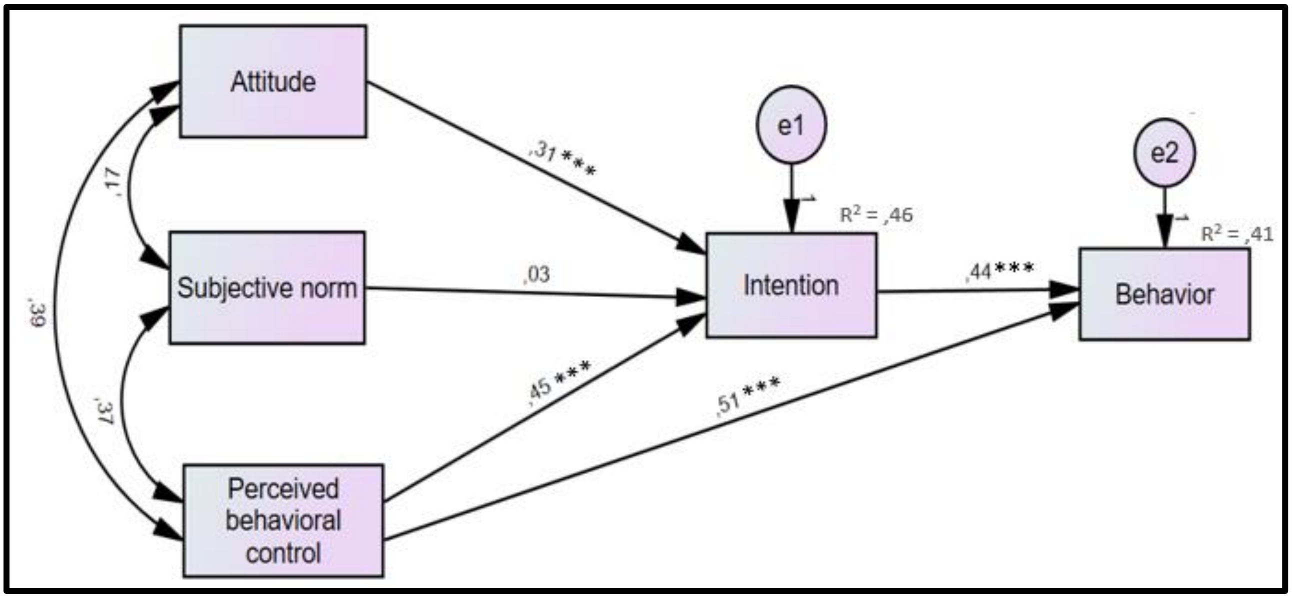

Figure 5.3. Results of the TPB structural model of farmers' behavior toward EbA practices
Note: ****p*<0.001

The inner model path coefficients, therefore, suggest that for the farmers of the study region, attitude, and perceived behavioral control have a positive effect on their intention to implement EbA practices while Subjective Norm does not have any effect on their intention. Among all of the parameters, perceived behavioral control has the most effect on behavioral intention with a path coefficient of 0.45. It means that a unit rise in the perceived behavioral control of the respondent will increase their intention to engage in the implementation of EbA practices at their farm level by 0.45 units.

For the dependent parameter, "Behavior", both "Perceived behavioral control" and "Intention" parameters have significant positive affection with the path coefficient of 0.51 and 0.44 respectively.

The squared multiple correlations (R^2) was 0.46 for intention and 0.41 for behavior (Figure 5.3), showing respectively the level of prediction of farmers' intention toward EbA adoption based on attitude, subjective norm, and perceived behavioral control and of farmers' behavior towards EbA decision based on farmers 'intention and their perceived behavioral control.

Based on the standardized regression weights results, the TPB equations for intention and behavioral prediction are respectively:

INT= (**0.31**) ATT **+ (0.03)** SN + **0.45** (PBC)

BEH = (**0.51**) PBC + (**0.44**) INT

Furthermore, a two-group analysis with constraint was done on the path model to find out whether the relationship figured out in the model is significantly different across gender groups. Two groups are distinguished (1) Male and (0) Female. The results of the constraint models in Table 5.7 showed that the chi-square difference for the constrained relationship between perceived-behavioral control and behavior (7,491) is significant at 0.05 level (p = 0.006) between male and female groups. The male group's perception of control over the use of EbA practice is higher (β=0.801) than for female group (β=0.220).

Table: 5.7. Gender differential on the TPB path model

Constrained Model	CMIN	P	β Female	β Male
Constraint_ATT-INT	2,868	,090	,197	,364
Constraint_PBC-INT	,083	,773	,401	,353
Constraint_SN-INT	,957	,328	,347	,147
Constraint_INT-BEH	2,934	,087	,065	-,024
Constraint_PBC-BEH	7,491	,006	,220	,801

5.6.1.4. Mediation Analysis

The study assessed the mediating role of intention on the relationship between attitude, subjective, and perceived behavioral control on behavior using a bootstrap sample of 5,000 with a 95% confidence interval. The mediation analysis summary is presented in Table 5.8**.** The results revealed a positive and significant indirect effect of the impact of attitude on behavior (β = 0.330, p= 0.000) in the presence of the mediator "intention" but an insignificant direct effect on behavior. Hence, intention fully mediates the relationship between attitude and behavior. Also, there is an insignificant direct path from the subjective norm to behavior, but a positive and significant indirect path through intention (β = 0.101, p= 0.000). Thereby demonstrating that intention fully mediates the relationship between subjective norms and behavior. Furthermore, the intention was found to have no mediation effect on the relationship between perceived behavioral control and behavior, since the direct path from perceived behavioral control to behavior is positive and significant (β = 0.511, p= 0.000), but the indirect path (β = 0.267, p= 0.000) through intention were found to be insignificant. Thus, this finding provides support to H2a and H2b.

Table 5.8: Result of mediation analysis

Hypotheses	Relationship	Direct effect Without mediator	Indirect effect With mediator	Mediation type	Conclusion
H2a	ATT--> INT --> BEH	0.352 (0.364)	0.330*** (0.000)	Full mediation	Supported
H2b	SN --> INT --> BEH	0.224 (0.093)	0.101*** (000)	Full mediation	Supported
H2c	PBC --> INT --> BEH	0.511*** (0.000)	0.267 (0.772)	No mediation	Not supported

***p⩽0.001

5.6.1.5. Moderation Effects Analysis

The study assessed the moderating role of Perceived behavioral control (PBC) on the relationship between Attitude (ATT) and Intention (INT); Subjective norm (SN) and intention as well as intention and behavior (BEH). The Moderation analysis summary is presented in **Table 5.8**. The results revealed that the interaction between ATT and PBC (β = 0.055, t= 1.122, p= 0.006), as well as INT and PBC (β = 0,144, t= 2.415, p= 0.016), are positive and significant whereas the interaction between SN and PBC is negative and significant (β = - 0.037, t= 0.940, p= 0.003). These findings show that there is a significant moderation effect of PBC on the three-relationship assessed.

In addition, the results of simple slope analysis conducted to better understand the nature of the moderator effects on the relationship from ATT and INT, SN and INT, and INT and BEH are shown respectively in figures 5.4, 5.5, 5.6. As can be seen in Figure 5.4, the line is much steeper for high PBC, this shows that at the high level of PBC, the impact of ATT on INT is much stronger in comparison to low PBC. This reveals that the higher the PBC over the EbA implementation, the stronger the association between attitude and intention. Hence, perceived behavioral control has a positive and significant moderating effect on the relationship between farmers' attitudes toward EbA implementation and their 'intention to perform EbA practices, supporting H3a **(**Table 5.9**).** Whereas it is shown in Figure 5.5 that the line is much steeper for low PBC, this shows that at a low level of PBC, the impact of SN on INT is much stronger in comparison to high PBC.

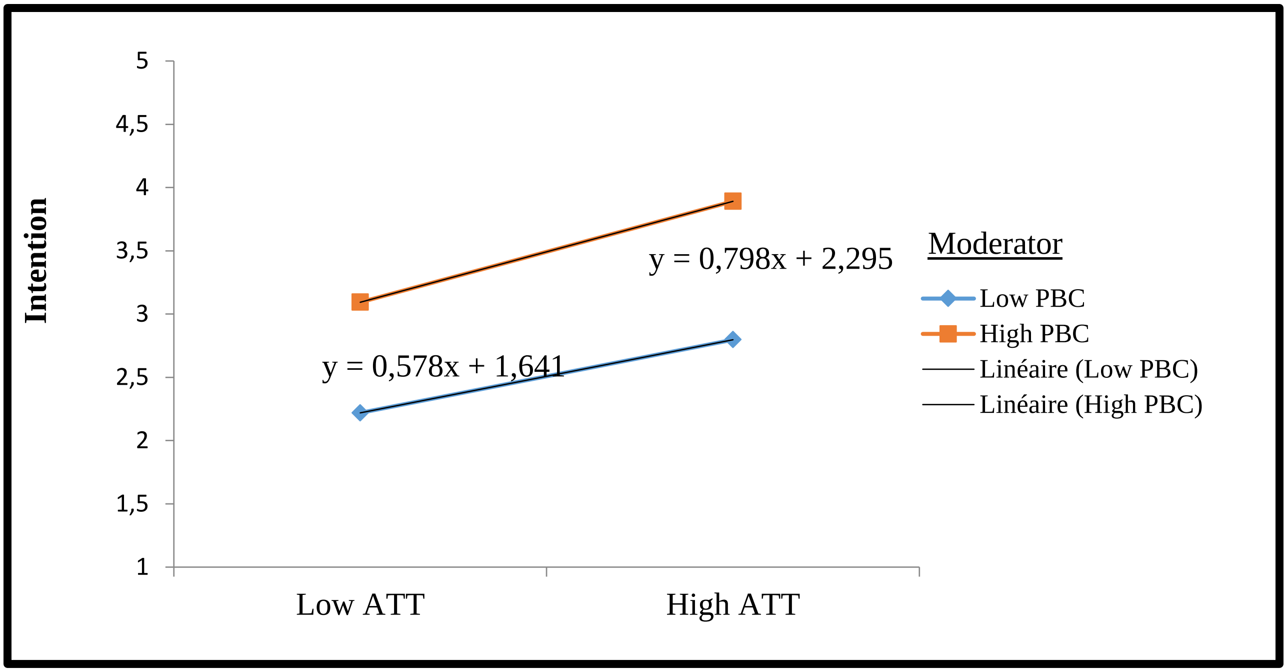

Figure 5.4. The simple slope of ATT (X) predicting intention (Y)

This demonstrates that as the level of PBC increased, the strength of the relationship between SN and INT decreased. Hence, perceived behavioral control has a negative and significant moderating effect on the relationship between subjective norms and farmers 'intention to perform EbA practices, supporting H3b (Table 5.9).

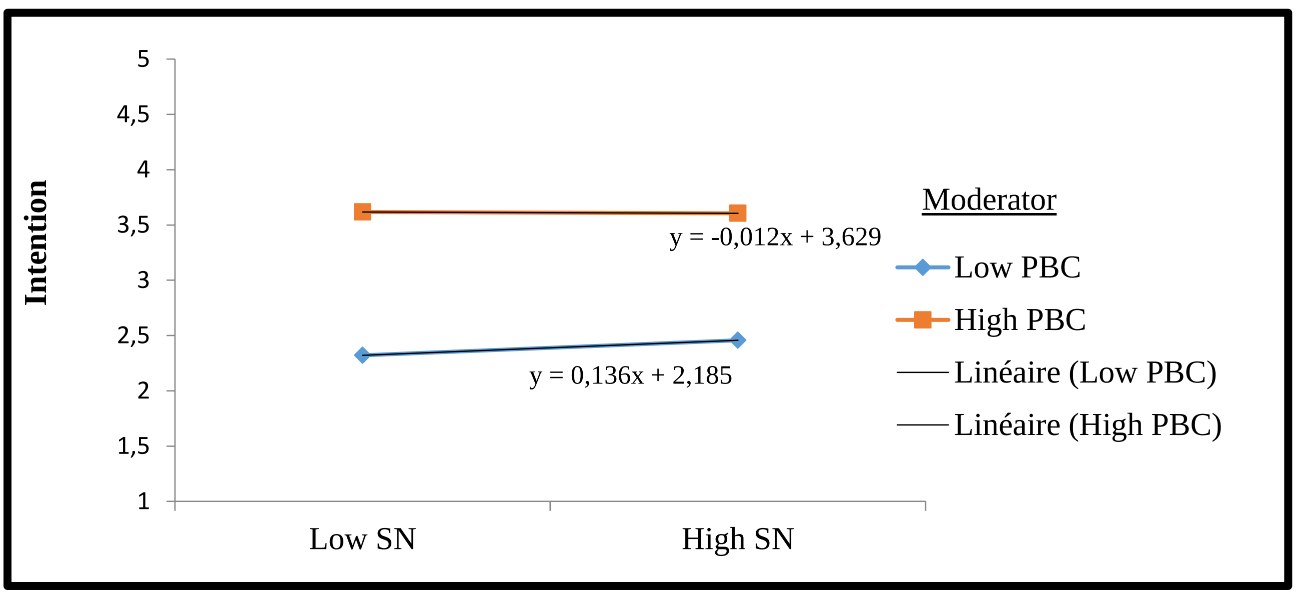

Figure 5.5. The slope of SN (X) predicting intention (Y)

As shown in Figure 5.6, the line is much steeper for high PBC, this shows that at a high level of PBC, the impact of INT on behavior is much stronger in comparison to low PBC. Hence, perceived behavioral control has a positive and significant moderating effect on the relationship between farmers' intention toward EbA implementation and their EbA behavior supporting H3c (Table 5.9). Whereas, the more they felt control over performing EbA practices, the less they were influenced by peer pressure in forming their intention toward EbA implementation.

Furthermore, by "probing the interaction", a better picture of the relationship between ATT to INT, SN to INT, and INT to BEH at different levels of the moderator PBC.

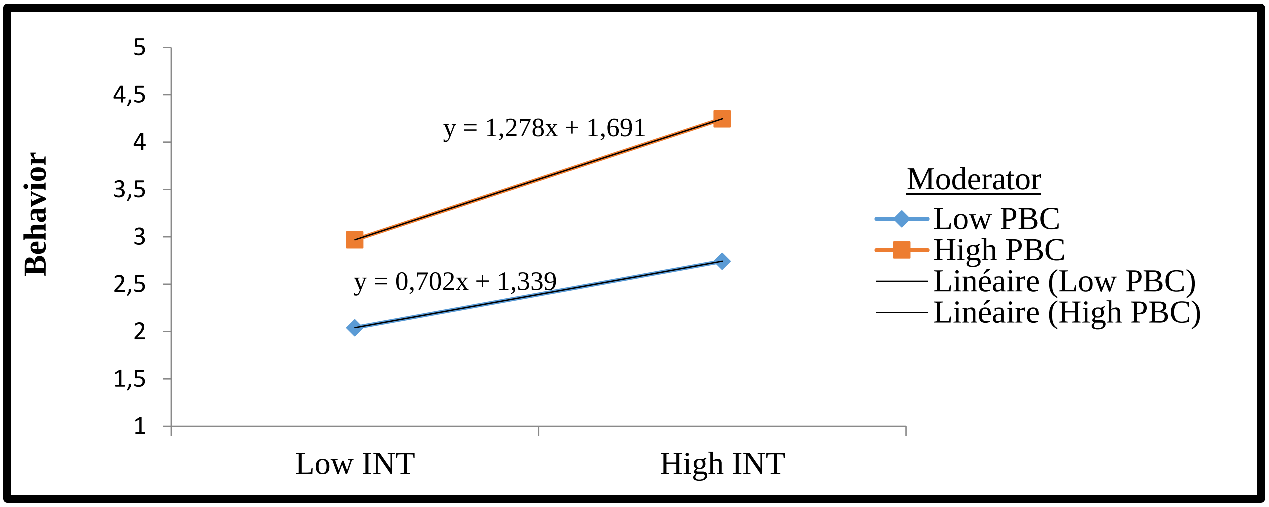

Figure 5.6. The simple slope of INT (X) predicting behavior (Y)

The results (Table 5.9) show that the moderator (PBC) is significant at all levels of tests (low-level, mean-level, and high-level) for ATT and INT, SN and INT, and INT and BEH. The unstandardized estimate values for the relationship between ATT and INT; SN and INT; INT and BEH at a low level, mean-level, and high level of PBC show that at a high level of PBC, the relationships from attitude to intention as well as from behavioral intention are stronger. In contrast, the relationship between the subjective norm to intention is weaker. Hence, farmers in the study region, are more likely to act on their intention toward EbA adoption, and report intentions aligned with their attitudes, when their perceived behavioral control is high.

Table 5.9: Moderation analysis summary

Hypothesized Relationship	Unstandardized Estimate	t-value	P-value	Results
Moderation test				
H3a: ATTxPBC --> INT	0.055	1.122	0.006	Supported
H3b: SNxPBC --> INT	-0.037	0.940	0.003	Supported
H3c: INTxPBC --> BEH	0.144	2.415	0.016	Supported
Probing the interaction of PBC				
ATT --> INT				
Low-level PBC: ATT --> INT	0.293	3.986	***	
Mean-level PBC: ATT --> INT	0.344	4.952	***	
High-level PBC: ATT --> INT	0.395	4.668	***	
SN ----> INT				
Low-level PBC: SN ----> INT	0.065	1.284	***	
Mean-level PBC: SN ----> INT	0.031	0.868	***	
High-level PBC: SN ----> INT	-0.004	-0.079	***	
INT --> BEH				
Low-level PBC: INT --> BEH	0.361	4.729	***	
Mean-level PBC: INT -->BEH	0.495	6.862	***	
High-level PBC: INT --> BEH	0.629	6.070	***	

5.6.2. Modelling Farmers’ EbA Adoption Decision

5.6.2.1. Statistical Assumption of the Predictor Variables

- **Reliability test**

Reliability analysis was assessed using Cronbach’s alpha. It is the measure of the internal consistency of the constructs in the study. A construct is reliable if the alpha (α) value is greater than 0.70 (Hair et al, 2013). The reliability test showed that the values of Cronbach’s alpha a for perceived behavioral control, Intention, perceived climate-related hazard, perceived exposition; perceived vulnerability, EbA affordability, and EbA benefits were found reliable at 0.74, 0.87, 0.91, and 0.77 respectively. Reliability results are summarized in Table 5.10.

Table 5.10. Reliability Statistics

Components	No of items	Alpha
Perceived behavioral control	3	0.74
Intention	3	0.87
Perceived climate-related hazards	7	0.81
Perceived exposition	2	0.75
Perceived vulnerability	7	0.85
EbA affordability	3	0.91
EbA benefits	6	0.77

- **Test of normality**

Before running discriminant analysis, the Kolmogorov-Smirnov test was employed to prove the data are normally distributed. The data is normally distributed if the p-value is greater than 0.05 (Gabor et al., 1961). The results in Table 5.11 show that the p-value of all the variables is greater than 0.05. Then we can assume that the predictor variables have approximately a multivariate normal distribution.

Table 5.11: Kolmogorov-Smirnov Test for checking normality

Variables	Kolmogorov-Smirnov	
	Statistics	**P-value**
Perceived behavioral control	.938	.224
Behavioral intention	.957	.492
Perceived climate-related hazards	.173	.121
Perceived exposition	.130	.200
Perceived vulnerability	.924	.090
EbA affordability	.127	.117
EbA benefits	.144	.200
Farm labor	.181	.087
Household source of income	.905	.051
Education	.918	.090
Farmland size	.180	.089
Age	.175	.110

- **Test of multicollinearity**

In addition, multi-collinearity among the predictor variables was also tested through collinearity statistics (Tolerance and variance inflation factor VIF) and diagnostics (condition index). Mayers (1990) suggests a tolerance value below 0.1 indicates a serious collinearity problem. According to (Allison, 2001), the Values of VIF exceeding 10 are often regarded as indicating multicollinearity. In addition, an informal rule of thumb is that if the condition index is 15, multicollinearity is a concern (Midi et al., 2010). The multicollinearity results are presented in Table 5.12**.** As the tolerance value of each variable is greater than 0.1, the Variance inflation factor (VIF) is less than 10, and the condition index is less than 15, we can assume that the data has no multi-collinearity issue.

Table 5.12: Collinearity statistics and diagnostic

Coefficients			
Variable	Collinearity statistics		Diagnostic collinearity
	Tolerance	VIF	Condition Index
Perceived behavioral control	.383	2.608	1
Behavioral intention	.402	2.448	3.14
Perceived climate-related hazards	.891	1.123	4.136
Perceived exposition	.527	1.897	4.963
Perceived vulnerability	.783	1.277	7.208
EbA affordability	.647	1.546	9.578
EbA benefits	.513	1.949	10.486
Farm labor	.714	1.400	14.374
Household source of income	.883	1.132	13.897
Education	.931	1.074	12.861
Farmland size	.847	1.181	4.378
Age	.974	1.027	1.023

5.6.2.2. Differentiation of farmers' EbA Adoption groups

Discriminant analysis was used to test our null hypothesis stating that the combination of behavioral, cognitive, and socioeconomic factors could predict farmers' EbA Adoption groups. Figure 5.5. shows the distribution of farmers according to their level of adoption. The majority of farmers (47%) are within the low EbA adoption groups; 34% are in medium EbA adoption groups and 19% are in high EbA adoption groups.

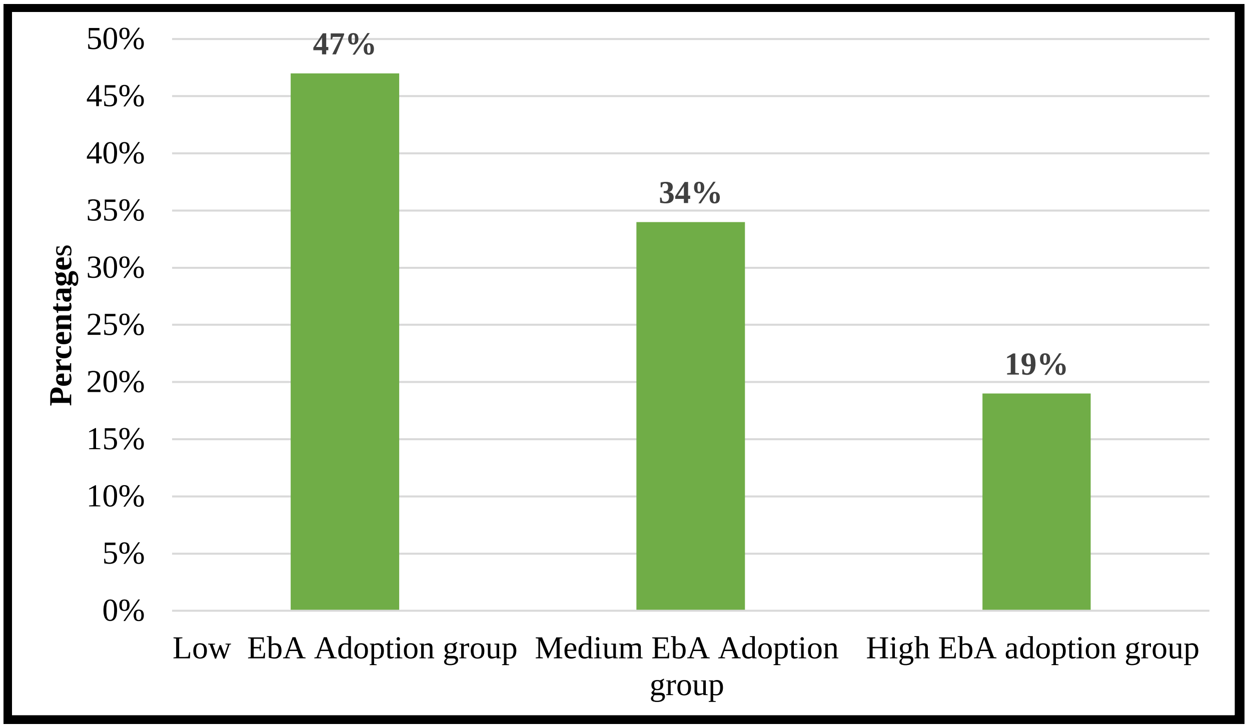

Figure 5.6. Percentage of farmers in the different EbA adoption groups

- **Group means and ANOVA test**

The study examined whether there is any significant difference between groups on each of the independent variables using group means and ANOVA. The group means analysis in Table 5.13 shows the difference between the three EbA Adoption groups for each discriminant variable. Farmers in the **low EbA adoption group**, have the lowest perceived behavioral control and the lowest intention to implement EbA practices compared to the others. Concerning cognitive variables, they have the lowest perception of climate-related hazards, exposure, vulnerability, EbA affordability, and EbA benefits. According to socioeconomic factors, farmers in the low EbA adoption group are the oldest, have the least education, have the smallest farm labor, have the smallest farmland size, and have the smallest household income. The group with **medium EbA adoption** is composed of farmers having the highest perceived behavioral control, the highest perceived vulnerability, and EbA benefits, and in terms of socio-economic factors, they are the youngest, have the highest labor force, and the highest income than farmers in the other two groups.

Table 5.13: Descriptive statistics.

		Group means (sd)			
Discriminant Factors	**Discriminating Variables**	**Low EbA Adoption (1) N= 200**	**Medium EbA Adoption (2) N= 143**	**High EbA Adoption (3) N= 82**	**Total mean**
Behavioral factors	Perceived behavioral control	3.92 (1.39)	4.50 (0.92)	4.37 (1.01)	4.20 (1.20)
	Intention	2.97 (0.74)	3.09 (0.58)	3.30 (0.41)	3.14 (0.58)
Risk Perception factors	Perceived climate-related-hazards	4.22 (0.38)	4.40 (0.30)	4.44 (0.30)	4.39 (0.33)
	Perceived Exposed Element at risk	2.91 (0.59)	3.57 (0.52)	3.80 (0.66)	3.52 (0.66)
	Perceived Household vulnerability	3.94 (0.53)	4.23 (0.60)	4.09 (0.52)	4.12 (0.57)
EbA value	EbA affordability	2.20 (0.44)	2.96 (0.91)	2.99 (0.77)	2.83 (0.84)
	EbA benefits	2.91 (0.59)	3.80 (0.66)	3.57 (0.52)	3.52 (0.66)
Socio-economic	Age	50. (13.00)	37 (12.16)	41 (12.58)	42.58(12.44)
	Education	1.68 (3.24)	2.62 (3.26)	3.60 (3.97)	2.43 (3.52)
	Farm labor	3.90 (2.95)	5.06 (3.39)	4.78 (2.81)	4.71 (3.07)
	Farmland size	3.10 (6.25)	5.09 (4.40)	6.13 (5.24)	4.92 (5.20
	Household income	2.17 (0.97)	2.27 (0.91)	2.22 (0.86)	2.22 (0.90)

Farmers in the **high EbA adoption** group showed higher behavioral intention, high perception of climate-related hazards, exposure, and EbA affordability in comparison with farmers in the other two groups. In terms of socioeconomic variables, they are more educated and have larger farmland sizes.Further, the ANOVA analysis Table 5.14 highlights the differential contribution of behavioral cognitive and socioeconomic variables by groups of farmers. The smaller the Wilks' lambda, the more important the independent variable to the discriminant function. In our case, the perceived vulnerability variable is the most important variable with Wilks's lambda equal to 0.477 for it produces a higher F value (231.577), followed by EbA benefits, perceived behavioral control, behavioral intention, and Perceived exposition. Wilks's lambda is significant by the F test for seven (07) independent variables out of twelve (12) variables used in the analysis.

The results reveal that the three groups of farmers based on their EbA adoption are more distinguished by behavioral and cognitive variables rejecting our null hypothesis supporting that a combination of behavioral, cognitive, and socioeconomic variables explain significant differences among farmers' EbA adoption groups.

Table 5.14: ANOVA comparison of the three farmers' EbA adoption groups

Tests of Equality of Group Means					
Discriminant variables	Wilks' Lambda	F	df1	df2	Sig.
Perceived behavioral control	0.814	48.238	2	422	.000
Behavioral Intention	0.865	32.959	2	422	.000
Perceived climate-related hazards	0.949	11.353	2	422	.000
Perceived Exposition	0.937	14.076	2	422	.000
Perceived vulnerability	0.477	231.577	2	422	.000
EbA benefits	0.771	62.780	2	422	.000
EbA cost	0.965	7.644	2	422	.001
Farm labor	0.982	3.913	2	422	.321
Household income	0.998	.350	2	422	.705
Education	.989	2.345	2	422	.097
Land size	.995	1.158	2	422	.315
Age	1.000	.040	2	422	.960

- **Test of equality of covariance matrices (Box's M)**

The Box M test of equality of population covariance matrices of the three groups of EbA adoption under study was tested. Box‘s M tests the null hypothesis that the covariance matrices do not differ between groups formed by the dependent variables. Since discriminant analysis assumes homogeneity of covariance matrices between groups, the study would like to see the determinants be relatively equal so that the null hypothesis that the groups do not differ can be retained. For this assumption to hold, the log determinants should be equal. When tested by Box‘s M, we are looking for a non-significant M to show similarity and lack of significant differences. The results reveal that the log determinants appear quite similar and Box‘s M is 135.348 with F = 4.423 which was found significant at the 1% level (Table 5.15), indicating a violation of the assumption of equal covariance matrices. Meaning that the EbA Adoption groups do differ from each other.

Table 5.15: Box's M test of equality of population covariance matrices of the three groups

Box's M	135.348
F	4.423
df1	30
df2	240161.710
p-value	.000***

Tests null hypothesis of equal population covariance matrices.

Table 5.16 shows that all the variance explained by the model is due to two discriminant functions. Wilks' lambda values for the two functions indicate the greater discriminatory ability of the first function which has the smallest value (0.404) and explains more variance (93.6%) in the dependent variable. The Sig ($p<0.001$) for the Chi-square test indicates that there is a highly significant difference between the groups in the two discriminant functions.

Table 5.16. Canonical Discriminant Functions

Eigenvalues					**Wilks' Lambda**			
Func-Tion[a]	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation	Test of Func-tion(s)	Wilks' Lambda	Chi-square	Sig.
1	1.274[a]	93.6	93.6	.748	1 through 2	.404	380.32	.000
2	.088[a]	6.4	100.0	.284	2	.919	35.30	.000

a. First 2 canonical discriminant functions were used in the analysis.

5.6.2.3. The determinants of EbA Adoption groups

To investigate the determinants of EbA adoption groups, the stepwise method was used for selecting the "best" variables to use in the model by removing independent variables that are not significant based on how much they lower Wilks' lambda, F value, and tolerance value. At each step, the variable that minimizes the overall Wilks' lambda, and which F value is greater than the entry value is entered. In our case, the results in Table 5.16 show that out of the twelve (12) variables used for the analysis, five variables (05) were entered based on their importance. Those variables are respectively perceived vulnerability, EbA benefits, perceived behavioral control, Intention, and perceived exposition.

Table 5.17. Variables in the analysis [a]

Step	Variable Entered	Wilks' Lambda							
		Lambda	df1	df2	df3	Exact F			
						Statistic	df1	df2	Sig.
1	Perceived vulnerability	.937	1	2	422.000	14.076	2	422.000	.000
2	EbA benefits	.887	2	2	422.000	12.976	4	842.000	.000
3	Perceived behavioral control	.845	3	2	422.000	12.279	6	840.000	.000
4	Behavioral Intention	.822	4	2	422.000	10.811	8	838.000	.000
5	Perceived exposition	.807	5	2	422.000	9.482	10	836.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a. a Maximum number of steps is 20.

Table 5.18 shows the correlation (in order of importance) of each variable on the discriminant functions. For function 1, perceived vulnerability is the best predictor with a coefficient of 0.925 followed by EbA benefits with a coefficient of 0.907 perceived exposition with a coefficient of 0.256, and perceived behavioral control is the least with a coefficient of 0.042.

Table 5.18. Impact of each variable on discriminant functions

Standardized Canonical discriminant function coefficients		
	Function	
	1	2
Perceived behavioral control	.042	.735
Behavioral intention	.186	.508
EbA benefits	.907	-.199
Perceived vulnerability	.925	-.145
Perceived exposition	.256	-.467

For function 2, perceived behavioral control has the most explanatory power with a coefficient of 0.735 followed by behavioral intention with a coefficient of 0.508, and perceived exposition has the least explanatory power with a coefficient of -0.467.

Table 5.19. contains the unstandardized discriminant function coefficients. They are used to construct the actual prediction equation.

Table 5.19. Unstandardized Canonical Discriminant Function Coefficients

	Functions	
	1	2
Perceived behavioral control	0.036	0.622
intention towards EbA	0.188	0.948
EbA benefits	0.750	-0.611
Perceived vulnerability	0.934	-0.210
Perceived exposition	0.368	-0.201
(Constant)	-1.420	2.940

Based on the unstandardized canonical discriminant function coefficients, the two functions are as follows:

Function1: Discriminant score = -1.420 + 0.036(PBC)+ 0.188 (INT)+ 0.750 (EbAbenef))+ 0.934 (Vul)+ 0.368 (Exp)

Function 2: Discriminant score = 2.940 + 0.622 (PBC)+ 0.948 (INT) - 0.611 (EbAbenef) – 0.210 (Vul) – 0.201(Exp)

Table 5.20 shows that the discriminant model classifies farmers into three predefined EbA adoption groups, based on behavioral (Perceived behavioral control and behavioral intention) and cognitive (Perceived Exposition; Perceived Vulnerability, and EbA benefits) information from each farmer.

Table: 5.20: Classification of farmers under EbA adoption groups

Classification Results						
		EbA Adoption level per farmer	Predicted Group Membership			Total
			Low adoption	Medium adoption	High adoption	
Original	Count	Low Adoption	104	71	25	200
		Medium Adoption	25	103	15	143
		High Adoption	1	8	73	82
	%	Low Adoption	52.0	35.5	12.5	100.0
		Medium Adoption	17.5	72.0	10.5	100.0
		High Adoption	1.2	9.8	89.0	100.0
a. 65.9% of originally grouped cases were correctly classified.						

The result reflects that the model classifies correctly better at 65.9% of the farmers under the three EbA adoption groups. Among the farmers having a low adoption level of EbA practice, 52% of them will continue to have low adoption of EbA practices on their farm, 35.5% will be within medium adopters, and only 12.5% will be classified as high adopters. For farmers having a medium adoption level, 72% of them will remain in that group, while 17.5% will fall into the low adoption group and 10.5% will increase their adoption level. Concerning farmers with a high adoption level, 89% will conserve their adoption level however, 9.8% will fall into the medium and 1.2% under the low adopter group. The Discriminant analysis is discriminating farmers into low, medium, and high adopters of EbA practices based on five important variables: perceived behavioral control, behavioral intention, perceived exposition, perceived vulnerability, and Perceived EbA benefits.

5.7. Discussion

The theory of Planned Behavior was used to gain a better understanding of how socio-psychological factors (attitude, subjective norm, and perceived behavioral control) influence farmers' intention and behavior to use EbA at the farm level for climate change adaptation. The finding revealed that attitude and perceived behavioral control are the best predictors of farmers' intention toward EbA adoption in the study area accounting for approximately 46% of the variance in intention.

According to the findings, farmers' attitudes have a positive and significant impact on their intention to implement EbA practices. A positive significant impact of attitude on farmers' intentions implies that positive attitudes towards EbA practices increase a farmer's likelihood of developing intentions to adopt such EbA practices. Farmers' positive attitudes towards EbA practices are dependent on their perception of the benefits of EbA practices on their farm output. Previous research (Atta-Naidoo et al., 2022; Faisal et al., 2020; Rezaei et al., 2019; Maleksaeidi & Keshavarz, 2019; Deng et al.,2016; Menozzi et al., 2015; Beedell and Rehman (2000) has found that attitude is one of the best predictors of farmers' ecological conservation intention. Studies including (Bonke et al., 2021; Tama et al., 2021; Dehghanpur & Zibaei, 2020; Faisal et al., 2020; Senger et al., 2017; Werner et al., 2017; Lalani et al., 2016; Wauters et al., 2009) discovered that attitude has the highest positive and significant effects on farmers' intention toward conservation practices, compared to other constructs. However, our findings show that perceived behavioral control is the most important factor influencing farmers' intentions to adopt ecosystem-based adaptation behavior. Consequently, farmers who can overcome the different limitations in adopting EbA practices such as lack of information and resources will gain the motivation and develop the intention to adopt and subsequently the adoption of such practices. These findings are consistent with previous research on conservation behavior (Li et al., 2022; Nguyen & Drakou, 2021a; Despotovic et al., 2019; Anh et al., 2019; Jiang et al., 2018; Senger et al., 2017; Zeweld et al., 2017; Chin et al., 2016, Deng et al., 2016), which suggests that greater perceived capability to apply EbA practices leads to greater intention to apply EbA practices.

Additionally, the findings of this study suggest that intention and perceived behavioral control, which together account for 41% of the variance in farmers' EbA behavior, are very significant determinants of farmers' EbA behavior in the study area. Farmers' intentions influence their EbA behavior in a positive and significant way, suggesting that having good intentions for EbA practices increases the likelihood that a farmer will use them. This is consistent with recent studies (Ataei et al., 2022; Rahimi Faizabadi et al., 2017), which found water conservation behavior was significantly determined by farmers' intentions. A similar study conducted by Deng et al. (2016) revealed that farmers' ecological conservation behavior is significantly and positively influenced by their intention.

Furthermore, the study demonstrates that intention fully mediates the relationship between attitude and farmers'EbA behavior as well as the subjective norm and farmers'EbA behavior., but has no mediation effect between perceived behavioral control on farmers'EbA behavior. This implies that attitudes toward the behavior, as well as subjective norms, influence indirectly farmers' behavior through intention. However, perceived behavioral control has a significant direct positive influence on farmers' behavior. As a result, behavioral intention in combination with perceived behavioral control can predict more farmers' planned EbA behavior in the study area. This finding is consistent with some studies that found that farmers' conservation behavior is not always explained solely by behavioral intention (Herath, 2013; Karami and Mansoorabadi 2008; Weber and Gillespie 1998). Moghim et al., (2021) discovered, however, that the intention variable played a full mediation role in the relationship between attitude, subjective norm perceived behavioral control, and sustainable environmental behavior in agriculture in Zanjan Township.

Moreover, the study found that there is a significant positive moderation effect of perceived behavioral control on the relationship between attitude and farmers' intention toward EbA as well as intention and Farmers' EbA behavior whereas, a negative and significant moderation effect of perceived behavioral control was found between subjective norm and farmers' intention toward

EbA. When the TPB was first proposed, Ajzen (1985) proposed that perceived behavioral control could interact with attitude and subjective norms to influence behavioral intention. That is, the relationships between attitude/subjective norms and behavioral intention are likely to vary depending on perceived behavioral control levels. According to Luszczynska et al. (2011), perceived behavioral control is likely to act as a moderator in the TPB because people who have higher perceived behavioral control are more confident in their ability to perform a behavior and thus more likely to translate behavioral intention into actual behavior.

Also, the study demonstrated that considering behavioral factors and cognitive factors such as risk perception and adaptation benefits enriches analyses of farmer decision-making toward EbA practices, and can lead to more realistic and effective agri-environmental policies in the study area. This result is consistent with previous studies on farmers' decision-making regarding the adoption of conservation practices (Ling et al., 2023; Ehsan et al., 2022; Khan et al., 2022; Dessart et al., 2019; Mase et al., 2017).

5.8. Summary

Researchers have been concerned about the general lack of spontaneous adoption of conservation practices among smallholder farmers. Several studies have been conducted to better understand the factors that are impeding or facilitating the adoption of conservation practices and their continued use by farmers on a larger scale. The majority of research has focused on economic drivers, with little emphasis on behavioral and cognitive factors influencing farmers' decision-making toward conservation farming practices.

This study took an integrative approach, examining how a combination of socioeconomic, behavioral, and cognitive factors influence farmers' decisions to implement a set of ecosystem-based adaptation practices in Togo's Savanna region. According to the study, behavioral (perceived behavioral control and intention) and cognitive factors (perceived vulnerability to climate risks, perceived exposition to climate risks, and perceived EbA benefits for climate change adaptation) contribute significantly to farmers' decision to adopt a low, medium, and high number of EbA practices on their farm. Consistent with other studies, the research also found that farmers' attitudes and perceived behavioral control have a significant positive influence on farmers' intentions to adopt EbA practices. Also, the study revealed that the higher farmers' perceived control over the use of EbA practices the stronger their positive evaluation of EbA practices (attitude) influence on their intention to adopt EbA practice. The presence of adequate resources and the ability to control behavioral barriers influence behavior performance. The more knowledge and resources farmers perceive, the greater their perceived behavioral control and the stronger their intention to perform behaviors will lead to a positive behavior toward EbA and subsequently to their decision to adopt a certain number of EbA practices at their farm level. These findings will be useful in promoting EbA practices in the agricultural sector and tailoring current interventions to farmers' specific needs. Approaches that focus more on psychosocial and cognitive factors should be used to promote EbA practices among farmers. Strategies for increasing adoption rates could include providing opportunities for farmers to experience the effectiveness and benefits of EbA practices, assisting farmers in removing technical and financial barriers to promote the adoption of ecosystem-based adaptation practices, and increasing farmers' awareness of their vulnerability and exposition to climate change.

CHAPTER 6: GENERAL DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

The purpose of this study was to gain a better understanding of farmers' use of Ecosystem-based Adaptation practices for buffering climate change risks on agroecosystems to develop better policies to promote sustainable agriculture systems in the Savanna region. This chapter presents a summary of the key findings, general discussion, conclusions, and recommendations regarding each specific objective and perspective.

6.2. Summary of the Findings

Research objective 1: To explore both observed changes in climatic parameters and the farmers' perceptions about the risks related to these changes;

To achieve this specific objective, this study used observed climate data (rainfall and temperature) from (1961 to 2021), an interactive workshop, and a household survey, to assess climate change trends, and characteristics as well as farmers' degree of awareness of climate change risks and the factors that contribute to them. The analysis of climate change trends and characteristics revealed ample strong and clear evidence of changing climate in the study area. The observed rainfall data at Dapaong and Mango stations revealed a 6.25% increase at Dapaong and a 5.35% decrease at Mango between 1961 and 2021. At both stations, this trend is characterized by a cyclic pattern of variations with alternating drier, normal, and wetter years. Dapaong station has recorded 21 years of wetter conditions, 17 years of normal conditions, and 22 years of dry conditions, while Mango station has had 24 years of wetter conditions, 9 years of normal conditions, and 27 years of dry conditions in the last 60 years. In addition, the findings showed an annual variation and trend in the number of rainy and dry days over the rainy season (from April to October). The differences between the number of rainy days and the number of dry days are negative throughout the rainy season at both stations. This fluctuation in the rainfall pattern showed evidence of poor distribution of rainfall, leading to an increase in the duration of dry spells and a shortening of the rainy season in the study area. Furthermore, the inter-annual mean temperature analysis revealed an increasing pattern of the temperature in the study area during the period under consideration.

The observed change in climate conditions in the study area is shared by 97.2% of farmers. Five main changes were perceived by farmers in the climate parameters mainly rainfall and temperature. Erratic rainfall, an increase in the duration of dry spells, an increase in extreme rainfall events, a shortening of the rainy season, and warmer temperatures were highly perceived as the most observable changes affecting agriculture production and livelihood through decreased water availability, decreased soil moisture, increased pest, and crop diseases, destruction of crops and farmland, damage to stored agricultural products, increased soil erosion, decreased soil fertility, decreased crop production and yields, and decreased agricultural income. Three categories of climate risk perception levels have been distinguished among farmers; households with high-risk perception, households with moderate-risk perception, and households with low-risk perception based on key identified drivers of climate change risk components. These drivers include loss of ecosystem services provided by cropland for farming, increased cropland degradation, cultivated land size, strong dependency on agricultural income, unsustainable farming practices, lack of access to sufficient farm labor, lack of knowledge on sustainable land management practices, lack of improved seeds, lack of access to climate information, lack of access to irrigation, lack of access to agricultural assets, and lack of access to the financial safety net.

Research objective 2: To assess farmers' perception of the effectiveness and co-benefits of existing Ecosystem-based Adaptation (EbA) practices to address climate change risks to agroecosystems

To accomplish this second objective, the study investigates the main EbA practices implemented by farming communities to adapt to climate change risks and assesses their perceived effectiveness and co-benefits among smallholder farmers, as well as the influential factors behind their perceptions. A framework developed by Vignola et al. (2015) was adopted to identify which of the reported agricultural practices are considered EbA practices for climate change and suited for smallholder farmers.

A total of eight practices were reported as being commonly practiced by the respondents to deal with climate-related risks and are categorized into **(1)** conservation agriculture practices (i.e., conservation tillage mulching, crop rotation, and intercropping); **(2)** soil and water conservation practices (i.e., grass hedges and stone bunds, and in-field water drainage channels); and **(3)** integrated soil fertility management practices (i.e., agroforestry and integrated crop-livestock systems). Our findings show that among those eight commonly used practices, five practices, namely agroforestry, crop rotation, grass hedges or stone bunds, in-filed water drainage channels, and intercropping, were perceived by smallholder farmers as effective in reducing their vulnerability to climate risks through the improvement of ecosystem service provision, the improvement of adaptation benefits, and livelihood and food security improvement. In addition, smallholder farmers perceived a wide range of socio-ecological co-benefits were identified and associated with each effective EbA practice. Agroforestry is regarded as the most effective EbA practice in the study area for improving soil fertility and nutrient regulation, agrobiodiversity conservation, crop productivity, and local income. Crop rotation is thought to be effective for improving agroecosystem functions, preserving biodiversity, ensuring food security, and lowering crop pest and disease incidence. Water infiltration, erosion regulation, and runoff control are all perceived to be improved by grass hedge/stone bunds and in-field water drainage channels. Intercropping is thought to boost crop productivity and food security.

Furthermore, using multiple regression analysis, the study revealed that food crop framing, farm size, agricultural group membership, education status, extension services, and farmland degradation were the most significant factors at 1%, 5%, and 10% influencing the perception of farmers towards the effectiveness of EbA practices.

Research objective 3: To model farmers' behavior and decision-making toward the implementation of Ecosystem-based Adaptation (EbA) strategies to reduce climate change risks on agroecosystems.

To fulfill this objective 3, Firstly, the study relied on the theory of planned behavior to identify the socio-psychological factors affecting farmers' behavior towards EbA adoption using the structural equation modeling approach and then used the combination of behavioral factors, cognitive factors, and socio-economic factors to model farmers' decision-making regarding EbA adoption by employing discriminant analysis.

For the socio-psychological factors that influence farmers' intention and behavior toward EbA adoption, our finding revealed that among attitude, subjective norm, and perceived behavioral control, perceived behavioral control was the most significant contributor to farmers' intention toward EbA adoption followed by attitude. In addition, the findings show that both perceived behavioral control and intention are good predictors of farmers' behavior toward EbA practices in the study area with a path coefficient of 0.51 and 0.44 respectively. Furthermore, the intention is found to exert significant indirect effects on the relationship between attitude and behavior, subjective norm and behavior as well as perceived behavioral control on behavior. Moreover, the study revealed the moderating role of perceived behavioral control on the relationship between attitude and intention; subjective norm and intention as well as intention and behavior. The results suggest that as scores on perceived behavioral control increase, the strength of the association between attitude and intention increases as well as the association between intention and behavior, whereas the strength of the association between subjective norm and intention decreases.

To model farmers' decision-making regarding the adoption of EbA practices at the farm level, the study considered intention and perceived behavioral control as behavioral factors based on their positive influence on behavior as well as their mediating and moderation role respectively. These behavioral factors were then combined with five main cognitive factors (perceived climate-related hazards, perceived exposition, perceived vulnerability, EbA affordability, and EbA benefits) and five socio-economic factors (household income, farm labor, land size, age, and education) to predict farmers' EbA adoption groups using discrimination analysis. Three main groups were created (low EbA adoption group, medium EbA adoption, and high adoption group) according to farmers' level of adoption of EbA practices. The findings show that behavioral and cognitive variables distinguish the three EbA adoption groups of farmers, rejecting our null hypothesis that a combination of behavioral, cognitive, and socioeconomic variables explain significant differences among farmers' EbA adoption groups. In addition, the discriminant model classifies farmers into three predefined EbA adoption groups, based on five variables out of the twelve considered in the analysis which is behavioral (Perceived behavioral control and behavioral intention) and cognitive (Perceived Exposition; Perceived Vulnerability, and EbA benefits). Two discriminant functions were obtained with the perceived vulnerability being the best predictor with a coefficient of 0.925 followed by EbA benefits with a coefficient of 0.907 perceived exposition with a coefficient of 0.256 and perceived behavioral control being the least with a coefficient of 0.042 for function 1. Perceived behavioral control has the most explanatory power with a coefficient of 0.735 followed by behavioral intention with a coefficient of 0.508, and perceived exposition has the least explanatory power with a coefficient of -0.467 for function 2, The results demonstrated at 65.9% that farmers' decision to adopt low, medium, and high EbA practices is significantly based on the perception of their vulnerability; their perception of EbA benefits in terms of adaptation to climate risks; their perception of the control they have over EbA practices their intention toward the adoption of EbA practice and the perception of their exposition to climate hazards.

6.3. General Discussion

Climate change can have an impact on the health and integrity of agroecosystems, with negative consequences for food security, by altering the provision of ecosystem services necessary for the good functioning of agricultural land (Semeraro et al., 2023). The sustainability of agroecosystems in West African countries is gradually jeopardized by climate change because these ecosystems are still predominantly rain-fed and thus vulnerable to climate-related hazards (Djihouessi et al., 2022). In the Savanna region of Togo, the degradation of agroecosystems has become one of the most important environmental problems exacerbated by the frequent occurrence of climate-related hazards causing mainly soil erosion and nutrient depletion posing a serious threat to agriculture production and household food security.

Several studies carried out in the Savanna region (Badjana et al., 2011; Gadédjisso-Tossou, 2015; Badameli and Kadouza, 2020; Yao et al., 2023) have shown that during recent decades, the region has experienced significant climatic variability, with a downward trend in rainfall and an upward trend in temperatures, as well as a succession of dry and wet periods and breaks in the pattern of climatic fluctuations as seen in West African countries. The trend analysis of rainfall and temperature carried out in the present study throughout (1961-2021) shows the same results as the previous studies even though the length of the study series and the periods chosen are different. Similar results have already been presented by (Issahaku et al., 2016) which showed that rainfall was decreasing, and temperatures were increasing in decadal times in the Upper East Region of Ghana. Balogun et al., (2023) revealed also a decreasing trend for rainfall and an increasing trend for minimum and maximum atmospheric temperatures over the Benin metropolitan region and Edo state in Nigeria.

Household surveys carried out among farming communities show that they feel both the changes in climate and their impact on their agroecosystems. The most significant changes in climate conditions perceived were increased dry spell duration, erratic rainfall, increase in extreme rainfall events, shortening of the rainy season, and warmer temperatures which increased the frequency and the intensity of flood and drought events. When these climate-related events occur in conjunction with socio-ecological vulnerability drivers, the impact on agroecosystems is magnified by increasing the rate of soil erosion, declining soil fertility, decreasing soil moisture and water availability, destroying crop and farmland, increasing the incidence of pest and crop disease, lowering crop production, yield, and income, and posing the risk of agriculture livelihood loss and food insecurity in the study area. These findings are consistent with recent studies on the effects of climate change on agriculture (Bibi & Rahman, 2023; Semeraro et al., 2023; El Bilali, 2021; Alvar-Beltrán et al., 2020; Dangi et al., 2018), which found that farmers are aware of changing climatic conditions and believe that because agriculture is so dependent on weather and climate, changes in climatic conditions impact agricultural production and farmers' livelihoods. Even though the change in the climatic condition and its associated impacts are well known by farming communities in the Savanna region, the level of climate change risk perception is different among farmers depending on the perception of their socio-ecological vulnerability. This result also corroborates a previous study conducted by Sahou (2010) which revealed that farmers' perceptions of climate change risks in Benin are not uniform; they differ depending on the farmers’ category and the natural conditions of the localities.

This study also found that farmers in the Savanna region have been applying Ecosystem-based adaptation practices including soil and water management practices (i.e., grass hedge/stone bunds and in-field water drainage channel); conservation agriculture practices (i.e., conservation tillage mulching, crop rotation, and intercropping); and integrated soil fertility management practices (i.e., agroforestry and integrated crop-livestock) to mitigate the negative effects of climate change on their agroecosystems. Among those practices, farmers were able to mostly implement and perceive the effectiveness as well as the co-benefits of five main practices, namely agroforestry, crop rotation, grass hedge/stone bunds, in-field water drainage channel and intercropping, in increasing ecosystem services provision, improving adaptation benefits and enhancing farmers’ livelihood and food security. Previous studies (Keesstra et al., 2018; Deng et al., 2016; Vignola et al.,2015; Pretty, 2008) have also proven the potentiality of Ecosystem-based Adaptation practices to provide multiple benefits to farmers’ food security, resilience, and productivity but also societal benefits such as carbon sequestration, biodiversity conservation, water security, erosion control, and land restoration. The use of EbA allows farmers to explore and gain more knowledge and skills about how to achieve sustainable agriculture. Farmers can increase their resilience to climate change and variability by diversifying and adjusting ecosystem-based adaptation practices at the plot or farm level (Shah et al., 2019b). Based on our study, farmers practicing more EbA strategies (such as in the locality of Mogou) have higher chances to adapt to climate change because of the wide range of co-benefits these strategies provide than those farmers employing one strategy or almost none.

The implementation of a certain number of EbA practices by farmers may likely reflect a combination of factors other than the adaptation benefits of these practices (Harvey et al., 2017b). According to Waseem, et al. (2020), the importance of sustainable agriculture varies by farmer, and it is influenced by their economic assets and behavior. The study indicates that the combination of behavioral factors and cognitive factors was significantly related to the number of EbA practices adopted by farmers. The results showed that farmers' decision to adopt a number of EbA practices is influenced by their intention and their abilities to perform EbA practices as behavioral factors. Climate change risk perception is also significantly influenced by their decision in addition to their perception of the adaptation benefits of these practices. These findings were consistent with previous research (Rizzo et al., 2023; Pierrette et al., 2021; Cakirli Akyüz & Theuvsen, 2020; Mutyasira et al., 2018b) on farmers' adoption of EbA, emphasizing the importance of considering behavioral and cognitive factors in promoting EbA practices among farmers. Adoption of EbA is almost certain, which will eventually increase farmers' adaptive capacity to climate change risks. It promotes better use of natural resources, aids in environmental protection, and reduces the use of external inputs. (Dessart et al., 2019). According to Vignola et al. (2015), Ecosystem-based Adaptation can be a particularly important adaptation strategy for smallholder farmers, who frequently lack the resources and capacity to access other adaptation options, such as the adoption of new technologies that require external inputs (e.g., improved seed varieties, irrigation systems, or increased fertilizer and pesticide use).

6.4. General Conclusions

The study's overarching aim was to investigate farmers' implementation of ecosystem-based adaptation strategies on their agricultural land to reduce climate-related risks in the Savanna region of Togo. First of all, it assessed the local level climate change information along with the farmers' perception of climate change indicators, impacts, and drivers of climate change risks on agroecosystems. In addition, it assessed the effectiveness and co-benefits of existing ecosystem-based adaptation practices used by farmers to adapt to climate change risks. Furthermore, it modeled farmers' decision-making regarding the adoption of ecosystem-based adaptation practices by combining behavioral, cognitive, and socioeconomic factors Accordingly, three key conclusions can be derived from this study which are related to each specific research objective.

Firstly, this study showed strong evidence of changing climate in the study area, which is also perceived by local stakeholders as well as farmers. These changes were perceived to have substantial impacts on agroecosystems in the study area. Based on farmers’ perception of the key drivers of climate change risks (hazards, exposure, and vulnerability) on agroecosystems, three categories of climate risk perception levels have been distinguished among farmers; households with high-risk perception, households with moderate-risk perception, and households with low-risk perception. Understanding farmers' perceptions of climate change, its impacts, and the drivers of risks on agroecosystems is critical for developing location-specific adaptation strategies that could improve farmers' livelihoods and food security while increasing the capacity of agroecosystems to resist, and/or recover from climate change risks.

Secondly, five ecosystem-based adaptation practices, namely agroforestry, crop rotation, grass hedge/stone bunds, in-filed water drainage channel, and intercropping, were perceived as effective in increasing agroecosystem resilience, adapting to climate change impacts, and improving livelihoods and food security. The implementation of those EbAs practices resulted in various socio-ecological co-benefits, which were perceived and correlated with the five practices. Some socio-economic factors and perceptions of farmland degradation were found to influence farmers’ EbA assessments. This demonstrates farmers' awareness and knowledge of the effectiveness and co-benefits of some agricultural EbA practices in reducing vulnerability to climate-related risks in the study area.

Finally, this study provides new perspectives on the influence of socio-psychological factors on farmers’ intention and behavior toward EbA practices using the Theory of Planned Behavior model. In addition, the decision-making model we used enriched our understanding of the complex interactions among behavioral, cognitive, and socioeconomic variables by showing how these interactions differentiate among farmers' EbA adoption groups. Behavioral factors (perceived-behavioral control and behavioral intention), as well as cognitive factors (perceived exposition; perceived vulnerability, and perceived EbA benefits), are the major factors that contribute to farmers' decision to adopt low, medium, and high EbA practices on their farm in a climate change context.

6.5. Recommendations

Climate change and its effects on agroecosystems and farmers' livelihoods require more attention and efficient management from decision-makers. The research findings of this study shed light on climate change, its impacts on agriculture, and farmers' climate change risk perception and constitute an important decision-making tool to help decision-makers and farmers improve the uptake of sustainable adaptation strategies and thus improve farmers' food security and the resilience of the Savanna region agriculture system to climate change.

From this study, it was noticed that farmers have undertaken actions to reduce climate change impact by implementing certain ecosystem-based adaptation practices and they have good knowledge of their effectiveness and co-benefits in reducing vulnerability to climate change and need to be upscaled. Farmers' control over the use of EbA practices; their intention toward EbA practices; their perception of EbA benefits; the perception of their vulnerability and their exposition to climate change influence significantly their decision to adopt low, medium, or high EbA practices on their farm.

Based on the findings of this study, some recommendations should be made to better assist farmers in addressing the effects of climate change and to mainstream ecosystem-based adaptation strategies into climate change adaptation planning in the agriculture sector to address land degradation issues related to climate change in the study area.

It is recommended to policy-makers, technical support structures, and downstream agencies responsible for mainstreaming and implementing adaptation policies to integrate climate risks and impacts, particularly in terms of agriculture livelihoods and agroecosystem functions and services as a central and integral part of climate adaptation and disaster risk reduction planning and implementation processes at the national and local levels. Systematic integration of the assessment of EbA effectiveness and co-benefits for agroecosystems and farming communities, into adaptation and disaster risk reduction objectives, strategies, policies, or measures is recommended so that they become part of national and local development policies, processes, and budgets at all levels and stages.

knowledge and information dissemination on EbA practices should be facilitated through field demonstrations, extension visits, training and radio programs, farmer-to-farmer exchanges to share knowledge on EbA implementation, effectiveness in delivering adaptation benefits, and tailoring EbA policies and programs for farmers in different socioeconomic and biophysical contexts to increase farmers' knowledge, farmers self-confidence, and willingness for reducing dis-adoption and ensure sustained adoption.

The combination of agroforestry, crop rotation, grass hedge/stone bunds, in-filed water drainage channels, and intercropping should be promoted as a solution to support and increase ecosystem services flow in agroecosystems.

Farmers' perception of vulnerability and exposition to climate change, their appraisal of EbA practices as well as their self-capacity and intention towards EbA have to be considered in EbA promotion projects or actions.

6.6. Perspectives

This research is not intended to be exhaustive in scope, but rather to provide an analysis of the implementation of ecosystem-based adaptation strategies in agricultural systems in the Savanna region to increase the ability of crops to adapt to climate variability through the delivery of multiple co-benefits that are appreciated as ecosystems services, adaptation benefits, and livelihood and food security.

Based on the findings of this study, some recommendations for future research are made to address gaps and questions that remain unanswered to better assist farmers in combating the effects of climate change.

As temperatures rise and rainfall variability is projected to increase in the future, the rate and magnitude of degradation of agroecosystems may be exacerbated which may have profound implications for agricultural livelihood systems and farmers' groups. In this context, several research avenues can be taken into account:

- to investigate the impacts of agroecosystem degradation, particularly soil erosion and soil impoverishment on agriculture yields in the context of climate change;
- to examine the impact of ecosystem-based adaptation strategies on farmers'income.
- to examine the sustainability of the identified EbA practices to provide further information on their potentiality to effectively address agroecosystem degradation issues in the study area.
- to examine policymakers' perceptions of ecosystem-based adaptation practices in agriculture to better understand the barriers to EbA implementation, to bridge the

knowledge gap in political decision-making regarding EbA and, as a result, promote its mainstreaming into agricultural policy plans.

- to expand this study by developing an Agent-based Model using the behavioral and cognitive characterization, related decision rules, and the utility functions of each effective EbA strategy identified in the study to explain farmers' decision-making regarding each effective practices and support policy-makers in developing tailored environmental policies

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APPENDICES

Appendix 1: The annual rainfall amount for the wet, normal, and dry years' conditions at Dapaong (1961-2021)

RAI Class Description	**Years**	**Annual Rainfall Amount (mm)**
Extremely wet (RAI ≥ 3.00)	2004	1647.3
	2002	1756.6
Very wet (RAI = 2.00 to 2.99)	1998	1270.3
	1994	1272.4
	2013	1284.9
	1973	1315.2
	2003	1321.6
	2001	1326.5
Moderately wet (RAI = (1.00 to 1.99)	1964	1223.5
	2016	1226.6
	1999	1233.9
	1974	1234.1
	2007	1245.5
	2009	1262.9
Slightly wet (RAI= 0.50 to 0.99)	1980	1103.5
	1989	1106.2
	1965	1110.1
	2014	1126.9
	1968	1138.5
	2006	1139.5
	1963	1142
Near normal (0.49 to –0.49)	1970	1003
	1993	1004.7
	1971	1007.4
	1988	1012.1
	2019	1015.8
	1992	1018.8
	1982	1027.4
	1996	1033.2
	1969	1050.6
	1961	1050.7
	2018	1063.1
	1975	1066.9
	2008	1067.6
	2012	1075.5
	1997	1093.6
	2011	1096.3
	2020	1098.7

Extremely dry (RAI ≥-3.00)	1979	603
	1966	686.4
	1978	710.7
	1983	776.8
Very dry (RAI = -2.00 to –2.99)	1990	765.3
	1985	779.8
	1995	782.1
	1984	794.4
	2021	815.2
	1977	818.4
	1976	825.4
	1972	827.6
Moderately dry (RAI = -1.00 to –1.99)	2000	863.6
	1986	867.8
	1962	934.4
	1991	942.6
Slightly dry (RAI = -0.50 to –0.99)	1987	957.8
	2017	962.0
	1967	980.9
	2010	986.4
	2005	990.6
	2015	996.1

Appendix 2: The annual rainfall amount of wet, normal, and dry conditions at Mango station from (1961-2021).

RAI Class Description	**Years**	**Annual Rainfall Amount (mm)**
Extremely wet (RAI ≥ 3.00)	1998	1376.5
	1999	1410.5
	1969	2009.2
Very wet (RAI = 2.00 to 2.99)	2007	1270.7

	1963	1272.2
	1968	1324.1
Moderately wet (RAI = (1.00 to 1.99)	1987	1159.8
	2004	1166.5
	1978	1179.4
	1962	1197.8
	1967	1200.9
	1996	1202.7
	1964	1215.6
	1982	1218.6
	2018	1222.7
	2020	1247.3
	2012	1262.7
Slightly wet (RAI= 0.50 to 0.99)	1976	1120.2
	1989	1127.4
	1979	1130.4
	1971	1133.4
	2019	1144.5
	2009	1147.8
Near normal (0.49 to –0.49)	1985	1036.2
	1986	1051.0
	1973	1052.5
	1970	1061.1
	1994	1069.1
	1983	1076.0
	1984	1076.3
	1991	1096.1
Extremely dry (RAI ≥-3.00)	2001	747.4
	2021	815.2
	1990	851.9
Very dry (RAI = -2.00 to –2.99)	2006	874.3
	2014	874.7
	2015	874.8
	2002	892.1
	2005	905.7
	2003	907.0
	1992	908.7
	1972	827.6
	1966	909.7
	1997	911.7
	1994	914.2
	2000	919.0
	1981	928.7
	2013	931.0
	1977	938.1

Moderately dry (RAI = -1.00 to –1.99)	2016	939.6
	2011	947.8
	1988	954.6
	2017	963.4
	1961	963.5
	1974	966.4
	1993	991.7
Slightly dry (RAI = -0.50 to –0.99)	1965	1018.7
	1975	1023.1

Appendix 3: Anti-Image Correlation Matrix

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16
X1	.671a															
X2	0.045	.553a														
X3	0.179	-0.545	.570a													
X4	-0.076	-0.053	-0.004	.578a												
X5	0.107	0.037	-0.069	0.077	.709a											
X6	0.029	-0.049	-0.083	-0.029	0.016	.574a										
X7	0.114	0.030	-0.003	0.148	-0.183	-0.016	.663a									
X8	-0.034	0.031	-0.033	0.108	-0.060	-0.035	0.090	.654a								
X9	0.021	0.024	-0.005	-0.135	-0.307	-0.011	0.043	-0.328	.630a							
X10	-0.040	-0.018	-0.086	-0.098	0.040	0.051	-0.240	-0.124	-0.055	.704a						
X11	-0.180	0.029	-0.083	-0.017	-0.012	-0.030	-0.132	0.001	-0.176	-0.187	.605a					
X12	0.086	-0.047	-0.020	-0.002	-0.027	0.325	-0.027	-0.012	0.065	-0.115	-0.015	.541a				
X13	-0.177	-0.029	0.011	0.063	-0.035	-0.074	-0.054	0.039	-0.047	0.094	-0.095	-0.232	.515a			
X14	-0.005	0.006	-0.043	-0.021	-0.034	-0.102	0.023	0.037	0.081	-0.008	-0.500	0.001	0.046	.600a		
X15	-0.033	-0.061	0.077	-0.117	-0.313	-0.032	-0.233	-0.189	0.023	-0.052	0.152	-0.038	-0.080	-0.094	.655a	
X16	-0.268	0.005	0.009	-0.026	-0.034	-0.114	0.171	-0.067	0.093	-0.066	-0.187	0.011	-0.018	0.037	0.044	.675a

Appendix 4: Total variance explained by extracted components using Principal Component Analysis

Components	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.509	15.949	15.949	3.509	15.949	15.949	2.702	12.280	12.280
2	3.009	13.675	29.624	3.009	13.675	29.624	2.702	12.280	24.561
3	2.662	12.101	41.725	2.662	12.101	41.725	2.694	12.244	36.805
4	2.364	10.746	52.472	2.364	10.746	52.472	2.354	10.702	47.507
5	2.045	9.294	61.766	2.045	9.294	61.766	2.176	9.890	57.397
6	1.780	8.089	69.855	1.780	8.089	69.855	2.069	9.403	66.800
7	1.146	5.208	75.063	1.146	5.208	75.063	1.818	8.263	75.063
8	.930	4.326	79.389						
9	.817	4.108	83.497						
10	.676	3.314	86.811						
11	.655	2.977	89.788						
12	.547	2.487	92.275						
13	.509	2.314	94.589						
14	.464	2.099	96.688						
15	.388	1.865	98.553						
16	.325	1.447	100.000						

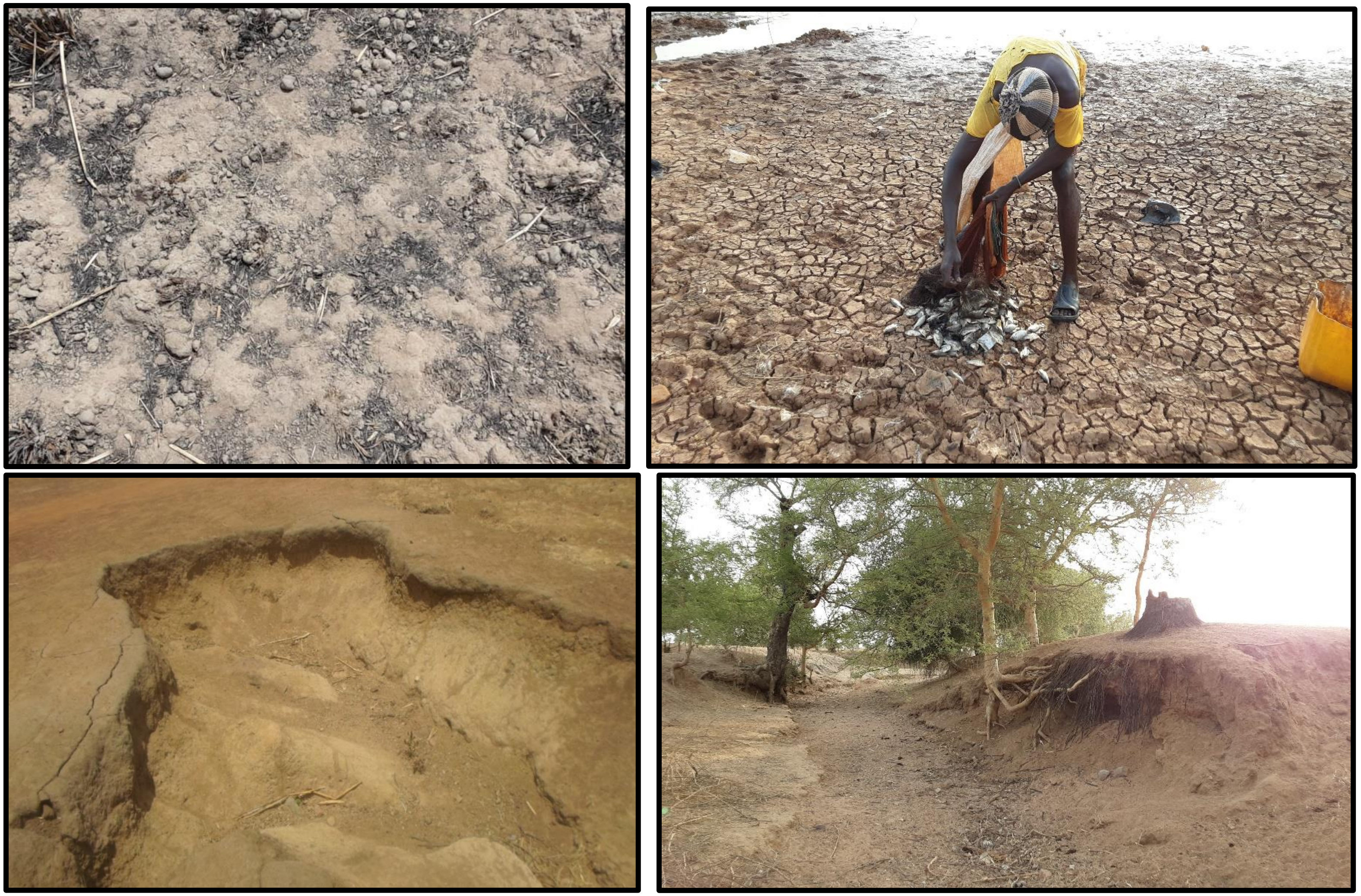
Appendix 5: EbA practices and EbA dimensions Spearman correlation coefficient

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

	Grass/stone hedges	Intercropping	Crop rotation	Agroforestry	In-field water drainage channel	Integrated crop-livestock	Mulching	Conserva-tion tillage	Ecosystem Service provision	Livelihood and Food Security improvement	Adaptation Benefits improvement
Grass/stone hedges	1.000										
Intercropping	0.120*	1.000									
Crop rotation	0.109*	0.317**	1.000								
Agroforestry	0.323**	0.212**	0.591*	1.000							
In-field water drainage channel	0.521*	0.445**	.376**	.189**	1.000						
Integrated crop-livestock	0.110*	0.013	0.077	0.427**	0.130**	1.000					
Mulching	0.117*	-0.027	.147**	-0.025	0.005	.374**	1.000				
Conservation tillage	0.714	-0.005	.145**	-0.029	0.041	.098*	.198**	1.000			
Ecosystem Services provision	0.230**	0.126*	0.524*	0.540*	0.407*	0.419**	0.052**	0.021**	1.000		
Livelihood and food security improvement	0.133*	0.416*	0.410*	0.681*	0.269**	0.064**	0.094**	0.040**	.201**	1.000	
Adaptation Benefits	0.503*	0.127*	0.405**	0.467*	0.522*	0.027**	0.078**	0.038**	.319**	.146*	1.000

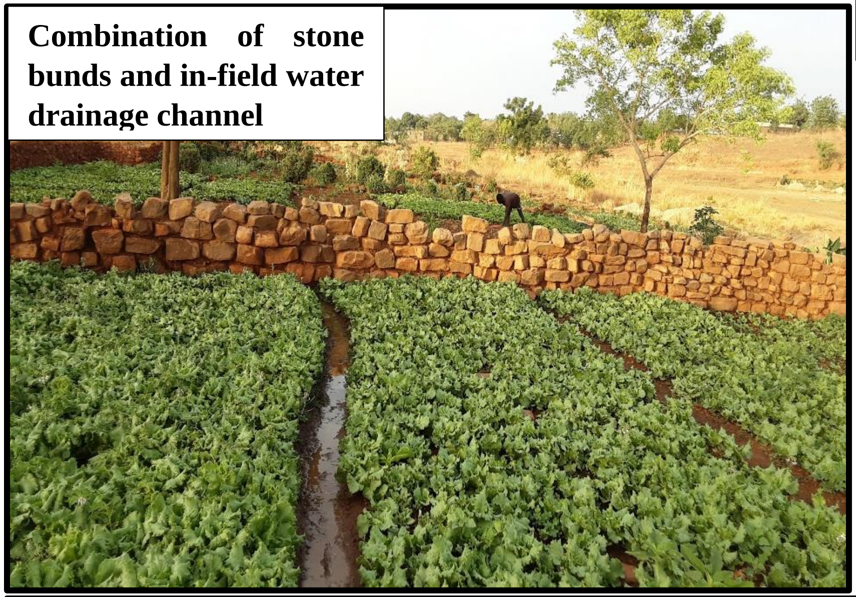
Appendices 6: Illustrations

Climate-related land degradation issues in the Savanna region



h

Ecosystem-based Adaptation practices in Savanna region



Combination of stone bunds and in-field water drainage channel

Agroforestry

Stone bunds

Combination Grass hedge and agroforestry

Participatory workshop and focus group discussion

Questionnaire survey

Appendix 7: Publications

climate

MDPI

Article

Perceptions of Climate Change Risk on Agriculture Livelihood in Savanna Region, Northern Togo

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Abstract: The agriculture sector in the Savanna region of Togo is especially vulnerable to weather fluctuations, which have an impact on crop production levels. However, farmers' decisions to implement adaptation strategies are directly related to their perceptions of climate change risk. The current study employed a participatory workshop and household survey of 425 farmers to examine the drivers of specific climate change risks of interest (risk of loss of livelihood for farmers) and measure farmers' level of climate change risk perception. A climate change risk perception score (CCRPS), descriptive statistics, principal component analysis, and K-means cluster analysis were used to analyze the data collected. The findings revealed that the most important changes in climate conditions affecting agricultural production in the study area were mainly the increased duration of dry spells, erratic rainfall, and an increase in extreme rainfall events. These climatic variations cause more floods and droughts, which, when coupled with socio-ecological vulnerability drivers, increase the impact of these events on agricultural livelihood, expose more farmers and their farmland, and contribute to the risk of farmers' livelihood loss in the study area. Based on farmers' appraisals of the occurrence of hazards, their exposure, and their vulnerability, farmers' perceptions of climate risk have been classified into three categories: high, moderate, and low. This finding sheds some light on farmers' climate change risk perception, which may influence their adaptation decision. These findings can be used to increase the uptake of adaptation strategies and thus the resilience of Savanna region agriculture to climate change.

Keywords: climate variability; impacts; exposure; vulnerability; farming activity

Citation: Kissi, A.E.; Abbey, G.A.; Villamor, G.B. Perceptions of Climate Change Risk on Agriculture Livelihood in Savanna Region, Northern Togo. *Climate* **2023**, *11*, 86. https://doi.org/10.3390/cli11040086 ecologies

Article

Ecosystem-Based Adaptation Practices of Smallholder Farmers in the Oti Basin, Togo: Probing Their Effectiveness and Co-Benefits

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Abstract: The ecosystem-based adaptation (EbA) strategy is considered an effective approach to address the impact of climate change while ensuring the continued provision of ecosystem services on which farming depends. However, understanding the EbA's effectiveness for smallholder farmers in the Savannah region remains limited. The focus of this study is to explore the EbA practices that have been implemented by farming communities in the Savannah region of Togo. The study aims to evaluate the effectiveness of these practices and the perceived co-benefits reported by 425 smallholder farmers who participated in the survey. Our findings show that five practices, namely agroforestry, crop rotation, grass hedge/stone bunds, in-field water drainage channel, and intercropping, were practiced mainly by smallholder farmers and perceived as effective in reducing their vulnerability to climate risks. In addition, the benefits observed were linked to all five EbA practices. As a result, we can determine the suitable combination of EbA practices that fulfil the requirements of smallholder farmers, including co-benefits such as food security, adaptation advantages, and ecosystem service provisions. Such findings provide insights for developing integrated agriculture and climate change policies suitable for weather-induced disaster-prone areas such as the Savannah region.

Keywords: agroecosystems; agroforestry; climate change adaptation; ecosystem services; effectiveness; perception; Savannah

Citation: Kissi, A.E.; Villamor, G.B.; Abbey, G.A. Ecosystem-Based Adaptation Practices of Smallholder Farmers in the Oti Basin, Togo: Probing Their Effectiveness and Co-Benefits. *Ecologies* **2023**, *4*, 535–551. https://doi.org/10.3390/ecologies4030035

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