KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI, GHANA

ADOPTION AND EFFECTS OF CLIMATE CHANGE ADAPTATION, AND LAND USE DECISION OF SMALLHOLDERS FARMERS IN THE SALINE AREA OF SINE-SALOUM, FIMELA SENEGAL

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DOCTOR OF PHILOSOPHY

In

Climate Change and Land Use

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CERTIFICATION

I hereby declare that this submission is my own work towards the Ph.D. in Climate Change and Land Use and that, to the best of my knowledge, it contains no material previously published by another person nor material that has been accepted for the award of any other degree or diploma at Kwame Nkrumah University of Science and Technology, Kumasi or any educational institution, except where due acknowledgment has been made in the thesis.

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DEDICATION

This work is dedicated to my lovely daddy, Elhadji Ibrahima Thiam, who has always been present for me in any situation, my lovely mummy Ramata Omar BA for the nice education she gave me, I'm grateful to her, and to all my brothers and sisters who I deeply love.

ABSTRACT

Soil salinity expansion is one of the most severe land degradation issues confronting farmers in Senegal, particularly in coastal areas such as Fimela.

With sea level rise, temperature rise, and rainfall decrease, soil salinity is increasing significantly. It has a negative impact on crop yields and farmers' livelihoods. Farmers developed land use adaptation strategies to deal with soil salinity. Nonetheless, despite adaptations, some farmers continue to complain about the negative impact of soil salinity on their outcomes. Then, this study investigates farmers' adaptation, the different factors that influence it, its implications for smallholder farmers' livelihoods, and farmers' perception of soil salinity and its impact. Data from face-to-face interviews of 288 households using the Krejci and Morgan's formula and GPS coordinates of households and each of their farms was collected. An agent-based model was used to understand land use adaptation to soil salinity expansion by considering farmers' perceptions of soil salinity expansion under climate change for simulation. A sub-model of household decisions, crop yield, and perception of soil salinity was developed and incorporated into the model. Three scenarios were considered to simulate the interaction between household agents and landscape agents over 25 years. Farmers' adoption is influenced by their assets and sociopsychological factors like threat assessment, coping assessment, and subjective norms. Farmers in Fimela do not have maladaptation thinking that may break their willingness to adopt strategies to cope with soil salinity. The ESR model shows that farmers' adoption of strategies to cope with soil salinity has a positive impact on groundnut yields and a negative influence on food security but has no significant effect on their millet yields. These findings have been validated by the simulation results, which show that the yield difference between farmers who perceive soil salinity expansion and those who do not is significant for groundnut but not millet over 25 years. As a result, it is critical to base policies in combating soil salinity effects on providing better methods of soil salinity adaptation strategies through scientific research. Policies should support a few pilot farmers in these precise and effective strategies to trigger other farmers to follow through the village and social influence by the farmer-to-farmer approach to enable farmers access and appropriation of these new methods.

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LIST OF ABBREVIATIONS AND ACRONYMS

ABM: Agent Based Model
AMOS: Analysis of Moment Structures
ATT: Average Treatment Effect on Treated
ATU: Average Treatment Effect on Untreated
CAREM: Coordination des Actions pour la Restauration des Ecosystems Mangroves
CFA: Communaute Financière Africaine
CFA: Confirmatory Factor Analysis
CFI: Comparative Fit Index
CR: Composite Reliability
CR: Construct reliability
EC: Electricity Conductivity
ESR: Endogenous Switching Regression
FAO: Food Agricultural Organization
FGD: Focus Group Discussion
FIML: Full Information Maximum Likelihood
FSP: Food Insecurity Prevalence
FSS: Food Security Status
GOF: Goodness-Of-Fit
HFIAS: Household Food Insecurity Access Scale
IPAR: Initiative Prospective Agricole et Rurales
IPCC: Intergovernmental Panel on Climate Change
IPWRA: Inverse Probability Weighted Regression Adjustment
LULC: Land Use Land Cover Change
NFI: Normed Fit Index
NGO: Non-Governmental Organization
NPCS: No-perceive soil salinity
OLS: Ordinary Least Squares
PCS: Perceive soil salinity
PMT: Protection motivation theory
PSM: Propensity Score matching
RMSEA: Root Means Square Error of Approximation
SEM: Structural Equation Modelling
SPSS: Statistical Package for Social Science
SRMR: Standardized Root Mean Squared Residual
TE: Treatment Effect
TLI: Tucker-Lewis-Index
TT: Effect Treated
TU: Effect Untreated

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CHAPTER ONE

1. INTRODUCTION

1.1 Background

Agriculture is an essential resource that feeds the world population, which continues to increase over time. Some land changes/land use and land degradation around the world, through climate change, negatively impact the sustainable development of these agricultural resources leading to an overall negative impact on food security (AGNES, 2020). Land degradation negatively impact food security a concept where all people have physical and economic access to sufficient, secure, and nutritious food that fits their dietary needs and food choices for an active and healthy life at all times, whether at the global, national, community, or household level (Shankar Gupta, 2019; Pinstrup-Andersen, 2009). The salinity of agricultural land is one of these permanent land degradation problems that continue to spread worldwide because of climate changes and threatening the agriculture sector. A soil is saline in general when in the root zone, the electrical conductivity of the saturation extract (EC) exceeds 4dS m^{-1} (approximately 40 mM NaCl) at 25 °C, and it has 15% exchangeable sodium. Crop yield is reduced at this EC, though some crops show yield reductions at lower ECs (Shrivastava and Kumar, 2015).

Salinization of land is a major worldwide environmental issue that has happened through natural and human modifications in land use over the last century soil (Penov et al., 2011). Soil salinization is likely to have adverse environmental and social consequences, potentially posing a risk of food insecurity to human populations (Szabo et al., 2016). It affects at least 400 million ha and seriously threatens the equivalent land area of 6.5% of the total land in the world (Faye et al., 2019). Saline lands are mainly located in Africa's arid and semi-arid climate zones, where about 38 million hectares of land, or 2% of the continent's area, are affected by salt (Faye et al., 2019). It significantly negatively impacts soil productivity in arable croplands because of its adverse effects on microbial activity and soil physical properties (Siddique et al., 2013), and it impacts farmers' livelihood strategies (Wondim et al., 2020). It negatively influences farmers' incomes and expenditures. It has emerged as a major factor contributing to lower crop production, implying a change in land use activities and a significant loss of productivity in various agricultural regions over the last several decades (Haider and Hossain, 2013).

Salinity as a land degradation problem has many causes, both natural and human, and will continue to expand as a result of the negative effects of climate change (Dasgupta et al., 2014). Climate change is indicated as a significant cause of this soil salinity expansion in coastal districts during the dry season (Dasgupta, et al., 2015). It operates through a rise in sea level, an increase in temperature, and a diminution in rainfall (Langevin and Zygnerski, 2013) and is described as 97% correlated with soil salinity dynamics (Dieng et al., 2017) in coastal area.

The coastal region in general has already suffered significant yield losses due to rising salinity, and coastal areas' losses will be intensified by further salinity increases in the upcoming years (Dasgupta et al., 2018). To deal with these consequences, growers may choose to fallow salinized land or continue cultivating less productive salinized land through switching crops and/or adjusting management practices as adaptation techniques (Welle and Mauter, 2017).

Despite these attempts, engineering and technical salinity management solutions may not be sustainable in the long run and methods used by farmers may not go in the long run while their costs are not supportable by farmers with low incomes (Islam et al., 2020). Then, the likelihood that many of the treatment options being adopted are low because they are economically unattractive (Bhuiyan, 2013). So, addressing these problems that present critical needs for developing novel adaptation patterns, including crop management practice changes and livelihood strategies is necessary (Tran et al., 2019). Therefore, because of these challenges in coping, farmers' adaptation to climate change and its effects such as soil salinity could be studied, as agriculture is a vital source of revenue for the vast majority of the rural residents (Toure et al., 2021).

In a context where climate change happening is a fact with different effects, developing an efficient adaptation system becomes a necessity for interested actors. Research by Alauddin and Sarker (2014) shows that farmers' decisions about adaptation strategies depend on factors such as farmers' perceptions of the long-term variations in climate variables and extreme weather. For its efficiency, these adaptation strategies designed to deal with potential future changes must be flexible enough to integrate new knowledge and information as it becomes accessible (West and Bianchi, 2013). Indeed, for that, the human adaptive response would imply perceiving, learning, and acting adaptively according to what they face (Nguyen et al., 2016). But farmers' adaptation is also related to their adaptive capacity or efficacy level, explained by factors such as information, technology, institutional conditions, and knowledge as the determinant of their resilience and also by socioeconomic and cultural factors (Nguyen et al., 2016). Then, for effective adaptation strategies, active involvement in social networks and networking by relevant actors that facilitate knowledge acquisition on adaptation strategies and practices is essential (Albert et al., 2012).

Many types of literature have found that farmers in developing countries perceive changes in environmental conditions and then implement alternative agricultural adaptation strategies to cope with these changes (Truelove et al., 2015). In most cases, this adaptation is defined as a deviation from habitual behaviours and a shift in attitudes and perceptions to persuade individuals that a change is both necessary and beneficial for long-term behaviour (Juárez-Nájera et al., 2010). This decision to shift their attitude toward protection needs is based on their assessment of the threat level they face (Mankad, 2016). If this threat is estimated to be high risk, people engage in protection motivation. Farmers assess their ability to deal with this threat by assessing their ability to act and the anticipated effectiveness of the action in mitigating the threat (Truelove et al., 2015). The efficacy of that action as a response depends on the belief that the adaptative response will work and the cost of these responses, which can be evaluated as monetary, personal time, or effort associated (Pourhaje et al., 2016). Then, the protection motivation theory, which integrates risk perception and coping assessment, provides a framework to investigate the importance of factors influencing farmers' risk adaptation, such as soil salinization (van-Duinen et al., 2015). Thus, socio-psychological variables can explain adaptation behaviour adoption (Below et al., 2012). To address these socio-psychological factors behind the adoption of adaptation to climate change, a few studies have employed the protection motivation theory (PMT), which has been demonstrated to be useful as a foundation for understanding adaptive behaviour (Dang et al., 2014).

1.2 Problem Statement

In Senegal, agriculture has always been perceived as the foundation on which the country's socioeconomic development is based (Faye and Du, 2021). It contributes around 8% of the country's GDP, with 73% of the population involved, and has significantly contributed to its social development through job creation, food security, and poverty alleviation (ANSD, 2014). Despite all efforts to promote sustainable agriculture, Senegal is facing the degradation of arable land, which causes large economic losses estimated at around 944 million US dollars per year (about 550 billion CFA), or 8% of the 2007 GDP (CNCR, 2020).

In Senegal, soil salinization is one of the most complex and prevalent soil degradation identified (Fall et al., 2014). Among 1.7 million ha of the 3.8 million hectares of agricultural land are salty in Senegal (Lindenmann, 2016). In Senegal, soil salinization affects almost all regions, in particular, the basins of the Casamance, Gambia, Sine Saloum, and Senegal River Delta (ISRA, 2012). In Sine-Saloum region in the mid-west of Senegal, salinization is among the most serious long-term environmental issues ascribed to the seawater rise and the hypersaline Saloum River (Faye et al., 2005). It has two causes: the rise of saline aquifers due to a lack of rains and a rise in sea depth, and a predominant marine influence due to the Saloum region's altitudes of less than 40 m, with a drastic reduction in the flow of rivers that stream into the Saloum estuary with strong evaporation and penetration of marine waters (Dieye et al., 2013). In the Groundnut Basin, which includes Fatick and Kaolack provinces, and where the main cultivated crops are rice, groundnuts, millets, and maize, salt-affected areas, which account for 17.49% of the land, are the see of seawater incursion from the Saloum River (Diome and Tine, 2015). This salinity covers a high percentage of land in the Groundnut Basin, particularly Fatick, with 33% of the region designated as a highly acid-salt-affected area (Thiam et al., 2019). This led to a decline in farmlands, making smallholder farmers the most susceptible to soil salinity expansion effects and exposed to livelihood challenges.

Climatic constraints, which are globally linked to climate change, continue to accentuate the phenomenon of land salinization and have always required adequate responses to mitigate their effects on the environment and populations (ISRA, 2012). As climate change progresses, water and soil salinization will become more severe in low-lying coastal areas (Dasgupta et al., 2018). It is accelerated by increased temperatures, irrigation mismanagement, and climatic shifts (Chaudhari and Sharma, 2013).

From a scientific and human point of view, the adverse effects of climate change concern the loss of arable land and the salinization of water and soil are sources of economic and ecological disturbances that degrade the living conditions of the populations in Senegal (ISRA, 2012). In consequence, the impact of land salinization has become a most important concern for governments. Due to drought, climate change, and the uncontrolled logging of mangrove forests, the salinity of the ground has increased, threatening the livelihoods of thousands of people living in the Saloum Estuary (Dieng et al., 2017).

Since this area has agriculture as its backbone and saltwater intrusion impacts livelihoods and adaptation alternatives, understanding the economic effects of salinity diffusion and adaptation planning is critical for long-term development and poverty mitigation with vulnerable littoral regions (Brecht et al., 2012). Few studies have focused on farmers' perceptions of soil salinity and how those perceptions influence their soil salinity adaptation and management action (Islam et al., 2020), despite the existence of substantial body of literature on salinization and its global consequences, such as land degradation.

Furthermore, relying exclusively on the economic principle of farmers choosing to adapt when the expected utility of an adaptive response is positive, main studies usually employ a variety of institutional, socio-economic, biophysical, and financial factors to explain decision-making of adaptation. Thus, traditional economic studies frequently lack the behavioural grounding essential to wholly explain and understand individual adaptation decision-making (Duinen et al., 2015). So, a good understanding of the land salinization issue that captures farmers' perception of soil salinity risks and behaviours is poorly understood and has yet to be effectively addressed in the existing literature (Islam et al., 2020). So, to help for better resilience of farmers to the expansion of soil salinization induced by climate change, there is a need to investigate and understand their way of coping with this phenomenon to improve their strategies to maintain or improve sustainable livelihood. For that, the mobilization of a profitable and effective response will necessitate, among others, an analysis of the spread of salinity, its ecological and socio-economic impacts, and the costs and socio-psychological aspects behind the prevention, adaptation, and remediation.

1.3 Research Questions

The study raises the following research questions:

1. What socio-psychological factors influence farmers' climate change adaptation strategies in response to soil salinity in the Fimela district, in Senegal?
2. What are the impacts of adoption of adaptation strategies farmers used in response to salinity on yields and households' food security?
3. Could the Land Use Dynamic Simulator (LUDAS) approach be used to investigate how farmers' decision-making through perception of soil salinity expansion have implications on their agricultural outcomes?

1.4 Objectives of the study

The principal objective of the research is to simulate climate change adaptation decision-making of smallholder farmers in Sine Saloum's saline area, Fimela Senegal.

Specifics objectives

Based on the research questions, the following specifics objectives were pursued in this work:

1. To assess socio-psychological factors that influence farmers' climate change adaptation strategies in response to soil salinity in the Fimela district,
2. To analyze the impacts of adoption of adaptation strategies that farmers use in response to salinity on yields and households' food security,
3. To simulate human decisions adaptation to salinization under climate change through soil salinity perception

1.5 Organization of the thesis

The thesis is organized into six (6) chapters. Chapter 1 presents the study's introduction, where the background, the problem statement, objectives, and research questions are presented. Chapter 2 provides the literature review that defines the different concepts used to understand and examine the topic. Chapter 3 is devoted to assessing socio-psychological factors that influence farmers' adoption of adaptation strategies in response to soil salinity due to climate change. Chapter 4 examines the impact of adoption of farmers' adaptation strategies in response to salinity on yields and households' food security. Chapter 5 depicts the simulation of smallholder farmers' adaptation decision-making impact on productivity. Chapter 6 summarizes the key findings from the study, the conclusions, and the policy recommendations.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

This section focuses on the descriptions and understanding of key concepts and theories from various scientific studies used and developed in this study to understand and examine the adaptation and implication of soil salinity issues in the Fimela district. Particular attention is paid to soil salinity changes, their causes and consequences for household livelihoods, and their relationship with climate change. The importance of adopting adaptation strategies in the face of risks such as soil salinity expansion and climate change, as well as the various analytical methods used in this work, such as the protection motivation theory and the importance of an agent-based model in simulating human decision-making, are presented.

2.2 Definition of concepts

2.2.1 Soil salinity change related to land losses around the world

"Salinity" refers to the concentrations of salts in soils or water, which can harm the growth of many plants and animals according to a certain level of content. It becomes one of the major causes of desertification, erosion, and land degradation, a widespread threat to the ecological structure and functioning of continental and coastal wetlands (Herbert et al., 2015). Soil salinization results from four major drivers: physical factors, population growth, economic pressure for more food production, and climate change impact (Bannari and Al-ali, 2020). It is one of the main problems contributing to soil productivity decline worldwide.

Despite the difficulty in estimating it accurately, the area of salinized soils is expanding and intensifying. About 20% of the world's cultivated land and 33% of irrigated land are estimated to be salt-affected and degraded, and estimates show that by 2050, salinity will affect 50% of the world's arable lands (Machado and Serralheiro, 2017). Soil salinity, as shown by Zaman et al. (2018) in Table 2.1 has expanded and is present in all continents around the world:

Table 2.1: Worldwide distribution of salt-affected areas (million ha)

Area	Saline soils	Sodic soils	Total	Percent
Australasia	17.6	340.0	357.6	38.4
Asia	194.7	121.9	316.5	33.9
America	77.6	69.3	146.9	15.8
Africa	53.5	26.9	80.4	8.60
Europe	7.8	22.9	30.8	3.30
World	**351.2**	**581.0**	**932.2**	**100**

Source: Soil Salinity: Historical perspective and a world overview of the problem (Zaman et al., 2018)

2.2.2 Source and causes of soil salinity process

Salinization is the procedure of enriching the soil with soluble salts, resulting in saline soil formation (Asfaw et al., 2018). Salinity can negatively affect the soil's physical condition (de-Vasconcelos, 2020). It causes an intensification in osmotic pressure making water more difficult for plants to mobilize, the toxicity of certain ions for plants (Cl^-, Na^+), and soil degradation (changes in the structural state and decrease in hydraulic conductivity) (FAO, 2006).

In the case of salinization, soils with high sodium concentrations, magnesium, and calcium absorbed on the soil exchange complex will be substituted by sodium, which has a low flocculating power leading to soil particles dispersion, accompanied by a decrease in hydraulic conductivity, infiltrability, and oxygen availability for roots (Machado and Serralheiro, 2017). High sodium concentration increases the pH of the soil, which has a toxic negative impact on plants' growth.

All salt found in water or soil originated from parent rock material through weathering, which occurs over geological time by the reaction of primary minerals with water O_2 and CO_2 to form secondary minerals and salt transported by water to oceans and move inland considerable distances by sea intrusion (Maas and Grattan, 2015). An excessive use of irrigation water causes soil salinity, mostly in arid areas, a shallow groundwater table, and poor drainage, which contribute to raising this groundwater and moving the salt content to the top (Qureshi et al., 2013).

Depending on their different causes, soil salinity can be classified into three types: primary or natural salinity, secondary or dryland salinity, and tertiary salinity or irrigation salinity[1].

1. Natural Salinity: It is a natural process where salt is accumulating during the rainfall process, sea advancement, or weathering of rock process.
2. Dryland Salinity: It is caused by the rising of groundwater that brings on top of the salt content that has as its origin the primary salinity process.
3. Irrigated salinity: A quantity of water used for irrigation is evaporating making the remaining water more concentrated in salt.

2.2.3 The nexus between climate change and soil salinity

Natural phenomena such as ocean currents, continental drift, the tilt of the Earth, comets, volcanoes, and meteorites have always contributed to global climate

[1] https://www.water.wa.gov.au/water-topics/water-quality

change (Kazeem, 2015). In addition to this natural phenomenon contribution, climate change impacts have been observed too in many sectors with greater clarity that these changes, caused mainly by the release of greenhouse gases, have as origins human activities (Cramer et al., 2006). Despite this, it remains difficult to clearly distinguish between human-induced change and natural variation in climate at small scales. Besides, evidence of long-term geophysical and biological changes caused by climate change is now apparent in many parts of the world through the earlier arrival of spring, the retreat of mountain glaciers (IPCC, 2007), and changes in primary productivity.

A close relationship does exist between variables that are changing and expected to change as consequences of global climate warnings, such as sea surface temperature, sea level rise, salinity, and water balance elements (Jakimavičius et al., 2018). Important changes such as sea-level rise due to the melting of small glaciers and the thermal expansion of oceans have been noted in this last 21st century as caused by climate change (Nicholls et al., 2014). Those changes associated with seasonal variations in weather, such as temperature and rainfall, changes in land use, and longer-term climate changes, can all impact surface water, groundwater, the flows between them, and the amount of salt they contain[2]. ncreased salinity, resulting in 0.5 million metric tons of net loss in rice production in countries like Bangladesh.

Since soil formation is intimately connected to the atmospheric and climatic systems via the carbon, nitrogen, and hydrological cycles, any change in the

[2] https://www.water.wa.gov.au/water-topics/water-quality

climate can affect soil properties leading to phenomena like land degradation such as soil salinization. Soil salinization occurs globally in various geographical zones with varying climates, particularly in arid and low semi-arid landscapes. As demonstrated by some studies change in climate in these arid areas is positively correlated with a continuous expansion in space and time of soil salinity through a decrease in precipitation and an increase in temperature. Besides that, the potential effects of climate change on coastal regions are an increase in salinity from saltwater intrusion by a progressive inundation due to sea level rise (Dasgupta et al., 2014), with also gradual consequences extended toward inland water and soil salinity due to climate change (Mahmuduzzaman et al., 2014).

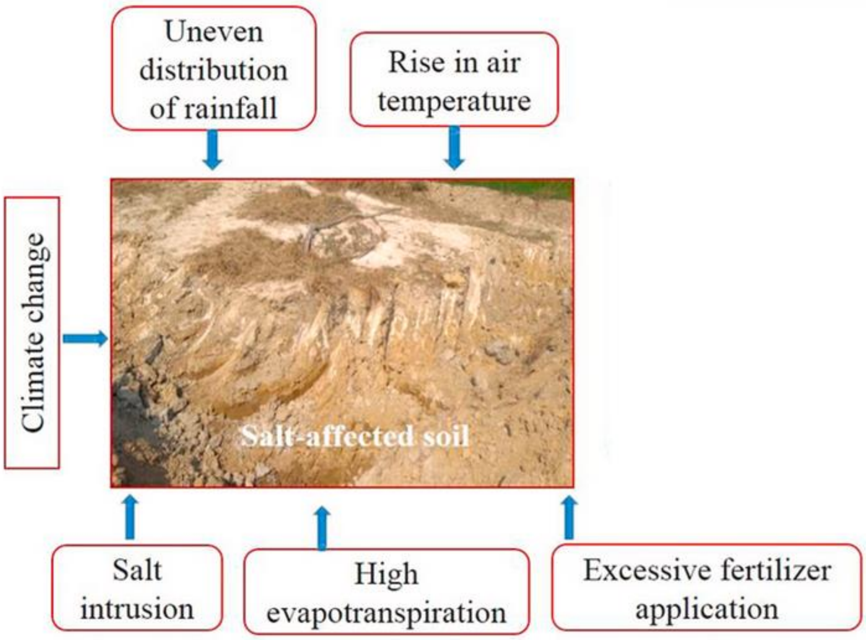

Figure 2.1: Relationship among climate change, land use and soil salinization expansion. Source: (Mukhopadhyay et al., 2021)

2.2.4 Farmers’ perception of soil salinity expansion and its causes

Whether or not farmers adapt depends on their knowledge and perceptions of the risks involved (Spaccatini et al., 2021). Then, how farmers perceive soil salinity expansion is important in their process of making adaptation decisions to cope with this threat. So, understanding farmers' perceptions of climate change, potential adaptation actions, and factors influencing adaptation to climate change becomes critical for improving policy to address the challenges farmers face (Fosu-Mensah et al., 2010) since farmers' risk management behaviours are influenced by their risk perceptions.

To cope with threats such as soil salinity, farmers usually implement a variety of strategies to mitigate the effects of agricultural risks based on how they perceive those menaces (Duong et al., 2019). Then, to improve risk management adaptations and bring institutional support, it is critical to understand farmers' risk perceptions (Deressa et al., 2011a) and the factors that influence them. Risks, particularly those related to climate change, must be evaluated and managed to update adaptation and mitigation efforts (Soubry et al., 2020). However, the efficacy of adaptation planning is determined by how actors perceive and respond to the hazards involved. The perception of farmers' risk differs depending on their socioeconomic background, resulting in different behaviours and decision-making (Duong et al., 2019). In addition to those factors, local knowledge, defined as the comprehension and the skills developed by populations and individuals specific to their living places, influence perceptions and responses to climate change in the short and long term (Rarai et al., 2022).

2.2.5 Soil salinity impact on household's livelihoods

Saline water intrusion threatens the lives of people and species living around the coastal zone and mangroves forest by subsequently affecting various sectors such as agriculture, people's health, ecosystems, and livestock (Islam, 2019; Shammi et al., 2019; Alam et al., 2017). The consequences of salinity on agriculture are known as reducing yield and soil fertility. It has affected about 40 million people directly, indirectly putting another 20 million people at risk and causing a net loss of 4.42 million of wheat in a region like Bangladesh, equivalent to 587 million US dollars (Habiba, Abedin, & Shaw, 2013). Salinity in saline regions becomes the key rural livelihood stressor for households.

Since through climate change, agricultural productivity and employment for the wage labourer are affected by salinity expansion, farmers in saline conditions are pushed out of the agricultural domain to non-agricultural livelihood as the only viable option to subsist. It affects the income-earning capacity of individual households in the long term, forcing them to migrate or develop entrepreneurship activities even if not all households can become entrepreneurs because entrepreneurship involves capital and specific skills (Sheikh and Rahman, 2018). Then in saline areas, insufficient livelihood and restricted adaptive capacity due to a lack of adequate physical and financial capital increase farmers' livelihood vulnerability (Islam and Sallu, 2014).

Salinization of land is generally technically impossible to find a solution to, and rehabilitation of this land is expensive and can represent 65% to 100% of the investment costs (FAO, 2006). So, this makes adaptation difficult and soil salinity's impact on farmers' livelihoods high. Population's livelihood is impacted by soil salinity increase in several ways: by making the entire coastal belt's water availability unsecured, putting poor people's lives in a more vulnerable situation, and by causing an increase in soil salinity which further reduces the agricultural productivity and puts enormous pressure on food security (Mahmuduzzaman et al., 2014).

2.2.6 Climate change and adaptation strategies

Land degradation is among climate change's most significant adverse effects on farmers' productivity. Due to their heavy reliance on agriculture and natural resources, smallholder farmers in developing countries are more vulnerable to the negative effects of climate change than those in developed countries (Chinowsky et al., 2011). To face this problem, coping which refer to short-term measures implemented by farmers to counteract the adverse effect of climate change (Antwi-Agyei and Nyantakyi-Frimpong, 2021) and adaptation becomes an important tool to cope for farmers. Adaptation practices are implemented to help communities such as farmers better cope with changes that may impact their activities. It can be seen as a cognitive process formed by people's values and beliefs, perceptions, personalities, motivations, goals, and culture that can be learned or seen as their responses to an external threat as climate change (Azadi et al., 2019).

Developing adaptation policies to face climate change and its effects is essential to mitigate environmental threat on human activities and well-being that are considered the most vulnerable in the system. So, understanding farmers' adaptation process to climate change is essential to determine vulnerable units and developing well-targeted adaptation plans (Below et al., 2012). These adaptative capacities of a community or region are based on the main features cited in the IPCC (2007)'s report: technology, economic wealth, information and skills, institution, infrastructure, and equity. The seventh and eighth conferences of IPCC parties, in respectively Marrakech in November 2001 and Delhi in November 2002, focused on adaptation to climate change and mitigation actions and formally recognized the dilemmas of adaptation for the developing nations, with a decision to assist these countries in adapting. Coming from the IPCC proclamation that there is no uncertainty that climate change from human-induced is happening, all societies have to learn how to cope with these predicted changes, which are weather changes and sea-level rise. This is sustained by the Delhi declaration on climate change and sustainability, which states that adaptation must be a high priority for countries and it requires imperative attention and actions.

In the domain of climate change, adaptation can be defined as "an adjustment in ecological, social or economic systems in response to observed or expected changes in climatic stimuli and their effects and impacts to alleviate adverse impacts of change or take advantage of new opportunities"(Adger et al., 2007). It involves adjusting actions to actual or future state climate to reduce vulnerability to harmful effects. It is felt locally, in cities and communities, firms and markets, by extending social networks or individuals and organizations, putting them at the frontline even if climate change is a global issue (NASA, 2020)[3].

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[3] https://climate.nasa.gov/solutions/adaptation-mitigation/

2.2.7 How should an adaptation action be?

Adaptation comprises actions taken by individuals, groups, and governments throughout society (Ford et al., 2013). It can be motivated by various factors, such as preserving economic well-being. As a relevant international, national, and local issue, it is possible to characterize a successful adaptation strategy or adaptation decision based on how these adaptations meet their objectives on a scale of application as well as the criteria used to assess it at each scale (Adger et al., 2005). These adaptations have to be effective and efficient but also based on equity and legitimacy through decision-making and depend on how institutions and social and cultural attitudes change (Sherman and Ford, 2014). But the available information also has a crucial role in defining adaptation to cope. Maas and Grattan (2015) specified that most adaptation actions are preventive or proactive and will be implemented before an event after carefully weighing the risks, benefits, and costs. Then, understanding the threat's causes and effects is critical for farmers to perform protective behaviours and expand the range of adaptive strategies available to them (Osberghaus et al., 2012). Thus, the lack of information about the causes and mechanisms of the threat can hinder any application of adaptation strategies methods and make decisions irrational. In addition, adaptive capacity, which is defined as a system's ability to adapt to climate change, mitigate probable damages, capitalize on opportunities, or deal with the effects, is critical in adopting adaptation (Ndamani and Watanabe, 2015).

2.3 Understanding adaptation to soil salinity under climate change

2.3.1 Remote sensing approach

Geographic Information Systems and Remote Sensing techniques are useful for detecting, monitoring, and predicting any environment's spatial and temporal changes and understanding its dynamics to create future scenarios (El-Saied, 2017). Land use and land cover change detection techniques have been used in fields such as water, vegetation change, land degradation (e.g., salinity), deforestation, soil erosion, and coastal changes (Abdelhaleem et al., 2021; Asfaw et al., 2018; Dubovyk, 2017). Soil salinization is a major consequence of changes in land use/land cover (LULC) in semi-arid and arid regions. Because it is a major environmental hazard, a careful monitoring of soil salinity status is essential and can be assessed through land use/land cover change (Allbed et al., 2018; Matinfar et al., 2013).

2.3.2 Socio-psychological factors behind adaptation behaviour

Studies have focused on demographics and economic predictors to study factors influencing farmers' implementation of adaptation strategies to face environmental risks due to climate change (Atube et al., 2021; Amare and Simane, 2017), such as land salinization expansion. However, little is known about the individual perception and psychological aspect that can guide farmers' adaptation and decision-making to face extreme climate change and its consequences (Azadi et al., 2019; Truelove et al., 2015; Bubeck et al., 2013).

Since adaptation mostly relies on actions set by individuals in their environment to face risk, it is essential to consider how socio-psychological factors may influence these actions (van der Linden et al., 2015). Then to be able to determine, understand, and address the public's perception, thoughts, and process of response about climate change effects, socio-psychological variables can be more important in the prediction of self-protective with more accuracy than socioeconomic variables by gathering important information concerning individual and household-level factors in socioecological systems (Azadi et al., 2019; Clayton, 2019; Maas and Grattan, 2015). Socio-psychological aspects such as motivation and perceived abilities should be considered to accurately predict future actions of adaptation (Maas and Grattan, 2015). Then, some theoretical foundations based on risk perception, adaptation assessment, adaptation intention, and maladaptation as components are beneficial in understanding adaptation behaviour and decision-making in the face of risks such as climate change and its negative effects (Dang et al., 2014). Those components are adapted from the main components of protection motivation theory (PMT): coping appraisal, threat appraisal, maladaptive coping, and protection motivation (Menard et al., 2017).

2.3.3 The Protection motivation theory

To understand the socio-psychological factors that may influence behaviours and decision-making, applying a psychological framework such as the protection motivation theory (PMT) is useful (Gebrehiwot and van der Veen, 2015). PMT was initially initiated as a theory in studies of health risks. Still, it has also been applied in other studies on protection behaviour, such as environmental problems, natural hazards, marketing communication, and other contexts (Dang et al., 2014). PMT, which is a positive function of perceived severity, vulnerability, response efficacy, and self-efficacy and a negative function of perceived rewards associated with maladaptive responses and the response costs of the adaptive behaviour, can induce two independent assessment processes: threat appraisal and coping appraisal (Rainear and Christensen, 2017).

The threat assessment focuses on the threat's source, the individual's perceptions of its severity, and vulnerability (Tchetchik et al., 2021). In the threat appraisal process, people estimate the threat by its likelihood to occur and its severity, and if the threat is highly risky, they engage in protection motivation actions (Truelove et al., 2015). However, fear also can be viewed as an additional intermediate variable of severity and vulnerability and the degree of threat that arises. This increases a person's motivation to engage in protective behaviour (Mankad, 2016), even if many intrinsic and extrinsic rewards can impact the likelihood of a maladaptive response (Posey et al., 2015). Simply put, "threat appraisal describes an individual's assessment of the severity of a potential threat stimulus when affected by it, as well as his or her vulnerability to the particular threat" (Osberghaus et al., 2012).

The coping appraisal is a second cognitive process with one's abilities and beliefs. It focuses on the individual's reaction to the threat and factors that alter the probability of an adaptive response, such as behavioural advice (Conner and Norman, 2015). It deals with the belief that the response will successfully reduce the threat (response efficacy) and the confidence in self-efficacy, meaning the capability to execute the response (Zhang et al., 2017; Kulviwat et al., 2014).

While factors such as the severity of the risk and its vulnerability may boost a person's incentive to participate in protective behaviour (Lee and You, 2020), the response costs in the coping appraisal may work to decrease this motivation due to an analysis of the available coping possibilities according to their different costs (Kothe et al., 2019). Then, since the willingness to engage in protection motivation is raised by the perceived risk intensity, the vulnerability factors, and the response effectiveness and decreased by the cost's response, both the threat and coping assessment must be high and adequate to achieve a reasonable degree of protection motivation. If the coping appraisal is low, the likelihood of engaging in non-adaptive behaviours like irrational belief or avoidance will be high.

Then adaptation is assessed through perceived adaptation efficacy, perceived self-efficacy, and perceived adaptation cost (Dang et al., 2014).

2.3.4 Agent-based model for human decision simulation

Agent-Based Models (ABM) is a rigorous conceptual framework used to explain human decision-making and understand the dynamics of social, economic, and spatial systems (Martin and Schlüter, 2015). Badham et al. (2010) describe ABM as a system modeled as a collection of autonomous decision-making entities named agents, each of which assesses its situation and makes decisions based on a set of rules and which may execute various behaviours appropriate for the system they represent. It can be applied in the different domain as Ecological Economics (Heckbert et al., 2010), social sciences, dynamics of the market (Dehghanpour et al., 2016), Land Use/Cover Change (Villamor, 2012), and others. Since individual behaviour is a complex system, then using differential equations increases its complexity exponentially as this behaviour becomes more complex. The agent-based model then enables dealing with complex individual behaviour, such as learning and adaptation (Wens et al., 2019).

To create a useful agent-based model, it is necessary to identify the agents with their attributes, whether human, organizational, or automated, accurately identify their behaviours, and appropriately represent their interaction in the system (Macal and North, 2009).

2.3.4.1 Definition of agent and its environment

The definition of an "agent" is diverse depending on the field of interest but converges in several points as described by the existing literature. An agent is a self-directed and autonomous entity that can operate independently in its milieu and its interaction with other agents, with a set of characteristics or attributes, with behaviours or decision-making capabilities and the ability to learn and adapt its behaviours based on its experiences (Müller et al., 2013). An agent is generally a decision-maker with states and behaviour rules in the system where they evolute. The environment as an agent is the location of various agent interactions.

2.3.4.2 Why the use of ABM: the strength and weakness of an ABM

It is advantageous to think in terms of an agent when the problem has a natural representation, when there are agents that adjust their behaviours and decision, and when agents must have a spatial component to their behaviours and relations, but also when there is a need to model the process by which agents form an organization, adapt, and learn (Macal and North, 2009). There are some important problems for which writing down equations is not always useful because they cannot often be completely solved. In such cases, using agent-based models can be beneficial in providing a model that illustrates its dynamical properties, testing and exploring the dependence of results on parameters and assumptions, and providing counter-examples (de Marchi and Page, 2014).

The disadvantage of the agent-based model vis a vis of mathematical modeling is that a single run of the model does not provide consistent information; robust results can be obtained only through multiple runs (Shi et al., 2014).

2.3.5 Land use dynamic simulator interaction model (LUDAS)

The LUDAS was first developed by Le et al. (2008) as an agent-based model for simulation of spatial-temporal dynamics of interconnected human–landscape systems. However, it has been revised and implemented in the Upper East Region of Ghana as MAS-LUDAS and GH-LUDAS by Amadou et al. (2018), Kazeem (2015), and Schindler (2009) in simulating agricultural land use adaptation decisions and as LB-LUDAS for capturing the gendered decision making in Sumatra, Indonesia by Villamor and van Noordwijk (2016). LUDAS is a model where the human population and the landscape surroundings represent a whole self-organized and interactive agent. The human-agent community comprises household, environmental, and policy information in land-use decisions (Villamor et al., 2011). The agent-based model, such as LUDAS, helps to analyze and examine these relationships among population growth (household patterns), ecosystem (via the land use patterns), agricultural system (structure of household livelihood), and adaptation responses to climate variability and change (Amadou et al., 2018).

CHAPTER THREE

3. ASSESSING SOCIO-PSYCHOLOGICAL FACTORS THAT AFFECT FARMERS' ADOPTION OF ADAPTATION STRATEGIES IN RESPONSE TO SOIL SALINITY

3.1 Introduction

In sub-Saharan Africa (SSA), millions of farmers struggle to feed their families due to soil degradation and land-use pressures caused by climate change (Buyinza et al., 2020). Climate change may appear through an unusual change in temperature and rainfall pattern, as well as more frequent and intense extreme weather events (floods, drought, storms) (Ali and Erenstein, 2017; Thompson et al., 2013), but also more frequent salinity invasion due to an increase in sea level compared to previous years' average sea level (Thi Nhung et al., 2019). Due to climate change, ineluctably, issues such as salinity intrusion in coastal areas occur and affect human livelihoods through different aspects. A global increase in sea level pushes saline water towards continental land due to inundation from the sea, making salinization one of the most serious issues for coastal regions (Thiam et al., 2019). Many countries in semi-arid and arid climate zones are affected by high and severe soil salinity problems: 400 million ha of land worldwide, with about 38 million hectares of land in Africa (Faye et al., 2019).

In Senegal, particularly along the coastal regions, soil salinity becomes a complex and prevalent type of land degradation caused by seawater intrusion (Fall et al., 2014), particularly in the Saloum River. Parts of this region are affected by seawater disturbance from the Saloum River reducing soil quality, limiting agricultural yields, and in some instances, resulting in the abandonment of farmlands in Senegal (Diome and Tine, 2015). Rice, an important food resource in Senegal, is the most affected agricultural activity by the salt intrusion. This has even led to the abandonment of rice farms due to high levels of salinity stress (Thiam et al., 2019; Sambou, 2015). A change in resource use may accompany deterioration in the physical environment. Therefore, adaptation becomes inevitable for communities that rely mostly on land for agricultural production for their livelihood. In climate research, IPCC (2007) describes adaptation as "the process of adjustment to actual or expected climate and its effects" such as salinity (Barros et al., 2014). The decision to adopt adaptation strategies could depend on farmers' perception of a threat, such as salinity expansion under climate change, its consequences on their activities, and the appraisal of their response efficacy (Phuong et al., 2018). Recent studies showed that factors such as the level of risk perception and adaptive ability influence adaptation, with additional behavioural and psychological aspects pointing to human cognition's role in climate change adaptation (Feng et al., 2017; Below et al., 2012). Adaptation decisions and behaviour of farm households differ and are also influenced by various variables such as cultural preferences, resource endowment, and expertise (Villamor et al., 2011).

The main objective of this chapter is to analyze the psychological factors that impact farmers' intentions to implement adaptation strategies in response to land degradation through salinity expansion as climate change’s result. The research expands the literature on climate change adaptation by using the protection motivation theory (PMT) and structural equation modeling to assess the psychological variables that may influence farmers' intention to adopt adaptation strategies against salinity. Previous studies on climate change adaptation strategies have mainly focused on demographic predictors, economics, and climatic constraints (Cedamon et al., 2018; Etshekape et al., 2018; Nahayo et al., 2016; Below et al., 2012). Also, the limited studies on psychological factors that underlie the adoption of adaptation measures to climate change in the literature did not focus on adaptation strategies against salinity (Buyinza et al., 2020; Bagagnan et al., 2019; Ling et al., 2019; Rainear and Christensen, 2017; Keshavarz and Karami, 2016; Mankad, 2016; Truelove et al., 2015; Dang et al., 2014; Juárez-Nájera et al., 2010). For instance, the study by Buyinza et al. (2020) argued that farmers' adoption of agroforestry as an adaptation strategy may be influenced by their opinions and behaviour of people surrounding them, as well as their individual perceived capacity to cope. Their study further indicate that farmers may fail to take up agricultural innovations merely because the new technologies do not match their community’s societal norms and traditions. The work by Mankad (2016) shows that psychological factors tend to influence human decision-making toward adopting biosecurity techniques. To the best of our knowledge, this study is the first to analyze the psychological factors that influence farmers’ adoption of adaptation measures against salinity.

This chapter is organized as follows. Section 1 has introduced the study. Section 2 presents the materials and methods. Section 3 is devoted to the results and discussions. Conclusions and recommendations are provided in Section 4.

3.2 Materials and methods

3.2.1 Description of the study area

3.2.1.1 Location

The research is conducted in Saloum which is located in the north of the Gambia and south of the "Petite-Côte" in Senegal and characterized by heavy land salinization. It is a delta formed by the confluence of two rivers, the Sine and the Saloum, and also a distributary of the sea and is gathering both the region of Kaolack and Fatick. This study covers the Fatick region, specifically the district of Fimela, which is a district located in the department of Fatick at 14 ° 7'60 "N, 16 ° 40'0" W and marked by strong land degradation (water erosion, salinization, soil poverty), a strong increase in salinization of water, and a rainfall deficit with difficulties in accessing inputs and agricultural equipment. The district has 16 villages, and its populations are strongly affected by the adverse consequences of severe land degradation due to salinization (Centre de Suivi Ecologique (CSE), 2015).

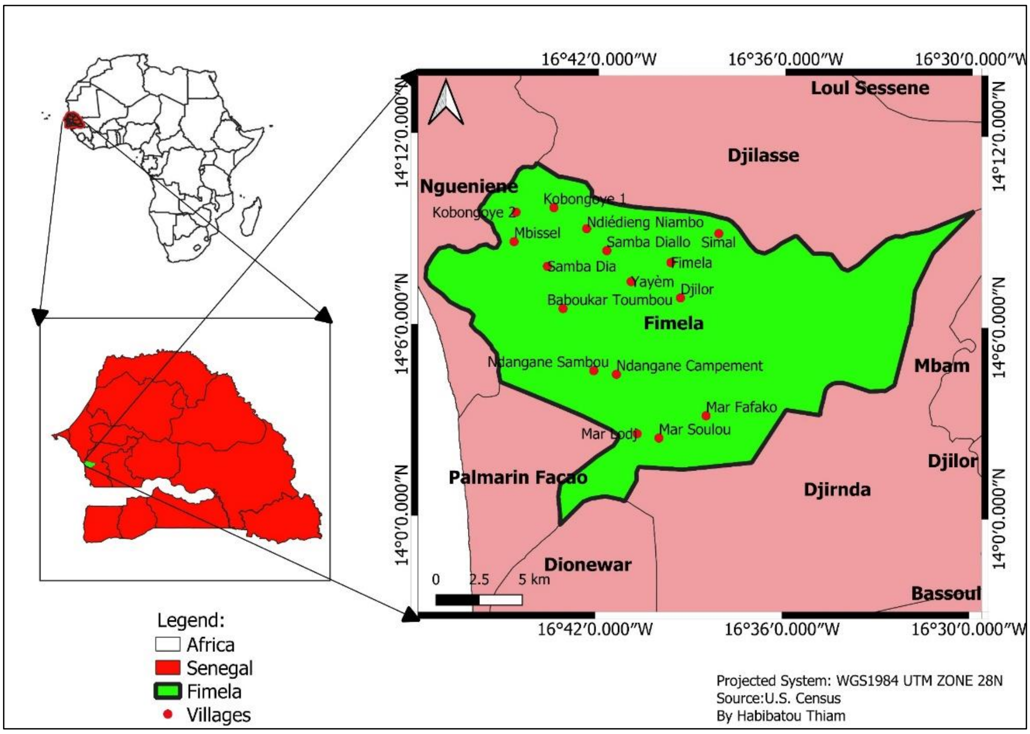


Figure 3.1:Presentation of Saloum study area: Fimela district.

Source: Author's own construction

3.2.1.2 Climate condition

The climate of the study region is the Sudanese tropical type marked by the Sahelo-Sudanese variant in the department of Fatick. The minimum temperatures vary from 21 ° C to 22 ° C, while maximum temperatures vary from 35 ° C to just over 36 ° C. The rainfall is irregular and weak and describes a north-south gradient varying between 600 and 900 mm on average/year (Centre de Suivi Ecologique (CSE), 2015). A large plain covers the region of Fatick. The climate is characterized by a prolonged dry season, warm from April to June, cool from November to March, and a short warm and wet season from July to October (Simier et al., 2004). This region is problematic due to the underlain superficial Continental Terminal aquifer surrounded by the hypersaline estuary (Dieng et al., 2017).

3.2.1.3 Vegetation

Somewhat concentrated forest formations mark the area. This vegetation is now threatened by several factors, such as recurrent bushfires, clearing, and excessive cutting of wood for various uses (ANSD, 2015). It is also an area where mangroves are present.

3.2.1.4 Soil types

There are four types of soils in this area: tropical ferruginous soils (“Dior” and “deck”), hydromorphic soils in valleys, halomorphic soils (saline or "tanne[4]" soils), and mangrove soils observed in islands and estuaries. The productivity of these soils is strongly affected by salinity due to the drop in rainfall and the high salt content of stagnant water and the water table, which can reach up to 10,000 mg / l per location (Centre de Suivi Ecologique (CSE), 2015).

3.2.1.5 Main ethnic group and socio-economic activities

The area is characterized by the variety of its customs and traditions and the main ethnic group is the "Serrere". The dominant activity in the area is agriculture which employs more than 90% of its population and has a large workforce. Millet is the main food crop in the area, followed by corn and rice, while cash crops are groundnuts and cashews. Fishing is also an essential activity in the area. It is located in a region where the exploitation of salt is very developed as an economic activity.

[4] *tans* are generated by aridic climatic conditions, heavy soil and water *salt* content, and can be represented by vegetation free zone, salt pans, salt swamp, unvegetated saline tidal flat, salt marsh, bare salt flat or high tide mud flats.

3.2.2 Theoretical framework

This study applies the PMT proposed by Rogers (1975) to understand farmers' decision-making process toward soil salinity threat. PMT is a social cognition theory originally developed by Rogers (1975) to deal with fear appraisal and behavioural change. He revised it and added a coping appraisal element (Maddux and Rogers, 1983). As a general decision-making model, such as Planned Behaviour Theory. that can deal with various threats, recent studies applied PMT in research on environmental problems such as natural hazards (e.g., drought) and adaptation to climate change (Neisi et al., 2020; Luu et al., 2019). When it comes to emphasize the role of fear in influencing behaviour change PMT becomes more adapted than some theory such as Planned Behaviour. PMT is also useful for analyzing psychological variables affecting farmers' intention to perform protection behaviours against climate change's negative consequences (Bagagnan et al., 2019; Regasa and Akirso, 2019). It addresses elements such as threat assessment, coping appraisal, maladaptive coping, and adaptation intention in the context of climate change as defined by Dang et al. (2014), see **Figure 3.2.**

The construct "threat appraisal" is determined by an individual's beliefs about how serious the consequences of the threat could be and his sensitivity to the negative consequences of the threat. Threat appraisal induces the individual's apprehension of the threat regarding its severity and perceived vulnerability, which refers to the individual's perception of suffering harm when exposed to a threat (Li et al., 2021). PMT helps to understand how farmers evaluate their private coping measures regarding perceived adaptation, perceived self-efficacy or response efficacy, and their perception of adaptation cost (Feng et al., 2017). Self-efficacy defines an individual's confidence in their ability to perform or carry out the suggested coping response against a threat. It does not reflect a person's skills but rather their judgments of what they can do with whatever skills they have (Kulviwat et al., 2014). Perceived adaptive or response efficacy indicates the belief in the effectiveness of the suggested coping responses in protecting oneself or others in averting the occurrence or the negative consequences of a threatening event (Ling et al., 2019). Perceived adaptation cost refers to the supposed costs that the coping responses of farmers to salinity will be at the individual's level. However, self-efficacy and adaptation costs can be related since an adaptive response may be difficult either because of high response costs or low self-efficacy (Le Dang et al., 2014).

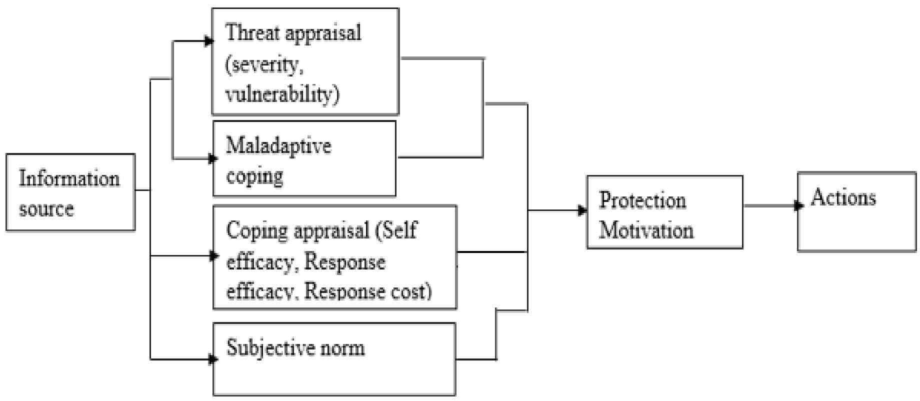


Figure 3.2: PMT in salinity expansion under climate change with the addition of subjective norms influence. Source: (Adapted from (Li et al., 2021; Dang et al., 2014))

Two additional constructs, named subjective norms and maladaptive coping, are hypothesized to impact farmers' intention to adapt in response to a threat such as a climate change in some cases (Luu et al., 2019). These subjective norms are defined by the expectation of other important persons' normative beliefs and opinions and the degree to which the person is ready to concur with these opinions (Tsai et al., 2016).

People with maladaptive coping appraisal (e.g., avoidance, fatalism, denials, hopelessness, and wishful thinking) may fail to involve in adequate information search and assessment of consequences (Frick et al., 2018), leading to an irrational protective decision. The maladaptive coping response is conceptualized by Rippetoe and Rogers (1987) as an independent predictor of protection motivation and may have a negative impact on threatening information for protection motivation (Faruk and Maharjan, 2022).

PMT has been proven to be a strong analytical framework to predict intention behaviour and its determinants in China, the United States, Thailand, New Zealand, and Australia in other contexts (Villamor et al., 2022; Li et al., 2021; Ling et al., 2019). In the case of salinity, a risk appraisal is addressed first by farmers to perceive or identify the salinity expansion threat before any evaluation of their coping option is performed. Then, farmers in saline conditions may engage in adaptive responses when the perceived that severity, vulnerability, self-efficacy, and response efficacy are high. However, predictors such as maladaptive may also have a negative impact on farmers' responses leading to un-protective actions. However, despite PMT is a rigorous framework that help to understand individual intention it has some limitations. It doesn’t consider all of the environmental factors and cognitive processes that may shape motivation.

3.2.3 Specification of structural equation modelling (SEM)

This study uses structural equation modeling (SEM) to explore the factors influencing individual actions. SEM was first suggested in 1972 (Goldberger, 1972) and was used as an efficient and reliable technique, mostly in behavioural research and social science (Deng et al., 2017). SEM is built using two procedures: (1) latent factors based on observed variables; and (2) the regression relationships. In this study, the latent variables were derived from the questionnaire that was based on PMT. The different variables used and the different relationships that could exist among the variables are defined using the PMT. Based on the PMT, items (questions) were defined in the questionnaire and use to build the different constructs define in the theory and needed for the analysis. For the second procedure, the regression relations between latent variables (named path analysis), see **Figure 3.3** have been defined for analysis based on PMT and a literature review (Deng et al., 2017). These relationships are composed of the following variables (see **Table 3.1**):

- **Coping appraisal** is measured by three observed variables: CA1, CA2, and CA3.
- **Threat appraisal** by two observed variables: TA1 and TA2.
- **Subjective norms** by two observed variables: SN1 and SN2;
- **Maladaptive** actions by three variables: M1, M2, M3;
- Adaptation strategies are combined into a composite to measure the intended behaviour by two variables: B111 and B222.

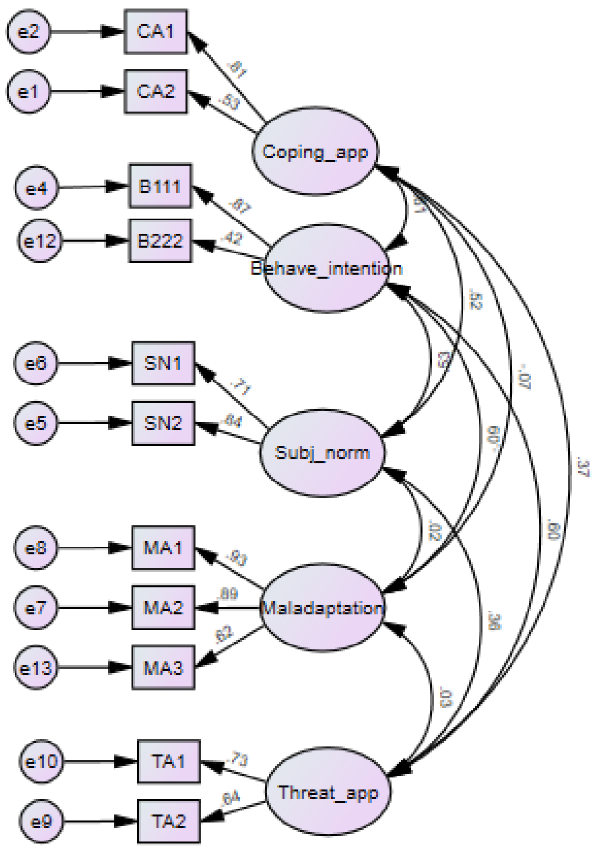


Figure 3.3: Path relationships between variables made for the measurement model. Source: Author's own compilation

To assess the effects of psychological factors on farmers' behavioural intention in saline conditions, a maximum likelihood estimation was run to solve the measurement model and developed SEM using the IBM SPSS Amos 26 software. This estimation is done in two procedures: firstly, the model's validity and reliability are assessed by running a confirmatory factor analysis (CFA), and secondly, the SEM will be tested to assess the defined relationships in the model. These two procedures are composed of six stages that define structural equation modeling: determining individual constructs, establishing the overall measurement model, designing a study to produce empirical outcomes, assessing the measurement model validity, specifying the structural model, and finally, evaluating the structural model validity.

Firstly, the goodness-of-fit (GOF) and construct validity are run, respectively, to assess the validity of the developed measurement model. The GOF is evaluated through the Chi-square test, the root means square error of approximation (RMSEA), and the comparative fit index (CFI). Secondly, construct validity is assessed by computing three indicators: the standardized factors loadings, **the average variance extracted (AVE),** and **the construct reliability (CR**). The two conditions essential for the validity of the measurement model are suitable GOF and construct validity (Dang et al., 2014).

Average variance validity (AVE): It explains the extent to which items are shared between the same construct in a structural equation modeling to get a good convergent validity (Urbach and Ahlemann, 2010). AVE is used to determine to what extent the observable variables defined by different items from the surveys explain the construct or unobservable variables. The stronger or higher the factor loading of an item is, the stronger its reliability to the construct in which it participates in its building is. A factor with a weak value should be removed to obtain good reliability (Eisinga et al., 2013).

Construct reliability (CR): It is used to measure how well the variables defined by different constructs are important in the developed structural equation modeling. Construct reliability is estimated based on the factor loading analysis. It refers to the consistency of the measurement findings in a certain range which is determined by the reliability of the coefficient. The stronger or higher the CR of a construct is, the stronger its internal consistency is. Construct validity must be proven using factor analysis before estimating construct reliability (Sujati et al., 2020).

3.3 Data Description

3.3.1 Sampling design

The area is mainly characterized by a population that belongs to the Seerere ethnic group (77% of the total sample), and agriculture is the principal activity and the main source of revenue (80% of the population) (Ndour et al., 2012). The study area includes 16 villages with a total population of 22,647 and 2,270 total households (NGO JED/ EEDS, 2019). It employed primary data collected with the aid of a survey performed in the 16 villages of Fimela covering a gradient from low to high saline conditions. Firstly, the study area was purposively selected due to its higher exposure to salinization (as described above), and data and literature on initial adaptation strategies were gathered from local institutions, such as Coordination des Actions pour la Restauration des Ecosystems Mangroves (CAREM) and Jeunesse et Development /Eclaireuses et Eclaireurs du Senegal (NGO JED/ EEDS), and adjusted by Focus Group Discussion. Secondly, the formula developed by Krejci and Morgan (1970) was used to determine the sample size for the study:

$$S = \chi^2 \times N \times P \times (1 - P) / (d^2 \times (N - 1) + \chi^2 \times P \times (1 - P)) \qquad \textbf{(3.1)}$$

S = required sample size of households

χ^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841)

N = the population size (total number of households of the sixteen village

P = the population proportion (0.50)

d= the degree of accuracy (0.05).

3.3.2 Data collection

A total of 320 households were obtained to be investigated by surveys. At the final stage, 288 farm households were randomly sampled for this study since two villages named "Ndangane Sambou" and "Ndangane Campement" were identified as tourist and fishermen villages with a limited number of farmers whose farmlands do not belong to them.

Knowing that the main farmers in the study area are holding small size farms, less than 10 ha, the targeted population of this study concentrated on smallholders farmers only. Data on personal, household, institutional, and farm characteristics, salinity adaptation strategies, and the perception of farmers on the adaptation strategies, climate change, and salinity were collected. The measurement used for the perception and PMT questions were based on a five-point Likert scale varying from one (most negative response) to five (most positive response). Two days of Focus Group Discussions (FGD), recorded by phone (one day for each group), were held with the assistance of Initiative Prospective Agricole et Rurales institute (IPAR) to test and refine the survey questions for the study area in addition to the consultation of local institution that deal with farmers in the place. The Focus Group Discussion was composed by 24 farmers of males and females who were chosen based on their farm profile and their location, that is a saline area, with the help of the authorities in the place. A pre-test of 14 farmers, different from those chosen during the focus group, was also done to validate the questionnaire before the survey. The survey was performed through face-to-face interviews from March to May 2021, and households were chosen randomly. The number of interviewees in each village was proportional to their households' numbers.

3.4 Variables measurements and estimation procedures

A structural equation modeling (SEM) is used to determine which constructs significantly influence farmers' intention to implement adaptation in reaction to salinity under climate change (see 3.2.3). The focus is on the different elements defined in the PMT, such as threat appraisal, self-efficacy, response efficacy and response cost, and maladaptation. These elements are investigated through different variables clearly stated in the survey, and other constructs, such as subjective norms, are added as defined in **Table 3.1**. Constructs are based on the different questions from the survey: the behaviour intention construct represents the dependent variable in the model. Threat appraisal, coping assessment, maladaptation, and subjective norms are constructs that represent the independent variables (**Table 3.1**).

Table 3.1: Construct building with different items

Constructs	Items	Descriptions based on survey questions	Coding (response choice)
Threat appraisal	TA1	How severe is salinity in your area or farm? (Severity)	5-point Likert scale (Not severe at all to extremely severe)
	TA2	Salinity expansion due to climate change has considerably decreased my productivity (Vulnerability)	5-point Likert scale (Strongly disagree to strongly agree)
Coping appraisal	CA1	Perceived adaptation efficacy in terms of productivity (Response efficacy)	5-point Likert scale (Very ineffective to very effective)
	CA2	Perceived self-efficacy	5-point Likert scale (Completely unconfident to completely confident)
	CA3	Perceived response cost (e.g., time, effort, etc.) (Response cost)	5-point Likert scale (Not costly at all to extremely costly)
Maladaptive coping	MA1	There is no need for any action to be taken to face salinity because these actions won't make any difference (Inaction)	5-point Likert scale (Strongly disagree to strongly agree)
	MA2	All issues are determined by fate and unchangeable by human (Fate)	
	MA3	I don't have motivation or energy to address the soil salinity problem (No motivation)	
Subjective Norms	SN1	My friends, neighbours and family are engaged in adaptation, so I'm doing so	5-point Likert scale (Strongly disagree to strongly agree)
	SN2	Almost all the village(s) is/are doing the same adaptation action/measures	

Behavioural intention	B111	Fertilizer-increase application (Organic fertilizers, chemical fertilizer, Spray peanut-millet-shell on surfaces, spray phosphor).	5-point Likert scale (not at all to very large extent)
	B222	Reforestation (Reforestation, replanting-mangrove, tree plantation around farm surface as protection).	

Source: Authors' own compilation

3.5 Results and Discussions

3.5.1 Descriptive Results

3.5.1.1 Descriptive statistics

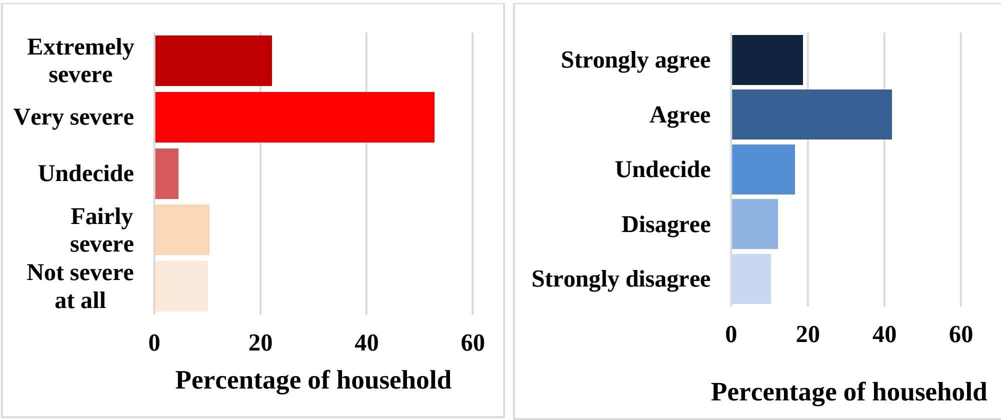
The descriptive statistics of the respondents are presented in **Table 3.2**. We find that around 61% of the respondents are affected by soil salinity in their farming activity, and 53% have lost part of their land or whole land (mostly rice farms) due to salinity expansion. A total of 22% of the respondents are not practising any adaptation measures.

Table 3.2: Descriptive analysis

	Sum	Std-dev	Mean	Percentage %
Farmers' claiming to be salt affected	177	0.49	0.61	61
Farmers' lands lost due to salinity	153	0.5	0.53	53
Currently engaged in adaptation practices	224	0.42	0.78	78

Note: variables represented are dummy (1=Yes, 0=No). Source: Author' s own Computation from Field Survey, 2021

Regarding threat appraisal, respondents' levels of severity and vulnerability to salinity are depicted in **Figure 3.4**. Of the respondents, 53% perceive the salinity expansion in their area as very severe, while 22% consider it extremely severe. The same respondents agree (42%) and strongly agree (19%) with the fact that they are vulnerable to this phenomenon.



(4a) Severity **(4b) Vulnerability**

Figure 3.4: Degree of farmer's perception of salinity threat appraisal on their activities: severity level (4a) and vulnerability level (4b).

Source: Author' s Own Computation from Field Survey, 2021

For coping appraisal, **Figure 3.5** depicts the perceived response efficacy (5a), self-efficacy (5b), and response cost (5c) of the respondents. Regarding response cost, respondents mostly perceive adaptation to salinity expansion in their lands as costly (55%) or extremely costly (15%). On the other hand, the respondents perceived their response efficacy as effective (44%) and very effective (28%), whereas the majority of them were confident about their ability to implement adaptation strategies (55%). Even though some farmers are not sure about the effectiveness of their method in terms of productivity (22%), most of them found their response in fighting salinity under climate change either effective or very effective (5a).

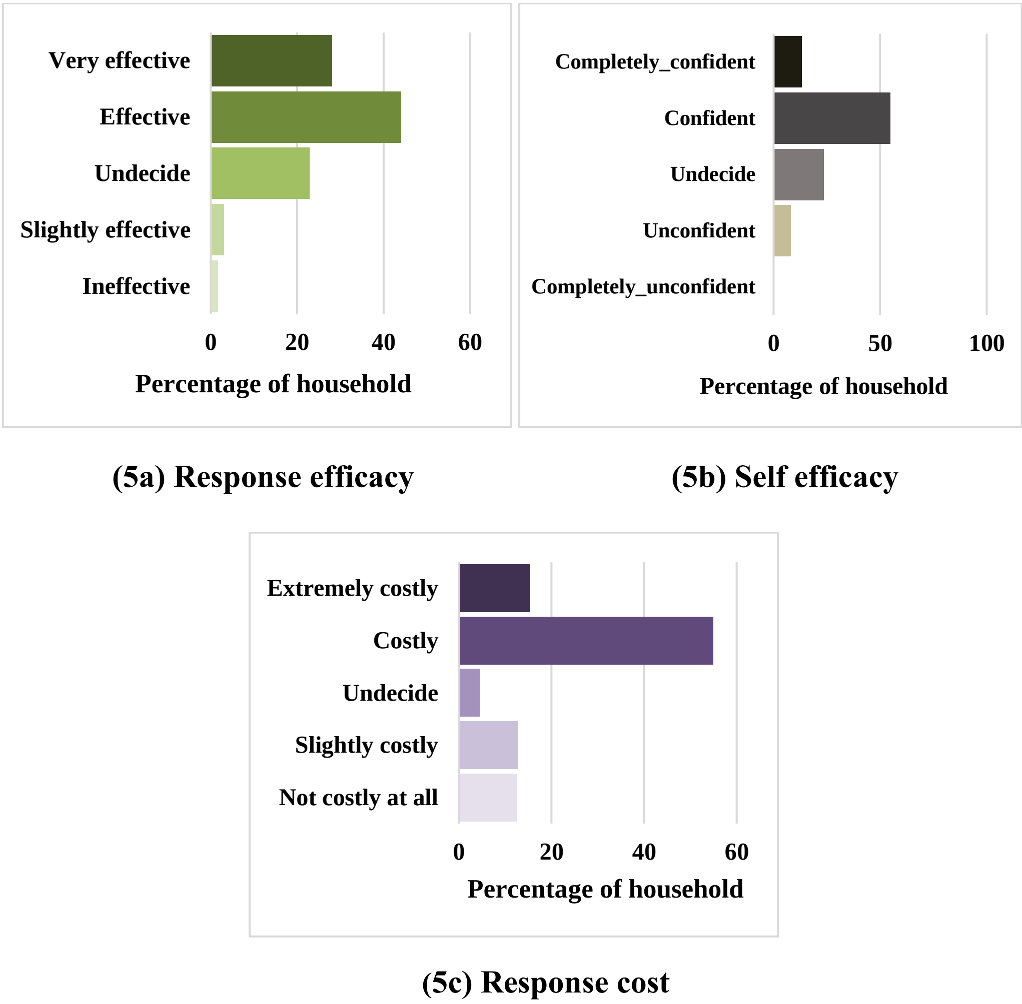
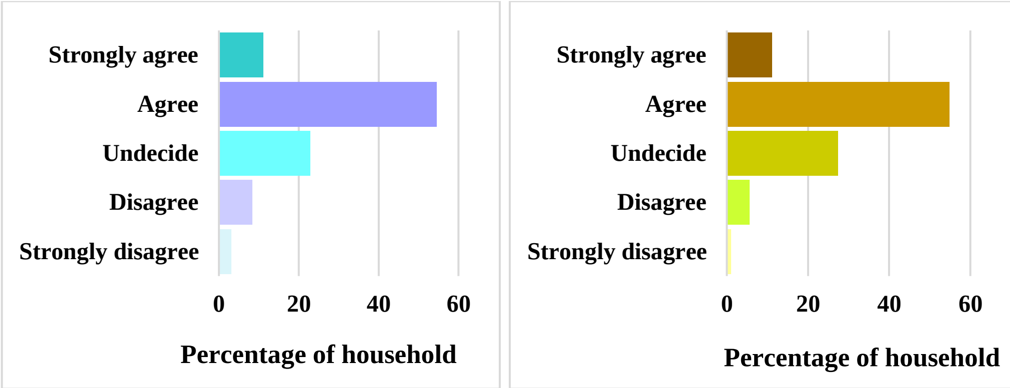


Figure 3.5: Farmers' perception statement of coping appraisal to salinity in Fimela: response efficacy (5a), self-efficacy (5b) and response cost (5c).

Source: Author' s Own Computation from Field Survey, 2021

For subjective norms, **Figure 3.6** depicts the perceived social influence (e.g., family, neighbors, or parents' decision) and surrounding villages' influence on the respondents. Most respondents agree on the point that they adopt an adaptation measure because their peers have the same attitude, with 54% for village influence and 55% for social influence. The undecided responses by farmers (23% and 27%, respectively) can be clarified by the fact that not all farmers are involved in adaptation, and some consider that they cannot give precise responses to the question.

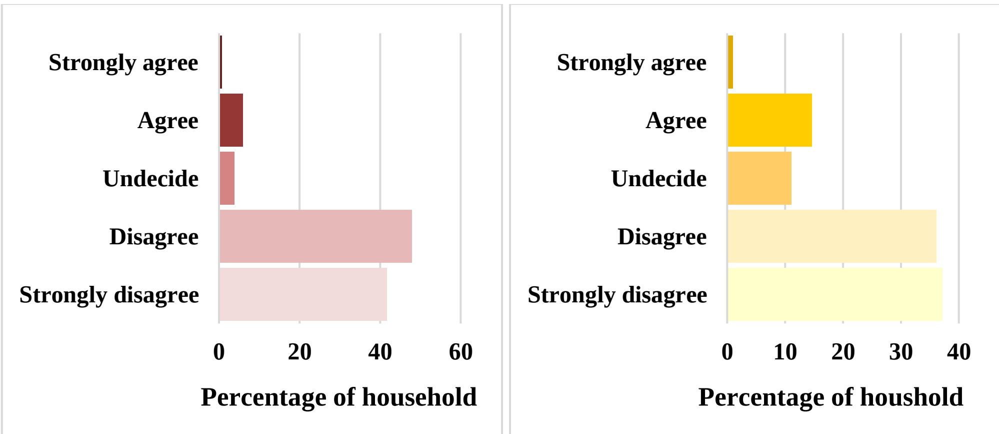


(6a) Social influence **(6b) Village influence**

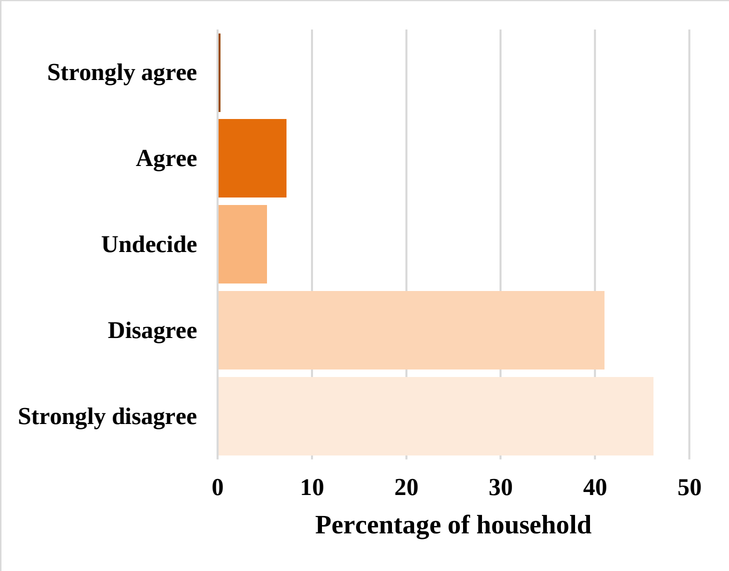
Figure 3.6: Farmers' perception statement of subjective norms to salinity in Fimela: social influence (6a) and village influence (6b).

Source: Author' s Own Computation from Field Survey, 2021.

For maladaptive coping, **Figure 3.7** depicts the result of the respondents' perceived inaction, motivation, and fate. In terms of inaction and fate, the highest percentage of the respondents disagree that salinity is a fate and any action is unnecessary (47% and 41%, respectively); whereas, in terms of motivation, 15% of the respondents agree that they have no motivation.



(7a) Inaction **(7b) Motivation**



(7c) Fate

Figure 3.7: Farmers' perception of maladaptation actions on salinity adaptation in Fimela: Inaction (7a), motivation (7b) and fate (7c) Source: Author's Own Computation from Field Survey, 2021.

3.5.1.2 Adaptation strategies

This section discusses the farmers' adaptation strategies against soil salinity. A total of 13 adaptation strategies were identified by the respondents (**Table 3.3**). These strategies were grouped into three, i.e., (1) fertilizer application; (2) reforestation (e.g., tree plantation, mangrove replanting, trees plantation around the farm); and (3) others (e.g., bund-building, abandon land, fallow, use of salt-tolerant crop). Since the others have a very low percentage and insufficient samples for the analysis, they have been aggregated into two adaptation groups: Increased fertilizer application and reforestation (**Table 3.4**). Some farmers have not adopted any type of strategies against salinity whether being affected or not.

Table 3.3: Strategies to mitigate the negative impact of soil salinity expansion in Fimela

Type of adaptation strategies	Frequencies	Percentages	Groups
✓ Reforestation	73	25.3	Reforestation
Trees around farms	1	0.3	
Mangrove reforestation	1	0.3	
✓ Peanut millet shell spray	112	38.9	Fertilizers-increase application
✓ Fertilizer increases	154	53.5	
✓ Abandon land	6	2.1	Others (not included for further analysis)
✓ Tolerant crop	1	0.3	
Distance from affected land	1	0.3	
Bund builds	1	0.3	
✓ Profit dams	16	5.6	
Phosphates[5]	7	2.4	
✓ Fallow	13	4.5	

✓ Represent the adaptations that have been listed in the questionnaire based on investigation and literature. Source: Author' s own Computation from Field Survey, 2021

Table 3.4: Strategies to mitigate the negative impact of soil salinity expansion in Fimela

Adaptation strategies	Number of respondents	Percentage of respondents practicing under: Salinity (%)	No-affected (%)
Increase fertilizer ap.	217	62	38
Reforestation	74	59	41

Source: Author' s own Computation from Field Survey, 2021

[5] White powder that farmer used in a raw state and they called it phosphate or phosphor

3.5.2 Empirical Results

3.5.2.1 Model validation

The goodness-of-fit (GOF) indices for the developed model are summarized in **Table 3.5**. Overall, the different threshold values suggest a good fit. The p-value of chi-squared shows a significant value instead of the inverse. In this case, a non-significant p-value indicates that the hypothesis model significantly does not deviate from the observed one. This result obtained is explained by the large sample size (more than 250), and a large sample size will always give a significant model (Feng et al., 2017). Thus, the p-value result is accepted.

Table 3.5: Overall model fit indices for the measurements and structural models

Statistic	Threshold	Measurement model	Structural model	Meaning of statistic
RMSEA	≤ 0.08	0.072	0.072	Root means Square Error of Approximation
SRMR	≤ 0.08	0.614	0.614	Standardized Root Mean Squared Residual
CFI	≥ 0.9	0.948	0.948	Comparative Fit Index
TLI	≥ 0.9	0.915	0.915	Tucker-Lewis Index
NFI	≥ 0.9	0.917	0.917	Bentler-Bonett Normed Fit Index
P-value of χ^2	> 0.05	< 0.05	< 0.05	Chi-square statistic

Source: Author’ s Own Computation from Field Survey, 2021

In addition to the validity of these indices, the standardized factor loadings are presented in **Table 3.6**, which contribute to the computation of the construct validity (i.e., loadings should have an absolute value that stands above or equal to 0.5 and is statistically significant as suggested by Sujati et al. (2020). **Table 3.6** indicates that all the standardized factors loadings are statistically significant, and the majority is greater than 0.5, except for one acceptable number (Feng et al., 2017).

Table 3.6: Overall model fit indices for the measurements and structural models

Variables	Items	Factor Loadings	AVE	CR
Threat appraisal	TA1 TA2	0.640*** 0.726***	0.468	0.637
Coping appraisal	CA1 CA2	0.530*** 0.805***	0.465	0.625
Maladaptation	MA1 MA2 MA3	0.927*** 0.891*** 0.619***	0.679	0.860
Subjective norms	SN1 SN2	0.712*** 0.845***	0.610	0.757
Behaviour intention	BI1 BI2	0.870*** 0.419***	0.466	0.609

Source: Author' s Own Computation from Field Survey, 2021

Table 3.6 shows loadings are positive for construct validity and indicate strong reliability of the observed variables to their associated construct variable in the model. The construct reliability and the average variance extract are indicators used to determine the model's convergent validity. Good reliability of a model is obtained with a CR greater than 0.6 and an AVE greater than 0.5, but studies have shown that an AVE of 0.4 is acceptable for good reliability (Dang et al., 2014; Feng et al., 2017). During measurement validity assessment in CFA, factors with very low loading may negatively affect the model's reliability and should be removed; such is the case of cost adaptation for coping appraisal construct. Response cost has been removed to get a better construct for coping appraisal. It appears to be the weakest predictor in this model. In this study, the findings in **Table 3.6** demonstrate that the model has acceptable convergent validity.

3.5.2.2 Structural model assessment

The structural model for adaptation intention is presented in **Figure 3.8.** The squared multiple correlations (R^2) associated with the latent variable behaviour intention is 57%, implying that the independent factors in the model can describe 57% of the variance in intention behaviour.

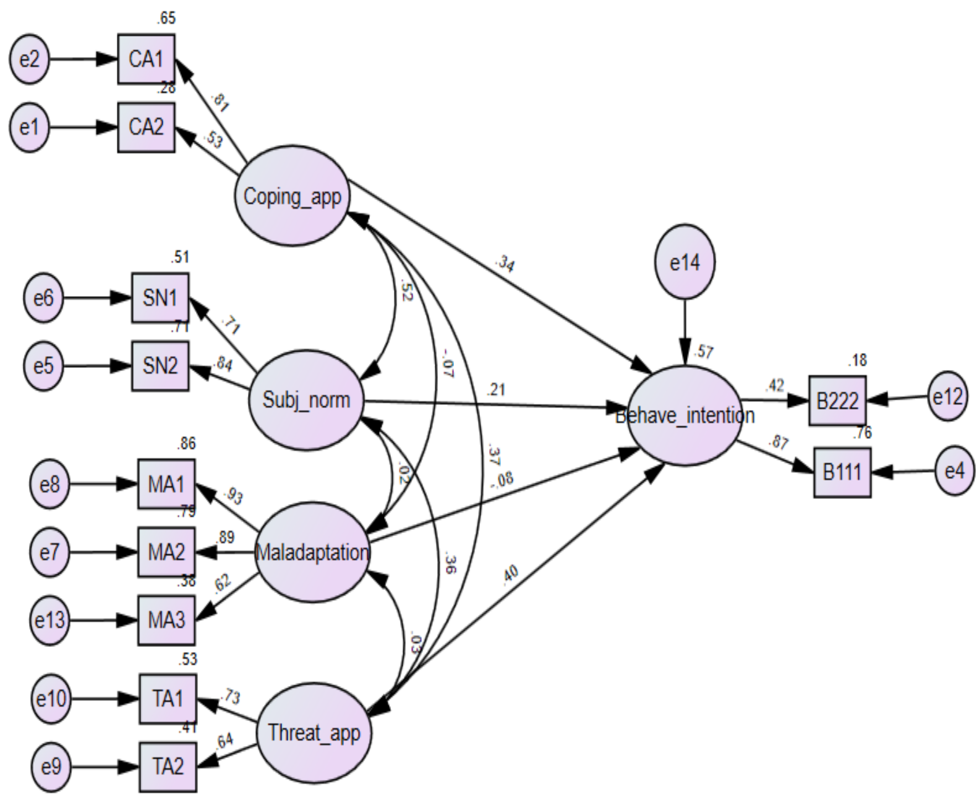


Figure 3.8: Overall model fit indices for the measurements and structural models. Source: Author's Own Computation from Field Survey, 2021

The results of different standardized path coefficients from evaluating the suggested structural model are represented in **Table 3.7**. The paths' coefficients results support the developed hypothesis above that there are significant relationships between the psychological factors defined by the PMT with the farmers' intention to adopt or not strategies to cope with salinity under climate change.

Table 3.7: Structural relations of psychological factors and perceived behavioural in soil salinity context

Structural Relations	Standardized parameter	C.R.	P (value)
Coping appraisal –> Behavioural intention	0.345	2.916	0.004***
Threat appraisal – > Behavioural intention	0.40	3.421	0.001***
Maladaptive coping –> Behavioural intention	-0.082	-1.347	0.178
Subjective norms –> Behavioural intention	0.212	2.151	0.032**

Note: *** significant at 1% level, ** significant at 5% level; CR=coefficient of reliability (excellent when up to 0.9).
Source: Author' s Own Computation from Field Survey, 2021

The results show significant and positive relationships between the intention to adopt and the coping appraisal, the threat appraisal, and the subjective norms. Therefore, maladaptive coping does not significantly influence farmers' intention to adopt. These results corroborate the study of Feng et al. (2017) and are in opposition to the findings of Ghanian et al. (2020). The response cost in the coping appraisal construct is no longer significantly contributing to the complete model goodness-of-fit, which is why it could not be considered in the model. Its factor loading was less than 0.3, contrary to the other items. This can be due to its weak correlation with the other variables.

Empirical findings of the structural model revealed that the greater the threat appraisal, the greater the intention to adopt an adaptation measure. Therefore, when a farmer perceives a strong severity of soil salinity in their area, they will more likely have a stronger intention to implement an adaptation measure. PMT results suggest that threat vulnerability and severity have positive effects on adaptive behaviour (Menard et al., 2017).

The intention to adopt also increases with farmers' coping appraisal through their self-efficacy and response efficacy. When farmers remark the effectiveness of their potential adaptations in addition to their capability to carry out the adaptation, their intention to adopt adaptation measures increases. This shows that the farmer's belief in his capability to implement an adaptation measure, but also his belief in the fact that adaptation can effectively prevent or reduce damage in the event of salinity, has an important influence on his intention to adopt this adaptation, as related by Bubeck et al. (2013) and Truelove et al. (2015). Then, a large degree of self-efficacy and response efficacy can motivate farmers to adopt adaptation measures.

In this study, subjective norms have an important positive influence on the farmers' intention to implement adaptation measures. Relatives or other villagers influence the farmers' decision-making. This indicates that those with higher social connections or networks with their friends, relatives, and neighbors would significantly have the intention to adopt. These findings are similar to those of Esham and Garforth (2013) and Truelove et al. (2015), who stipulate that social networks significantly affect farmers' adaptation since adaptation measures are learned through experience and observation of neighbors. This is in accordance with Bubeck et al. (2013), who find a significant influence of social environment on the implementation of flood mitigation measures.

Therefore, the maladaptive coping is negative and has no substantial influence on farmers' intention to adopt. These results are comparable to many other findings, such as Dang et al. (2014) and Feng et al. (2017) on climate change, but in opposition to the findings of Bubeck et al. (2013), who stipulated that the maladaptive responses have a significant negative influence on flood mitigation. It means that farmers' inaction, reliance on fate (fatalism), and lack of motivation to implement adaptation strategies do not influence farmers' intention to adopt adaptation against salinity. Therefore, farmers in the study area mainly do not have unproductive ideas that inhibit their willingness to adopt adaptation strategies against salinity effects on their farming activities.

3.6 Conclusions and policy recommendations

This research investigated the psychological variables that may affect farmers' behaviour in preventing or fighting salinity under climate change in Fimela. This has been done because knowing about the psychological factors that drive farmers' behaviour can be more useful in making development decisions than knowing strictly about demographic, technological, or economic variables. For example, because the new technologies are unsuitable for the social standards and traditions of the community, some farmers may simply refuse to adopt agricultural innovations. This study demonstrates how the different components of PMT influence farmers' behaviour in their adaptation. The findings show that coping appraisal (self-efficacy and response-efficacy), threat appraisal, and subjective norms significantly positively impact farmers' adaptation in the study area. However, maladaptive coping, in this case, does not have a significant effect on farmers' adoption of adaptation as well as cost adaptation has not been considered since it does not permit a goodness-of-fit of the model.

These findings are particularly important for forward-looking policies since they emphasize potential entry points for interventions by extension officers from NGOs and governments to increase and support the adaptive capacity of farmers against salinity threats in the area. The study also supports that PMT is relevant for supporting models on adaptation behaviour against climate change effect as soil salinity. It also provides a baseline understanding of how farmers under saline conditions behave in terms of coping in Fimela.

The findings indicate that to implement policies to cope with soil salinity, NGOs or governments need to consider strategies that may boost farmers' capacity evaluation of their self-efficacy and the efficacy of their responses. It will also be useful to provide information about the threat of soil salinity expansion, its causes, and its long-term consequences on farmers' livelihoods. This can be done by investing in information and knowledge about the threat in their production and distribution since how farmers appraise a threat positively influences their adoption of adaptation strategies to soil salinity. Policies that consider the influence of social parameters will also be useful since the tendency of farmers to copy from their immediate environment is strong. So, accompanying policies supporting a few pilot farmers in precise and effective strategies can trigger other farmers to follow the same example through the village and social influence by farmer-to-farmer approach, farmer field schools, and training by extension officers.

This chapter considers only the psychological factors that can influence farmers' intention to adopt, while other factors, such as economics and demographics, may also affect farmers' adoption intention. Then, future studies should consider both psychological factors and other factors, such as the involvement of agencies, economic and demographic factors, and environmental concerns.

CHAPTER FOUR

4. IMPACTS OF FARMERS' ADAPTATION STRATEGIES IN RESPONSE TO SOIL SALINITY ON PRODUCTIVITY AND HOUSEHOLD'S FOOD SECURITY

4.1 Introduction

In rural Senegal, food staples such as millet are grown for domestic consumption (Randriamamonjy et al., 2020). In contrast, groundnut production may effectively generate income and create jobs (Touré et al., 2021). Groundnut farming is the primary agricultural activity through which rural populations can make a livelihood over time, and it generates about 35% of the annual household income in Senegal (Ndiaye et al., 2016). Senegal's cereal production systems are extensive and highly dependent on weather and climate-related effects (Faye et al., 2022). In many areas of Sub-Saharan Africa (SSA), soil degradation is a significant impediment to food security that negatively impacts rural crop production (Faye et al., 2021). Land salinization is a major global environmental change affecting crop production like groundnut and millet (Abu Qaoud et al., 2023; Taufiq et al., 2016) in areas such as the rural district of Fimela in Senegal. Environmental changes such as salinization through natural and human land use changes over the last century are likely to have detrimental environmental and societal effects, placing human communities at risk of food instability (Szabo et al., 2016).

Land salinization affects at least 400 million ha, seriously threatening the equivalent land area of 6.5% of the world's total land (Faye et al., 2019).

According to the World Bank (2000), sea level rise caused by climate change will submerge many low-lying areas by 2050, and salinity incursion will become more severe as the effects of climate change accelerate. Salinity spreads from exposure to the inland coast, limiting crop output (Baten et al., 2015). Then, because of its detrimental effects on microbial metabolism and soil physical characteristics, it significantly negatively impacts soil yield in arable croplands (Siddique et al., 2013) and negatively affects farmers' livelihood strategies (Haider and Hossain, 2013). It has emerged in recent decades as a major factor responsible for land degradation and lower crop production, implying a shift in land use activities (Singh, 2022). This soil salinity threat becomes more important due to climate change with the sea level rise, temperature increase, and the diminution in rainfall (Khamidov et al., 2022; Baten et al., 2015).

Then, to reduce or eliminate the impact of the salinity expansion threat on their livelihood, farmers implement adaptation strategies in the hope that they will positively impact their livelihood (Habiba, Abedin, Shaw, et al., 2013), such as farm products and, by extension, their food security. Studies such as Ali and Erenstein (2017) found a positive connection between these farmers' adoption of climate change adaptation and food security. The exact relationship has been proven with rice yield in China (Huang et al., 2015) and Nepal (Khanal et al., 2018). Thus, many researchers have analyzed the implication of climate change adaptation on yield and food security (Araya et al., 2020; Shabbir et al., 2020; Hasan et al., 2018; Wossen et al., 2017). Despite this, the widely acknowledged literature mainly focuses on climate change adaptation. But few, if any, are specific to the implications of adaptation to soil salinity expansion, particularly in the Fimela saline zone.

Adaptation strategies are short-run actions taken to assist people in getting through a hard time, regularly with the expectation that the "normal" state will return soon (Bertana et al., 2022; Schoenefeld et al., 2022). The adaptation measures are frequently tools that farmers frequently have in their store of strategies for dealing with uncertainty and risk, with requirements primarily concerned with know-how or technology. But in some instances, it is essential to develop new methods or completely alter processes because they are often expensive, and if the situation does not improve, it may turn maladaptive over time (Juhola et al., 2016). Given that, maladaptation can result from poorly designed adaptation strategies, in which exposure and sensitivity to the effects of a threat are increased or do not improve as a consequence of action taken (Findlater et al., 2022). It occurs when an action results in conditions that are worse than the ones that were initially addressed (Magnan et al., 2016). Adoption of adaptation becomes more than a loss of time and money in that case, even if identifying whether a particular adaptation strategy was successful or even a complete success is frequently difficult but required for decision-makers (Schipper, 2020).

Some studies (Zheng et al., 2021a; Issahaku and Abdulai, 2020; Adolwa et al., 2019) found that adoption of adaptation practices significantly increase crop income and reduce crop risk to climate change. However, costs linked to adaptation practices may make choices more complex and dependent on the expected yield and the availability of inputs (Molua, 2002). Also, farmers engaged in adaptation can often fail in their strategies due to incomplete information about their environment or poor coordination of the adaptation method leading to inefficient results (Schipper, 2020).

This study aims to analyze whether the strategies adopted by farmers to combat soil degradation from increasing salinization have a positive impact on their livelihoods by increasing their production and food security and whether they benefit from the increase in their food production. Research has been done on analyzing farmers' adaptation to climate change effects and its determinants. Still, studies that focused on adaptation in saline conditions and whether these adaptations have positive impacts as expected have yet to be done or are very infrequent in literature if it exists.

Such information can be used to determine whether farmers' adaptation measures against soil salinity are sustainable under climate change conditions and then develop a better technical adaptation system in case the measures do not achieve the real expectations.

4.2 Materials and methods

4.2.1 Empirical strategy

Soil salinity adaptation may affect farmers' yields and food security. Farmers' adaptation conditions may have a positive impact on yields (Abid et al., 2016) by helping to mitigate the adverse effects of soil salinity case (Cuevas et al., 2019), thereby increasing agricultural production, which is a major source of income for rural farmers. Firstly, through a positive yield result, farmers' adaptation can positively impact farmers' food security Ali and Erenstein (2017), which essentially depends on their production and the net return they gain from it. However, the adaptation may have unexpected effects because farmers may use a type of adaptation that is not optimal due to their limited knowledge about a threat, but also because the cost of better technology is too high for their limited financial resources (Douxchamps et al., 2016). Secondly, by positively affecting yields and food security, adaptation can positively impact farmers' livelihoods (Fadina and Barjolle, 2018) by giving them better resources to ensure essential needs for subsistence. This decision can be guided by the utility they may gain by making a specific choice.

As described in many studies (Zheng et al., 2021; Alene and Manyong, 2007; Tesfaye and Tirivayi, 2003), the farmers' decision to adopt can be modeled within a random utility framework. In this framework, the farmer is assumed to adopt if he expects that a gain U_i^A from adoption is larger than a gain U_i^n from not adopting. A latent variable I_i^*, which represents the utility difference between adopter and non-adopter $I_i^* = U_i^A - U_i^n > 0$, is considered. Thus, this latent variable can be expressed by equation 4.1 as a function of observable variables defined in the vector Z as below:

$$I_i^* = \rho_i Z_i + \varepsilon_i \quad with\ I_i = \begin{cases} 1, & if I_i^* > 0 \\ 0, & otherwise \end{cases} \qquad \textbf{(4.1)}$$

Here in equation 4.1, I_i^* describes a binary indicator variable that equals 1 if the *i*th farmer adopts adaptation strategies and 0 if he does not, Z is a vector of exogenous variables represented by demographic factors, plot characteristics (size, land tenure…), institutional services access, resources etc. The ρ is a vector of parameters to be estimated and ε_i an error term assumed to be normally distributed with a mean of zero. It includes factors unknown or unobserved but known by the farmer himself.

The farmer's utility I_i^* to choose adoption of adaptation strategy is not observable, but the decision I_i to choose adoption of adaptation or not is observable and represented as above. An ith farmer will choose to adopt a strategy against salinity instead of not if it provides great expected utility considering at the same time other factors in Z vector.

A probit model is used to estimate the equation (4.1). The probability for farmer *i,* with characteristics Z, to choose to adopt or not can be represented as (Zheng et al., 2021):

$$P(I_i = 1) = P(I_i^* > 0) = P(\epsilon_i > -\rho Z_i) = 1 - F(-\rho Z_i) \qquad \textbf{(4.2)}$$

Here, the F as described by Zheng et al. (2021) is the cumulative distribution function for ϵ_i. A full information maximum likelihood (FIML) is used to estimate the latent variables with STATA version 15 (Quan et al., 2019).

4.2.2 Impact evaluation using the endogenous switching regression (ESR)

Since unobservable characteristics of farmers, like skills, may affect both adoptions of adaptation and outcome yields, then the adoption of adaptation to salinity is assumed to be potentially endogenous (Birthal et al., 2022; Naghi et al., 2022; Sedebo et al., 2022; Zegeye and Meshesha, 2022). Thus, to bypass this matter, an endogenous switching regression estimation can be used to estimate the effect of adaptation to salinity on the different outcomes by a full information maximum likelihood (FIML) (Di Falco et al., 2011). The FIML estimates both the adoption and the outcomes equations jointly, in other words, the probit criterion and the regression equation to yield. It is an econometric technique that uses a maximum likelihood to simultaneously estimate the parameters of a system of equation models (Mokatrin, 2011).

The ESR model has two significant benefits over other approaches: (1) it can adjust for selection bias caused by both observed and unobserved factors, overcoming the limitation of PSM and IPWRA methods; and (2) it helps to identify factors that impact yields and food security for adopters and non-adopters, overcoming the problem of the TE (Zheng et al., 2021).

Selection instruments shall be used as exclusion restrictions for identifying the model. The selection instruments must directly affect the adoption of adaptation strategies, which is the selection variable, but not the outcome variables(Quan et al., 2019; Di Falco et al., 2011). Then in this case study, the instrumental variables must affect the adoption decision and not the outcomes that are yields and food security. Then in this study, the variable "Village influence and Social influence" which mostly respect the properties, according to understanding from the field, will be used as an instrument.

This part outlines the impact of adoption of adaptation on yield and food security. We follow Zheng et al. (2021) and Kassie et al. (2015) to define the method used to analyze adoption's impact on yield and food security. Following these studies, a production function Y_{ij} represented by the relationship between the yields and food security (Y) and a different set of exogenous variables (both continuous and binary) with vector Z as defined below is defined and estimated. The non-adoption option is denoted as $I = 0$, and the adoption option as $I = 1$. Thus, the production function to evaluate yield and food security implication of adaptation used is given as:

Regime1: $Y_{1i} = \rho_1 Z_{1i} + \gamma_{1i} \quad if\ I = 1$ **(4.3)**

Regime 0: $Y_{0i} = \rho_0 Z_{0i} + \gamma_{0i} \quad if\ I = 0$ **(4.4)**

Y_{1i} and Y_{0i} are outcome variables that represent the farmers' yields and food security variables for each option, respectively Z_{1i} and Z_{0i} are vectors of exogenous variables when ρ_1 and ρ_2 are parameters to be estimated and, γ_{1i} and γ_{0i} refer to the error terms that define the uncertainty faced by farmers, and it satisfied Esperance (γ) = 0 (normality). In this study, there are observable factors captured by the variable Z in equations (4.3) and (4.4) but also unobservable factors that may contain useful information and may create a bias. Heckman (1979) proposed a solution in two steps to cope with this selection bias. Firstly, a probit regression (4.1) is used to model the selection process and adaptation in this case, and a new variable called the Inverse Mills Ratio is calculated based on the probit regression. Secondly, this Inverse Mills Ration is added to the regression analysis (3) and (4) as an independent estimator variable (Mokatrin, 2011). The study of Kassie et al. (2015) shows that a consistent estimation of ρ necessitates the inclusion of the selection correction terms of the alternative choices in equations (4.3) and (4.4), and it can be obtained by estimating the following ESR model, equations 4.5 and 4.6.

Regime1: $Y_{1i} = \rho_1 Z_{1i} + \mu\beta_{1i} + \alpha_{1i} \quad if\ I = 1$ Adopters **(4.5)**

Regime 0: $Y_{0i} = \rho_0 Z_{0i} + \mu\beta_{0i} + \alpha_{0i} \quad if\ I = 0$ Non-adopters **(4.6)**

Here, α is the error term with a conditional mean of zero, μ is the covariance between ε_i and γ , and β is the Inverse Mill Ratio used to capture selection bias arising from unobservable variables, computed after estimating equation 4.1 and include them in equations (4.3) and (4.4) and rewrite them as equations (4.5) and (4.6) (Bourguignon et al., 2007).

4.3 Estimation of the counterfactual and treatment effect

Estimations allow an understanding of factors that may affect farmers' adoption of adaptation and, at the same time, the influence of these adoption of adaptations on outcomes, yields, and food security. An endogenous switching model regression can be used to calculate the counterfactual and estimate the effect of adoption of adaptation on the outcomes (Zheng et al., 2021; Kassie et al., 2015; Teklewold et al., 2013). Following literature review (Birthal et al., 2022; Sedebo et al., 2022; Kassie et al., 2015; Teklewold et al., 2013), an ESR is used to estimate the counterfactual and average treatment effect (ATT), which is the treatment effect of adoption on the outcomes and which is computed by the difference of outcomes for the treated equation (4.7) and its counterfactual defined by equation (4.9) below. The counterfactual is defined as the outcomes that a treated individual should obtain if he chooses not to adopt instead of adopting and the outcome that would be obtained by an individual who does not adopt if he would have chosen to adopt (instead of not). These scenarios can be defined with the equations below derived from equations (4.5) and (4.6):

Adopters with the actual situation (adopting case):

$$E[Y_{i1}|I = 1] = \rho_1 Z_{i1} + \mu_1 \beta_{i1} \qquad \textbf{(4.7)}$$

Non-adopters with the actual situation (No adopting any strategy):

$$E[Y_{i0}|I = 0] = \rho_0 Z_{i0} + \mu_0 \beta_{i0} \qquad \textbf{(4.8)}$$

Adopters in case they had decided to not adopt (Counterfactual case):

$$E[Y_{i0}|I = 1] = \rho_0 Z_{i1} + \mu_0 \beta_{i1} \quad \textbf{(4.9)}$$

Non-adopters in case they decided to adopt (Counterfactual case)

$$E\left[Y_{ij1}\middle|I = 0\right] = \rho_1 Z_{i0} + \mu_1 \beta_{i0} \quad \textbf{(4.10)}$$

Following studies as cited above, the ATT can be derived by computing the differences between equations (4.7) and (4.9). For this case, it is giving:

$$ATT = E[Y_{i1}|I = 1] - E[Y_{i0}|I = 1] = (\rho_1 Z_{i1} + \mu_1 \beta_{i1}) - (\rho_0 Z_{i1} + \mu_0 \beta_{i1}) =$$

$$Z_{i1}(\rho_1 - \rho_0) + \beta_{i1}(\mu_1 - \mu_0) \quad \textbf{(4.11)}$$

The endogenous switching regression is used for the comparison of the expected yields and also food security in case the farmers adopt a strategy against salinity (4.7) concerning non-adopters (4.8) and to investigate the expected yields and food security in the counterfactual situation (4.9) that the adopters do not and (4.10) that the non-adopters adopt. These measures are important to provide possible responses to change adaptation responses to salinity in case of need.

Equations (4.7) and (4.9) are the observed expected outputs and (4.8) and (4.10) are the counterfactuals expected outputs. ATT is the effect of treatment on the treated, and ATU is the effect on the untreated. ATT represents the effect of adoption of adaptation to salinity on groundnut yields and food security of farmers that decide to adopt, and ATU is the effect of the treatment on the untreated defined by farmers that are not adopting adaptation.

4.3.1 Data description

The same data collection method used in Chapter 3 was used in this section. Data were collected between May and June 2021 from a farm household survey in the rural area named Fimela. This area is located in a zone called Sine Saloum, which is identified as one of the main regions in Senegal that are facing many troubles due to increased soil salinity caused by the rise of the sea level. All 16 villages in the Fimela commune were considered, from higher salt-affected villages to the lower salt-affected ones. The number of farm households to be surveyed was determined by calculating the ratio between the number of households in each village and the determined sample size, see Chapter3.

A structured questionnaire was used to obtain information about demographics, farm characteristics, perception level about climate change, salinity level, incomes, yields, and food security level. For food security, nine questions were defined based on the HFIAS (Household Food Insecurity Access Scale). To pretest the questionnaire, an exploratory survey on 14 farmers and two days of a focus group was conducted. The focus group discussions (FGD) were conducted with the assistance of IPAR (Initiative Prospective Agricole et Rurales), where 24 farmers (composed of male and female) were present over two days. The survey was performed through face-to-face interviews from March to May 2021, and households were chosen randomly. The number of interviewees in each village was proportional to their households' numbers.

4.3.2. Measurements of treatment and outcome variables

The treatment variable refers to the farmer's adoption of adaptation strategies, represented by a binary variable equal to 1 if the farmer adopts an adaptation strategy in response to soil salinity during the 2020 production year and 0 otherwise.

The outcome variables in this study refer to groundnut and millet yields and household food security. The variable *yield* is represented by groundnut and millet production, the main crops cultivated for cash income and food consumption in Fimela. Yields refer to groundnut and millet yields per hectare for each farm household production. In this case study, the yield value is derived from a field investigation in which farmers were questioned about the number of bags they had during the relevant season and converted to kilograms. The groundnut and millet yields (kg/Ha) were derived by dividing the output in kilograms (Kg) by farm size in hectares (Ha) measured with GPS.

The food security indicator employed in this study refers to the household food security status (FSS) derived from the Household Food Insecurity Access Scale (HFIAS) that focuses on the access point. The score is computed by summing the different scores for each household from the nine questions on the Household Food Insecurity Access Scale (Desiere et al., 2015; Gebreyesus et al., 2015). The FSS is defined by 1 (score-household = (0 to 4) if the household is food secure and 0 (score-household = (5 to 27) if the household is insecure (Diallo et al., 2020). The independent variables examined in the ESR model (see **Table 4.1**) have been identified based on relevant studies (Zheng et al., 2021a, 2021b; Diallo et al., 2020; Kassie et al., 2015; Wang et al., 2013; Di Falco et al., 2011).

4.4 Results and discussion

4.4.1 Descriptive results

The household and farm characteristics of the sampled farmers are shown in **Table 4.1**. The interviewed farmers were classified into treatment (those who adopt adaptation against soil salinity effects) compared to the non-adopters group.

Adopters and non-adopters are similar according to age, education, and the number of household members. Nevertheless, they have significant mean differences across some independent variables; adopters are likelier to have higher groundnut yields and more household assets than non-adopters. However, food security scores and millet yields are lower. The summary results also show adopters have more social and village apprehension on adoption of adaptation strategy than non-adopters. But, since the confounding factors should be controlled, these results cannot be used for inference regarding the impact of adopting an adaptation strategy on farmers' outcomes. Therefore, the endogenous switching regression will be applied in this study for more reliable results.

Table 4.1: Structural relations of psychological factors and perceived behavioural in soil salinity context

Variable	Definitions	Adapters (N=217) Mean (SD)	Non-Adapters (N=71) Mean (SD)
Dependent variables			
Food security	Household food insecurity access scale ranging from 0 to 27	6.19 (3.97)	5.17 (3.94)
Groundnut Yield	Yield of groundnut in kg/ha	1273.02 (1016.63)	974.46 (860.58)
Millet Yield	Yield of millet in kg/ha	475.09 (460.44)	401.69 (487.12)
Independent variables			
Age	Age of respondent in years	54.41 (12.36)	54.1 (14.01)
Education	Number of years of formal education	5.1 (3.88)	4.89 (3.29)
Sex	Dummy variable equals 1 if household head is a male and 0 otherwise	0.88 (0.32)	0.93 (0.26)
Household size	Number of people in the household	11.7 (5.87)	12.49 (6.01)
Groundnut size farm	Size of groundnut farm in acres	1.44 (0.8)	1.6 (0.94)
Millet size farm	Size of millet farm in acres	1.44 (0.73)	1.59 (1.09)
Credit access	Dummy variables equal 1 if household head has access to credit and 0 otherwise	0.17 (0.38)	0.23 (0.42)
Extension services	Dummy variables equal 1 if household head has an access to	0.31 (0.46)	0.28 (0.45)

	extension services and 0 otherwise		
Family-labor	Dummy variables equal 1 if farmer uses family labor and 0 otherwise	0.97 (0.18)	0.93 (0.26)
Paid-labor	Dummy variables equal 1 if farmer uses paid labor and 0 otherwise	0.26 (0.44)	0.34 (0.48)
FBO-member	Dummy variables equal 1 if household head is a member of FBO and 0 otherwise	0.13 (0.34)	0.13 (0.34)
Salt-affected	Dummy variables equal 1 if farmers perceive salinity affects crop outcomes and 0 otherwise	0.62 (0.49)	0.59 (0.5)
Household total assets	Total value of household asset in thousands of CFA	1347.36 (2165.81)	825.15 (876.92)
Instrumental variables			
Village influence	Dummy variables equal 1 if villages surround is doing same adaptation and 0 otherwise	0.84 (0.37)	0.11 (0.32)
Social influence	Dummy variables equal 1 if relatives and neighbors are adopting same adaptation and 0 otherwise	0.81 (0.4)	0.08 (0.28)

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Source: Author' s Own Computation from Field Survey, 2021

Table 4.2 examines farmers' food security through an analysis of the HFIAS. The descriptive analysis shows that 59.03% of the respondents are food insecure in the study area meaning that their members are living in hunger or fearing hunger. 40.97% are food secure meaning that those households have constant physical and economic access to enough food to satisfy their dietary needs for a fruitful and healthy existence (FAO,1983).

Table 4.2: Food security status distribution

Food Security Status	Percentage distribution
Food secure	40.97
Food insecure	59.03
Total	100

Source: Author' s own Computation from Field Survey, 2021

Most households are food insecure, particularly slightly food insecure **Figure 4.1**. Among the food insecure households, 23% are extremely severe food insecure, with their score of food security ranging from 11 to 27, as shown in **Figure 4.1**. The household food insecurity access score was defined by adding the scores obtained from 9 specific questions about food security. This gave a range of different household food insecurity access prevalence: slightly food insecure, moderately food insecure, and extremely severe food insecure. **Figure 4.1** describes the food insecurity prevalence (FSP) in all insecure households in the surveys for adopters and non-adopters. In this case, the varying between the two groups is unimportant, particularly concerning the slight food insecurity class. A slight difference is shown between the moderately and the extremely insecure classes. Non-adopters are more often in extreme food insecurity than adopters in this case. But in general, the FSP shows that most of the food insecure households are in a situation of slight food insecurity (5-7) rather than extreme food insecurity (11-27).

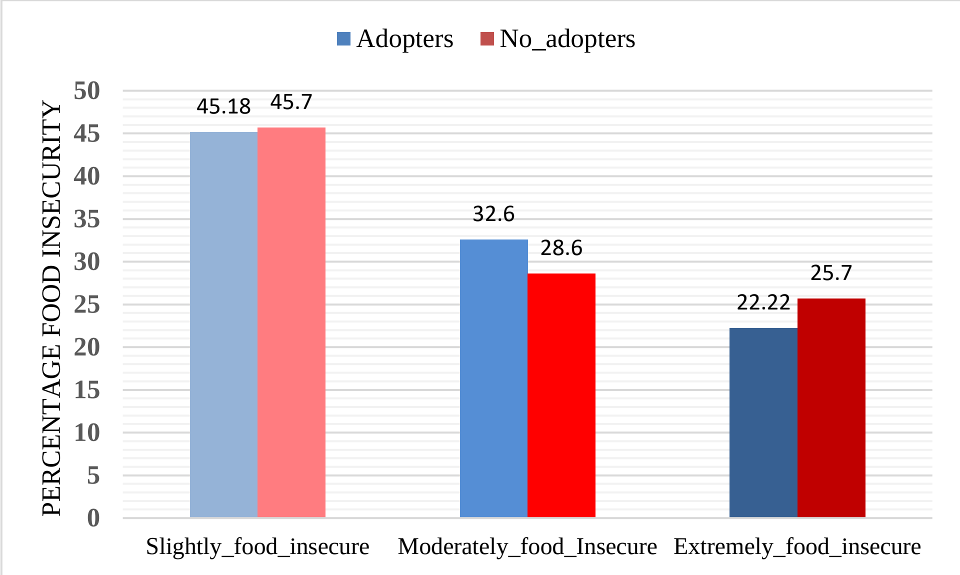


Figure 4.1: Categorization of households for adopters and non-adopters based on their food insecurity status. Source: Author' s own Computation from Field Survey, 2021

Table 4.3: Distribution of mains salinity's adaptation strategies (under climate change) by household food security status

		Food insecure	Food secures	Total
Currently engaged in adaptation practices	No	29	35	64
	Yes	141	83	224
Total		170	118	288

*1=food secure (0-4); 0=food insecure (0=5-27). Source: Author' s own Computation from Field Survey, 2021

The results in **Table 4.3** display that those farmers who are currently engaged in adaptation strategies are mostly in food insecurity situations than in food security conditions. The inverse is displayed for farmers who are not engaged in adaptation practices.

4.4.2 Analytical results of adaptation's impact on yields (Millet and groundnut) and food security: Empirical Results

The empirical results are presented in two parts: the estimates from the selection equation, which analyzes the factors influencing the use of adoption or not of strategies to cope with soil salinity, and the outcome equation, which analyses the factors influencing farmers' outcomes (groundnut and millet yield, food security). The results that estimate the determinants of adoption and its impact on groundnuts are presented in **Table 4.4**. The outcomes and the adoption equations jointly are estimated by the full information maximum likelihood as presented in the methodology for each outcome. The selection equation represents the results regarding the determinants of the adoption in **Table 4.4, 4.5** and **Table 4.6,** and the determinants of each outcome are represented in the third and fourth columns of the same tables. Thus, the coefficients in the selection equation in both tables can be interpreted as a probit regression. Since the identification of the model requires the existence of an instrumental variable that appears in the selection equation and not in the outcome equations (Jaleta et al., 2015; Kassie et al., 2015), in our case, from the field, the village influence and social influence are used as indicated above. Therefore, village influence and social influence are expected to affect the adoption and not the outcomes, yields, and food insecurity directly.

4.4.2.1 Determinants of adoption of adaptation strategies in response to soil salinity

For the selection part that represents the adaptation (**Table 4.4** and **Table 4.5**), the variable representing the total household assets of the farmer is positive and significantly different from zero concerning the groundnut and millet outcomes. It suggests that farmers with more household assets (finance and agricultural materials) are more expected to adopt adaptation strategies against salinity than the inverse. This can be explained by the fact that those farmers can afford the materials and adaptation needs more than those who struggle to obtain resources.

Huang et al. (2015) and Wang et al. (2014) have yielded similar results by demonstrating that household and community assets significantly influence farmers' adaptation behaviours to cope with drought in China. The village influence and social influence are also positive and statistically different from zero in both selection equations, indicating that farmers are more likely to adopt or copy adaptation when their neighbors, parents, or the side villages are adopting adaptation measures against salinity. These findings support the importance of learning from others in adopting adaptation strategies in response to soil salinity and are consistent with the findings of Tran et al. (2019) and the study of Ensor and Harvey (2015), who state and develop that innovative knowledge is made through formal or informal communication with neighbors, relatives, or friends' networks in adaptation to salinity and flood risk in Vietnam. Concerning **Table 4.6**, the size of the millet farm is also statistically significant and negative, implying that the smaller the millet farm, the more likely the farmer will adopt adaptation strategies in response to soil salinity. This result is opposite to the conclusion of Marie et al. (2020), which stipulates that producers with large farm sizes are more likely to adopt adaptation against climate change in Ethiopia. However, it is consistent with the findings of Abunga-Akudugu et al. (2012), who observed that farm size has a positive relationship with farmers' adoption of modern technology. The result of this study can be attributed to the fact that millet is the main food consumed in a rural area like Fimela. So, for food security, farmers with small shares of millet production are pushed to adopt adaptation when they are affected or threatened by soil salinity expansion to ensure food security. Thus, a farmer affected by salinity due to climate change will be more motivated to adopt adaptation measures to survive than those with more space for cultivation.

4.4.2.2 Determinant of outcomes variables (Groundnut and millet yield, food security)

The estimation shows that household size has a significant and positive impact on farmers' yields of groundnut and millet, both for adopters and non-adopters as found by Adebayo et al. (2018). The results in **Table 4.4** and **Table 4.5Error! Reference source not found.** show that farm size is important in explaining groundnut yield for adopters and millet yield for adopters and non-adopters. Their coefficients are negative and significant for adopters and non-adopters for millet and adopters for groundnut. This indicates that small farms obtain more yields than large farms because input requirements are easily covered for small sizes compared to large sizes. The result is supported by the inverse farm size-productivity relationship (Debrah and Adanu, 2022; Ricciardi et al., 2021; Abdulai and Huffman, 2014) but is opposite to Aragón et al. (2022) arguments on the existence of a significant relationship between yield and farm size. In that case, the smaller the farm size, the more the farmer produces a higher yield for non-adopter with millet.

Table 4.4: ESR results of adoption of adaptation strategies in response to soil salinity and its impact on groundnut yield

VARIABLES	Adaptation	Groundnut yield for adopters	Groundnut yield for non-adopters
Independent variables			
Age	0.110 (0.082)	5.843(40.20)	12.641(48.884)
age2	-0.0009(0.00071)	-0.017(0.357)	-0.031(0.433)
Education	0.035(0.0415)	10.399(17.005)	18.99(32.95)
Sex	-0.554(0.560)	91.029(260.433)	556.998*(334.257)
Household size	-0.033(0.024)	29.947***(11.319)	52.395***(17.541)
Farm size	0.045(0.166)	-466.103***(83.47)	-112.891 (102.552)
Credit access	-0.468(0.378)	371.717 **(178.046)	128.17(263.07)
Extension services	0.053(0.320)	8.819(146.645)	-124.454(219.808)
Household total assets	0.31213**(0.161)	252.182***(68.474)	188.982(121.154)
Family labor	0.088(0.643)	407.99(387.349)	861.902**(404.878)
Paid labor	-0.189(0.351)	144.6(155.074)	757.514***(247.687)
FBO member	-0.234 (0.424)	334.449*(197.606)	-462.803(337.242)
Affected by salt	-0.395(0.300)	-6.746 (137.140)	-540.37***(188.673)
Instrumental variables			
Village influence	1.976***(0.310)		
Social influence	1.572***(0.313)		
Constant	-7.015(3.236) **	504.3(1,228)	-1,962(1,510)
lnsig_1		6.790***(0.053)	
lnsig_2			6.473***(0.095)
Rho1		-0.442**(0.200)	
Rho2			-0.275(0.260)
LR chi2(41)	248.59***		
Log Likelihood	-2085.941		
Observation	250	193	57

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Source: Author' s own Computation from Field Survey, 2021

Farmers' education and age do not significantly impact groundnut and millet yield and adoption of adaptation strategies against salinity in the study area. This finding may be explained by Schultz (1975), Rosenzweig (1995)'s results, as cited by Reimers and Klasen (2013). They claimed that in very traditional agricultural settings where assignments are typically relatively simple, the returns to education should be lower compared to developed countries facing rapid technological change, like in rural Africa, such as Fimela. Variables indicating farmers' access to credit and participation in farmers' organizations have positive and statistically significant coefficients for the adopter group and not for the non-adopters group. It suggests that farmers with access to credit and those participating in farmers' organizations tend to have higher groundnut yields in the adopter group. In contrast, it has no significant effect on yield for non-adopters, although the effect on millet yield is not significant. These results coincide with the findings of Mwaura (2014), who demonstrates that farmers' organizations' results in increasing yield may be significant or not depending on the speculation, but also of Missiame et al. (2021), who demonstrate that access to credit improves the technical efficiency of cassava farmers in Ghana.

Table 4.5:ESR results of adoption of adaptation strategies in response to soil salinity and its impact on millet's yield

VARIABLES	Adaptation	Millet yield adopters	Millet yield non-adopters
Independent variables			
Age	0.070(0.076)	28.203(17.94)	-7.036(38.25)
age2	-0.0006(0.0006)	-0.232(0.160)	0.073(0.354)
Education	0.023(0.040)	1.829(7.668)	-18.77(20.456)
Sex	-0.632(0.502)	158.854**(101.302)	-238.387(220.680)
Household size	-0.015(0.023)	12.95***(5.056)	4.170(11.09)
Farm size	-0.103(0.155)	-216.88***(40.34)	-179***(66.756)
Credit access	-0.170(0.336)	-28.258(78.554)	-220.363(153.163)
Extension service	0.119(0.295)	60.335(65.776)	133.974(135.515)
Household total assets	0.295** (0.134)	80.225***(29.161)	86.269(63.745)
Family labor	-0.204(0.646)	280.920(176.407)	285.715(281.572)
Paid labor	-0.345(0.308)	93.86(67.720)	155.456(147.481)
FBO member	-0.130(0.377)	72.121(89.858)	-50.358(184.96)
Affected by salt	-0.462(0.288)	-117.618**(60.505)	7.568(121.541)
Instrumental variables			
Village influence	1.915***(0.294)		
Social influence	1.469***(0.284)		
Constant	-5.374** (2.813)	-727.7(538.0)	439.2(1,077)
lnsig_1		6.003***(0.049)	
lnsig_2			6.072***(0.087)
Rho1	0.078(0.212)		
Rho2		0.063(0.199)	
Log Likelihood	-2056.794		
LR chi (41)	243.07***		
Observations	268	202	66

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Source: Author's own Computation from Field Survey, 2021

Farmers' household total asset variable tends to significantly and positively affect yield for the adopters' group for groundnut and millet crops. In other words, farmers with many assets (finance and materials) are likelier to get more groundnut and millet yields. This can be because a household with more assets can mostly pay for agricultural inputs such as fertilizer, machines, and others than those with fewer assets, as explained by Abdulai and Huffman (2014). On the other hand, the variable gender is positive and statistically significant for non-adopters with groundnut yield but positive and significant only for adopters concerning the millet crop. This means that gender is positively impacting millet yield and slightly on groundnut yield, meaning there is a difference in productivity between male and female farmers. This may be explained by Chon (2020)'s study in Kenya, which stipulate that gender influences the traditional food crop finger millet in rural Kenya. Most men in rural areas have migrated to cities for work, and women have become more prevalent in food crop production, such as millet for family consumption (Devkota et al., 2016). The findings in **Table 4.4** also reveal that the family and paid labor may significantly explain the outcome difference obtained. In particular, farmers who employ more or most family and paid labor have mostly higher yields than those who do less, as seen in the non-adopter group for groundnut crops and as demonstrated by Dutta et al. (2020) for maize yields. And as expected, the variable that represents the soil affectation by salt is negative and statistically significant. This means that farms with less soil salinity problem mostly have more yields than those more affected in the study area, for the non-adopter's group with groundnut crops and adopter group with millet crops.

For food security, the result in **Table 4.6** shows a significant and positive coefficient for total household assets; the more assets a household has, the more food secure it is. This result is confirmed by Guo (2011), who stipulated that when income is controlled for, household assets have an additional impact on food security status, and by Abdullah et al. (2019), who revealed that both physical and non-physical assets are crucial for assessing a household's food security status. For the labor variable, the ESR shows that the non-adopter's group is more food secure when they need less paid labor for their farms' activities. Adopters exhibit higher food security as expected when less threatened by salinity expansion in their farm activities. The results for the adopters' group in extension services contradict many studies, including the one of Maponya and Mpandeli (2013). It is significant but negative, demonstrating that farmers without access to extension services are more food secure. This could be explained by the fact that most farmers claim not to have access to extension services in their areas for various of reasons.

Table 4.6: ESR results of adoption of adaptation strategies in response to soil salinity and its impact on millet's yield

VARIABLES	Adaptation	Food Security adopters	Food security of non-adopters
Age	0.125(0.081)	0.132(0.168)	-0.442(0.308)
age2	-0.0009(0.007)	-0.001(0.0015)	0.003(0.003)
Education	-0.043(0.044)	-0.041(0.074)	-0.098(0.173)
Sex	-0.399(0.544)	-0.240(1.084)	0.516(1.720)
Household size	-0.025(0.022)	-0.022(0.048)	0.034(0.098)
Size millet farm	-0.374**(0.180)	-0.355(0.411)	0.991(0.660)
Size groundnut farm	0.182(0.198)	0.126(0.394)	-0.666(0.653)
Credit access	-0.433(0.355)	-0.929(0.747)	1.103(1.395)
Extension service	0.117(0.309)	-1.934***(0.628)	1.345(1.186)
Household total asset	0.197(0.154)	0.515*(0.300)	0.439(0.629)
Family labor	0.188(0.622)	2.427(1.598)	-0.640(2.319)
Paid labor	0.823(0.325)	-0.271(0.660)	-3.118**(1.32)
FBO member	-0.389(0.401)	-0.059(0.824)	1.314(1.716)
Affected by salt	-0.153(0.299)	-1.323**(0.581)	-0.702(0.977)
Instrumental variables			
Village influence	1.352***(0.396)		
Social influence	2.067***(0.319)		
Constant	-6.653**(0.280)	2.699(5.083)	12.73(11.887)
lnsig_1		1.322***(0.056)	
lnsig_2			1.191***(0.097)
Rho1		-0.775***(0.174)	
Rho2			-0.219(0.267)
Log likelihood	-688.37		
LR chi (44)	200.41		
Observations	238	184	54

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Source: Author' s own Computation from Field Survey, 2021.

Table 4.7: ESR results of adoption of adaptation strategies in response to soil salinity and its impact on millet's yield

Outcome variables	Farm household and treatment effect	Means Outcome		Average treatment effect
		Adopters	Nonadopters	
Groundnut yields (kg/ha)	ATT (Adopters)	1277.33	827	450.4(42.41) ***
	ATU(Non-adopters)	1424.8	971.7	453.1 (78.74) ***
Millet yields (kg/ha)	ATT	479.757	481.173	-1.416 (14.162)
	ATU	420.512	401.452	19.060 (24.897)
Food insecurity	ATT	6.023	4.633	1.390 (0.214) ***
	ATU	7.923	5.001	2.924 (0.388) ***

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Source: Author' s own Computation from Field Survey, 2021

The estimates for the average treatment effects (ATT) are presented in **Table 4.7**. The ATT, as described above, shows the impact of adopting adaptation strategies on the different outcomes yield for millet and groundnut and food insecurity. The ATT considers the selection bias from the fact that adopters and non-adopters may be systematically different (Abdulai and Huffman, 2014). The results reveal that farmers' adoption of adaptation strategies in the saline condition is increasing farmers' groundnut yield significantly but does not have a significant effect on farmers' millet yield. This causal effect is about 450.4 kg/ha of increase for the groundnut crop. The type of adaptation strategies can explain the insignificant effect on millet yield. The main adaptation strategy in the area is "increasing the use of fertilizer" used by 75% of farmers. This, at a certain level, differently from groundnut crop, can have a negative effect on soil fertility and productivity. So, even if farmers believe this adaptation is effective in dealing with salinity, the effect is negative or insignificant. Excess fertilizer causes excessive fertilizer accumulation in the ground, which degrades water quality and changes the soil by increasing salt concentration, which can harm beneficial soil microorganisms (Bisht and Chauhan, 2020). As a result, it is critical not to exceed these limits by over-fertilizing the land. Guan et al. (2022) and Ahmad et al. (2020) show that fertilizer application that is irrational and excessive may have a negative impact on foxtail millet yield.

Furthermore, within this adaptation, many farmers stipulate that they use daily domestic waste as fertilizers in their farms to cope with soil salinity. This approach ignores that some elements in household waste, such as plastic, harm the soil. These waste plastics' consequences may threaten soil health and food security (Meng et al., 2020). Plastic waste poses significant threats to wildlife by choking, starving, transferring, and releasing chemicals into ecosystems (Steinmetz et al., 2016). The difference in results between groundnut and millet can be attributed to the fact that groundnut requires more fertilizer than millet (Steinmetz et al., 2016), so a fertilizer increase may be more supported by groundnut crops.

For food security, those who adopt adaptation strategies are more food secure in case they don't adopt than in case they adopt. This means that the type of adaptation used to cope with salinity in the study area is ineffective. This result can be explained in correlation with the impact of this adaptation type on millet yields. The main food consumed in a rural area in Senegal, as Fimela, is millet, so any effect on this crop may directly or indirectly affect farmers' food security.

Estimation results for the average treatment effect on the untreated, as presented in **Table 4.7**, are confirmed by its ATT results for groundnut yield. It displays that adopting adaptation strategies has a positive result on groundnut yield. Then, farmers who do not adapt to soil salinity could gain a surplus of 453.1 kg/ha if they adopted adaptation strategies against soil salinity expansion. The same analyses can be done for food security. Farmers who have not adopted adaptation strategies to cope with soil salinity could be in a food insecurity situation if they adopted adaptation to cope. The impact on millet yield in the ATU case is not significant too, so it can't be interpreted in this case.

4.5 Conclusion and policy recommendations

This chapter helps to examine the various socioeconomic factors that may influence farmers' adoption of adaptation strategies against soil salinity and the impact of these adoptions on farmers' groundnut and millet yield and household food security in Fimela, Senegal. An endogenous switching regression approach has been used to conduct the analysis.

The results show that farmers' adoption of adaptation strategies in response to soil salinity impacts yields, in this case, depending on crop type. The impact of farmers' adoption of adaptation strategies in response to soil salinity on groundnut yield and food insecurity in the study area is positive and has no significant effect on millet yield. The non-significant impact of adaptation on the millet yield can be attributed to the type of adaptation that could not be more efficient above a certain level. This absence of significant impact on millet yield indirectly influences food security in the same way since, as stipulated above, the primary food consumption in a rural area such as Fimela in Senegal is millet. The results also show that farmers' decision to adopt depends on their farms' millet size, total household assets, and the village and social influence around them.

This study's results suggest that it could be essential or even practical for government or NGO to put in place policies that may improve household capital and community network to facilitate farmers' adaptation behaviour. It also suggests a need to review farmers' adaptation strategies to cope with salinity in Fimela since an insignificant effect has been particularly found on millet yield and indirectly negative impact on households' food security. It becomes important to develop good coping strategies with researchers, different from the existing farmers' strategies, and look for a fluent channel that may help to impose it on farmers in a situation of salinity threat area. Since the “village and social influence” influence farmers' adoption of adaptation, it can be interesting to target a group of farmers for different and efficient strategies, hoping that the good and better results will influence other farmers to adopt more efficient strategies than what they previously thought was efficient. This policy must be accompanied by providing or helping farmers to acquire more needed materials in the sense of coping against the expansion of salinity in their area since this variable positively influences farmers' adaptation.

CHAPTER FIVE

5. SIMULATION OF AGRICULTURAL LAND USE ADAPTATION IN RESPONSE TO SOIL SALINITY PERCEPTION: LUDAS MODEL

5.1 Introduction

Analyses of climate change impact, such as soil salinity expansion on agricultural land use, involve understanding complex systems approach with human and environmental dynamics. This interrelationship between climate change and its impacts is addressed in many studies using a Multi-agent System (MAS) (Matthews et al., 2007; Robinson et al., 2007). One of the main instruments of this approach is the agent-based model (ABM) used to provide the information needed to understand the interrelation between environmental and societal problems (Amadou et al., 2018). ABM consists of representing a number of human agents that interact among themselves and with their environment. The environment is represented by landscape agents as land components hosting natural processes such as crop/forest evolution which can alter in response to human intervention (Le et al., 2012). As a result of this change, human agents make a decision that affects the socio-ecological environment, resulting in multiple and variable feedback loops among and within sub-systems on various scales (Le et al., 2012).

When analyzing human decision-making, simple regression analysis tools do not consider the aspect of land use/land cover change, i.e., the environmental system. Then ABM contributes to addressing this issue by simulating the human-environment system's influence when analyzing human decision-making's impact on its outcomes in the present and future (prediction) (Schreinemachers and Berger, 2011).

As a result, an increasing number of ABM has been developed in recent years for assessing farmers' decision-making in terms of environmental challenges, particularly in the simulation of climate change adaptation (Badmos et al., 2015; Berger and Troost, 2014) in modeling natural, social, and engineered complex systems (Chen et al., 2016; Wilensky and Rand, 2015). ABM also analyzes ecological economics research questions such as natural resource management, market dynamics, urban system modeling, technology and management practice, innovation and diffusion, and psychological aspects of human decision-making and behaviour change (Heckbert et al., 2010). Wens et al. (2019) also used an ABM for integrating the dynamics of human behaviour into drought risk assessment, while Berger and Troost (2014) used it to assess how policies affect farmers' responses to climate change in agriculture.

To avoid misguided adaptation efforts, using ABM to implement farmers' adaptation decision-making based on their perception of a threat is critical and should be considered (Hyun et al., 2019; Zafar et al., 2016). Most adaptation and behaviour modeling exercises do not consider community knowledge for predicting future decision-making and land use change under climate change effects, particularly soil salinity expansion. For this reason, this study is concentrated on exploring the implication of community knowledge of soil salinity on their outcomes in the specific context of the saline area, Fimela. This chapter focuses on incorporating community knowledge, through farmers' perceptions of soil salinity expansion, into their adaptation decision-making process to assess the impact on yields. In this case, the Land Use Dynamic Simulator (LUDAS) is used to explore or investigate the implications of knowledge of farmers when making decisions. In the end, the model should allow us to capture and understand the implication of soil salinity perception on agricultural crop production through farmers' adaptations in the research area.

5.2 Materials and methods

The multi-agent system (MAS), particularly the LUDAS model as described in this chapter, is used to assess the level of understanding of farmers on the expansion of soil salinity over their croplands and its impact on their millet and groundnut yields by considering the human-environment system. This specific study follows the studies of Amadou (2015) and Le et al. (2012), which respectively use the Sky-LUDAS and LUDAS models to simulate respectively agricultural land use adaptation under climate change in Ghana and model the land use decision in an agent-based model.

5.2.1 Multi-agent system (MAS)

The MAS model is an agent-based system that many studies have used for modeling complex dynamic systems such as human-landscape systems. In natural resource management and farming systems, for instance, it has been used to investigate decision-making processes, land use/land cover trends (Schindler, 2009), and how payment for ecosystem services affects the interactions and trade-offs between ecosystem services (Villamor, 2012). MAS can also be used as an alternative decision-making tool to enhance complex supply chain agility through responsiveness, flexibility, and speed (Giannakis and Louis, 2016). A

MAS is known as a composed of autonomous intelligent agents[6] interacting and cooperating to accomplish common and individual goals (Madureira and Santos, 2005). It is composed of different agents which are virtual autonomous entities able to perform a given task using perceived information from the environment agent and their changes (Ferber, 1997). Many tools, such as mathematical equations, can be used to represent MAS. However, in comparison to the other tools, ABM is a low-resource solution due to its ability to be combined with other modeling methods, its parallel execution capability, which speeds up the modeling process, and its ability to explore emergent behaviour due to agent proactivity (Dorri et al., 2018).

Agents, represented by both individual and collective entities, in MAS should be:

1. Autonomous: they should be able to make their own decision
2. Socially able: should be able to interact and communicate with other agents
3. Reactive: would be able to respond to their environment after perceiving information from it
4. Pro-active: capable of making a decision and adapting their own behaviour for handling heavy and complex tasks
5. Temporally continues: An agent should be able to run processes continuously
6. Mobile: It should be able to move itself from one state to another.

[6] An intelligent agent is a computer programme that can make decisions or provide a service based on its surroundings, user input, and experiences. https://www.techtarget.com/searchenterpriseai/definition/agent-intelligent-agent

5.2.2 Sub-models

5.2.2.1 Modelling farmers’ perception of soil salinity and its causes

1. **Comparison of farmers' perceptions of climate parameters and meteorological data**

Any adaptation measures' success would imply that farmers have the correct perceptions of the threat and its causes (Fierros-González and López-Feldman, 2021). Hence, local knowledge and experience are critical in understanding a threat and its consequences in developing coping strategies to deal with it. In other words, understanding individual households' or communities' perceptions and adaptation strategies in a specific area aid in generating additional information pertinent to policy and initiatives addressing sustainable development challenges in the face of variable and unpredictable environments (Legesse et al., 2013).

Climate change has been demonstrated to positively affect soil salinity expansion in time and space through decreased precipitation and increased temperature (Corwin, 2021; Bannari and Al-ali, 2020). According to some studies, such as (Islam et al., 2021), farmers in saline areas perceived soil salinity as the most serious climate change-related problem, followed by an increase in temperature and erratic rainfall. As a result, farmers' misconceptions about climate parameters like rainfall and temperature may influence their perception of soil salinity expansion in their area. Then, before considering the perception of climate parameters in the regression analysis, the farmers' perception of rainfall and temperature change in this study was compared to meteorological data to assess whether the respondents correctly perceived the changes and their impact. So, to estimate that a respondent accurately perceived the variability and change of climate, the analysis of ANACIM's climate data must concur with the following response of the respondent from the survey: 1) strongly agree and agree about an increase in temperature happening in the last 20 years, 2) Strongly disagree and disagree about a decrease in rainfall' quantity and frequency happening in the last 20 years (Amadou, 2015).

For that, the annual average of each parameter was computed based on those data, used to establish the trend and explore their annual variability within the periods. To establish the tendency and examine inter-annual variability, all of the climate data parameters were standardized.

The annual rainfall anomaly index (RAI) is analyzed by following the formula of Rooy (1965) and adapted by Freitas (2005):

$$RAI = 3\left[\frac{N-\bar{N}}{\bar{M}-\bar{N}}\right] \qquad \textbf{(5.1)} \qquad \text{For positive anomalies}$$

$$RAI = -3\left[\frac{N-\bar{N}}{\bar{X}-\bar{N}}\right] \qquad \textbf{(5.2)} \qquad \text{For negative anomalies}$$

Where N represents the current yearly rainfall in mm, $\bar{N}$ the series' yearly average rainfall (mm), $\bar{M}$ the average of the series' ten greatest yearly precipitation (mm), and $\bar{X}$ the average of the series' ten lowest yearly precipitation (mm).

And for the minimum and maximum temperature, the anomaly indexes are calculated using the following formula:

$$TAI = \frac{T_i-\bar{T}}{\delta} \qquad \textbf{(5.3)}$$

Where T_i is the annual observation of year *i*, $\overline{T}$ is the average temperature, and δ is the standard deviation of the temperature.

2. **Analysis of farmers' perception of soil salinity expansion and its causes**

Further, a binary logistic regression model is employed to identify the variables that may affect farmers' perceptions of climate change (Roco et al., 2015a; Oguz and Assefa, 2014; Basbas et al., 2013; Deressa et al., 2011b) and its effects on soil salinity. The same approach is used in this study to identify variables that may affect farmers' perception of soil salinity expansion. The model characterizing the farmers' perception is specified as:

$$Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \qquad \textbf{(5.4)}$$

Where P_i is the predicted likelihood of farmers' perception code 1 if a farmer perceived the soil salinity expansion as severe and 0 if they do not $(1 - P_i)$. β_0 is the intercept term and β_1 …, β_k are the coefficients for each descriptive variable X_1,…, X_k. The coefficients are estimated using the maximum likelihood method with the SPSS software.

The following **Table 5.1** depicts the different variables that have been used for the binary logistic regression.

Table 5.1: List of variables that may influence farmers' perception on soil salinity expansion

Variables	Description	Data sources	Direct linked
Dependent variables			
Perception of salinity	Perception on soil salinity expansion	Field surveys (2021)	Household population
Independent variables			
h-age	Farm household head's age	Field surveys (2021)	Household population
h-gender	Farm household head's gender	Field surveys (2021)	
h-rainfall quantity in the last 20 years	Perception on quantity of rainfall decrease in the area	Field surveys (2021)	
h-rainfall frequency in the last 20 years	Perception of farmers on frequency of rainfall decrease in the area	Field surveys (2021)	
h-temperature in the last 20 years	Perception on temperature increase in the area	Field surveys (2021)	
h-climate change cause salinity	Do climate change cause salinity increase?	Field surveys (2021)	
Institutional and natural variables			
h-information	Information about climate and salinity expansion	Field surveys (2021)	Household population
P-elevation	Household elevation	GIS based calculations	Patch Landscape

Source: Author's own compilation.

5.2.2.2 Modelling land use adaptation choice

As introduced in the framework above, the adaptation approach, in this case, shows how adaptation as a process is driven by external factors such as farmers' perception of their near environment (temperature, rainfall, sea level rise), but also by a multidimensional urge determinant that may define farmers' choice, **Figure 5.1**. This **Figure 5.1** shows adaptation process from farmers' perception to its impact on farmers outcomes and the environment.

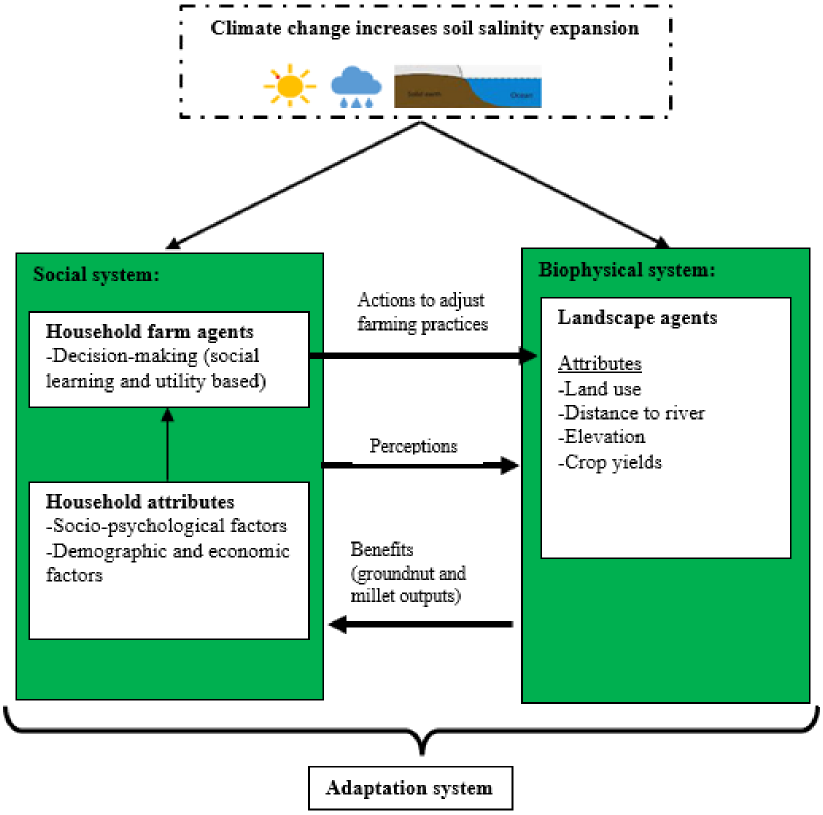


Figure 5.1: Framework of adaptation behaviour system of farmers in saline condition. Source: Adapted from (Villamor et al., 2022).

Knowing that the strategy of humans in making choices is related to preference function, the considered approach in this analysis is the random utility using the multinomial logit (m-logit) model MNL. In this section, the different factors that affect households' adaptation are identified in addition to the psychological factor, as defined in the third chapter. Several studies have used the multinomial model to investigate and describe the factors influencing producers' adaptation and decisions in various situations (Antwi-Agyei et al., 2021; Marie et al., 2020; Fadina and Barjolle, 2018b). In this particular case, the MNL is used to parametrize the decision-making regarding the determinant of adaptation type choice to define the adaptation decision sub-model for this analysis (Thiam, 2019; Amadou, 2015a). The MNL model is described as follows:

$$P(y_i = k) = \frac{exp\ (X_i\theta_k)}{1+\sum_{j=1}^{j} exp\ (X_i\theta_j)} \qquad \text{with j=1,2,3} \qquad \textbf{(5.5)}$$

Where, P denotes the predicted probability of adaptation to select an option y_i for the i_th household, j represents type of adaptation strategy category, X represents the explanatory factors used in the regression and θ , the various coefficients.

The MNL is estimated using the maximum likelihood based on the household and land attributes dataset.

In this study, the dependent variable is defined by adaptation with three categorical alternative responses that are: 1) "increase fertilizer", 2) "reforestation" or 3) "no adoption" of any of them. MNL requires setting a base category before running the maximum likelihood. In this case, reforestation is used as the base category due to its small representation in the sample compared to the others.

The independent variables that may impact households' adaptation choices can be categorized into three groups: household and land characteristics, socio-psychological factors, and policies and natural attributes characteristics, as defined in **Table 5.2**.

Table 5.2: Table of different variable for the MNL regression

Variables	Description	Data sources	Direct linked module
Dependent variables			
P-land use (adaptation type)	1 for Increase-fertilizers, 2 for reforestation, 3 for No-adoption	Field surveys (2021) and observation	Patch Landscape
Characteristics of households and farms			
h-age	Farm household head's age	Field survey	Household population
h-size	Household size		
h-Assets	Total household asset[7] (CFA)		
h-size-groundnut	Size of groundnut farm (ha)	Field assessment	Patch Landscape
h-size-Millet	Size of millet farm (ha)		
Socio-psychological factors			
h-Severity (TA1)	Severity of salinity in your area or farm	Field survey	Household population
h-Vulnerability (TA2)	Farmer vulnerability to salinity		
h-Self efficacy	Perceived self-efficacy		
h-Response efficacy	Perceived adaptation efficacy in terms of productivity		
h-Social influence	My friends, neighbors and family are engaged in adaptation, so I'm doing so		
h-Village influence	Almost all the village(s) is/are doing the same adaptation action/measures		
Policies and Natural attributes characteristics			

[7] The total household assets are the residual value of farmers' assets in terms of CFA device

h-Extension services	Accessibility to agricultural extension	Field survey (2021)	Household population
h-FBO member	Member of farmer organization		
P-Elevation	Digital elevation model	GIS based calculation	Patch Landscape

Source: Author' s compilation

5.2.2.3 Land use/cover classification

Modeling land use/land cover needs a map classification to represent the environment agents for simulation needs. In this study, a supervised land use/cover classification is made using a landsat8 image of 2020 from the National Institute of Pedologic in Senegal, represented by a spatial resolution of 30 x 30m. The LULC classes were identified through visual interpretation based on remote sensing data; the land cover types were then corrected based on more than 350 field investigation points covering the different land use types and collected by GPS. The classification has been made using QGIS software, and the image was geo-referenced to the UTM WGS 1984 projection system. Seven types of land use/cover classes have been defined in the area: settlement, mangrove, forest, cropland, water bodies, sabkha, and salt marshes, see **Figure 5.6**.

5.2.2.4 Modelling agricultural yield as sub model

The agricultural land use dynamic was modeled in this section to represent the agricultural yield sub-model for the agent base model. To model agricultural yield in the area, the Cobb Douglas (1928), a simple production function that explains yields depending on different predictor variables, was used. The Cobb-Douglas function explains, with the different elasticity, how yields as output variable evolute when one predictor (input) factor changes, the other inputs remaining unchanged. The formula is stated as follows:

$$P(L, K) = aL^{\alpha}K^{\beta} \qquad \textbf{(5.6)}$$

Where P represents the overall agricultural farm plot's production, L is the labor input (use of farm labor), K represents the capital input (e.g., fertilizer use, etc.), α and β are the elasticity, and it evaluates the output's responsiveness to a unit shift of an input.

Definition of the different variables used for the Cobb-Douglas function:

The dependent variable is represented by groundnut and millet yield in this study, **Table 5.3**. These two crops are the main crops harvested in the area, and they are important in farmers' livelihood in terms of food use (millet and groundnut) and source of income (groundnut). Rice crops are not considered in this case since the number of farmers who harvest rice is very small in this sample, so not very representative in terms of number. This is explained by the fact that most farmers have abandoned rice crops, explaining that they have lost their lands or a part of their land due to salinity expansion or that the quantity of rains these last years has not been important to allow them to harvest rice. The data on the concerned crop were collected during the survey (2021), where the quantity harvested was assessed in terms of bags by farmers, converted to kg, and divided by the plot area (ha), which was calculated for each farm plot using a GPS.

Table 5.3: Table of variable used for agricultural yield sub-model

Variables	Description	Data source	Direct linked module
Dependent variables			
P-yield-groundnut	Yield of groundnut plot (kg/ha)	Field survey (2021)	Patch landscape
P-yield-millet	Yield of millet plot (kg/ha)		
Independent variables			
h-household-size (labor)	Member of family member (use as labor for agricultural activities)	Field survey (2021)	Household population
h-paid-labor-amount	The financial amount of paid labor for agricultural activities (CFA)		
h-total-assets	Household total assets		
h-chemical-fertilizer	Quantity of chemical fertilizer use (kg)		
P-size-of-plot	Plot area occupied by each crop (ha)	Field measurement with GPS calculation	Patch landscape
P-elevation	Digital elevation model		
P-Slope	Angle of the plot's slope (degree)	GIS based calculation	

Source: Author's own compilation

5.2.3 Data sources and general description

In this chapter, qualitative and quantitative household and farm characteristics data have been used in addition to GIS data based that were calculated. The first type of data was collected during surveys within the 16 villages of the Fimela area with a semi-structured household questionnaire in 2021. A total of 288 households were concerned, and a pre-test of 14 households was done. For the second type of data, coordinates of households' houses and farms were collected during 2021 fields and extract values for household and farms' elevation, distance from river and slopes by using their respective maps (raster) computed using land Sat8 image (2020) by ArcGIS and QGIS also used. Two days of focus groups with the IPAR institute have been used to evaluate the questionnaire and to readapt the framework of the different approaches. The descriptive statistics of most of the data have been done in chapter 3.

5.2.4 Description of the standard procedure of the model

The MAS, LUDAS, is the modeling approach used in this research as an ABM to simulate farmers' household adaptation decisions. It follows the ODD protocol (Overview, Design concepts, and Details), which is used as a formal procedure to describe and document the Agent-Based Models (ABMs) (Grimm et al., 2006). Its goal is to make model descriptions more understandable and complete and provide uniformity in defining such models. However, to adapt the ODD procedure in socio-ecological study, it has been redesignated as ODD + D (ODD + Decision) by which ABMs include human decision-making (Müller et al., 2013; Grimm et al., 2010). ODD+D protocol is used under MAS to describe the simulation by LUDAS.

5.2.4.1 Overview

5.2.4.1.1 Purpose

The Land-use dynamic simulator has been first designed by Le (2005) to simulate land-use decisions in the forest edges of Vietnam. Further, it has been modified by Villamor (2012) to LB-LUDAS to explore policy options by quantifying the possible ES trade-offs arising from the agents' preferences in

Indonesia. It has also been readapted by Schindler (2009) and Amadou (2015) in Ghana Upper East Region as GH-LUDAS forecast land-use/cover patterns based on socioeconomic indicators and as SKY-LUDAS to provide some insights into how household farming systems deal with climate change. This model aims to investigate the complex dynamics of the agro-environmental and human decision systems.

For this particular study, the LUDAS, with regards to its general framework, is used to gain an understanding of how households' farming systems cope with soil salinity expansion in Fimela, as well as how their perception of soil salinity expansion in their area influences their crop system. The farmers' perception of soil salinity expansion is assumed as the principal factor guiding the adoption of adaptation to soil salinity expansion, see **Figure 5.1**.

5.2.4.1.2 Agents, states variables and scales

The LUDAS model considers two categories of agents with specific attributes: human and landscape agents.

1. The **human agents** are denoted by the individual households' farm. The state variables of households' farms' agents, in this case study, consider several indicators that are related to social identity (e.g., age, ethnicity, gender), socio-psychological factors (e.g., PMT's variables), physical resources (e.g., labor, lands), financial resources (e.g., households' assets) and institutional access (e.g., credit access, extension services, farmers' organization).

2. The **landscape agents** are represented by the environmental attributes. It is represented by the congruent of land pixels corresponding to GIS-raster layers such as digital elevation model, wetness index, distance to the river, and land use/cover. The temporal and spatial units are one-time steps representing one year, an area covers by 367 km^2 (Sow and Seck, 2021), and the size of the pixel is 30m x 30m.

5.2.4.2 Process overview and schedule

For the simulation programme, the main time loop called a yearly production cycle, includes sequential stages, and integrated with patch-based processes, are agent-based. The main steps stated in LUDAS during the simulation are: 1) set up the initial system's state, 2) update agent and patch attributes, 3) adopt behaviour parameters, 4) agricultural land-use decision, 5) update agent and patch attributes change, 6) create new agents and 7) calculate crop yield. The whole scheduling programme of the LUDAS is more details in the studies (Amadou, 2015a; Villamor, 2012; Le et al., 2008). The coding is done in Net Logo software version 6.4, and all households farmers' agents (turtle) and landscape agents (patches) are called and assigned tasks to complete in simultaneously (synchronizing actions).

5.2.4.3 Design concepts

In reality, humans employ diverse strategies beyond profit maximization when making decisions concerning land use (Miyasaka et al., 2012) in adopting adaptation against a threat. For that reason, the LUDAS model is defined following the algorithm: learning (agents based their decision on updated information), individual sensing (getting knowledge such as perception of soil salinity in this case), interaction (within households' agents and with their environment too), heterogeneity (e.g., in terms of variable states and space location) and stochasticity (Amadou et al., 2018).

To observe the implication of farmers' perception on their agricultural systems, the expected outputs of the model are farmers' crop yields. The system is designed so that only farmers who perceive the threat of soil salinity expansion in their area will adopt adaption to adjust their land-use systems depending on some socio-economic demographic indicators. The design refers to numerous factors that affect the dependent variables defined for each sub-model. The model was parametrized based on empirical data collected during the field survey, field measurements, focus groups, and spatial data used to define the different sub-model.

5.2.4.4 Details

i. Initialization

The initialization stage consists of two steps. In step 1, the GIS raster data, which is the land use/cover produced, the distance from the river, the digital elevation model, and village boundaries, are imported at the initial state (t=0). The data on the selected household population (Ns) are loaded, and the overall population size (Nt) sets. The step 2 consists of applying spatially limited random rules to create landholdings of the newly generated households in step 1.

ii. Input data

For the simulation, the inputs are categorized into two types: data and parameters. The data are GIS-raster and households' data organized as text and used for the initialization phase. Moreover, the parameters are needed for the parametrization and calibration of the model using various external sub-model. The calibrated parameters are mostly the coefficients from the different sub-models. The model employed a yearly population growth rate of 3.1% following the 2019 census of ANSD in the Fatick region.

iii. Sub-models

Sub-models and procedures used for the simulation are presented in **Table 5.4**.

Table 5.4: Table of variable used for agricultural yield sub-model

Names	Brief description of sub-model function	Entities involved
Initialisation	1) Import sampled household and GIS data, 2) generate the remaining households and their landholdings, 3) Create household pixel link, 4) Generate household coefficients	Landscape, Household
AdaptationChoice	Calculate the willingness of farm household to choose a type of adaptation	Household
AgricultureYieldDynamics	Annually calculate agricultural yields in response to inputs production, perception of soil salinity and adaptation choice	Landscape, Household
FarmersPerception	Under AdaptationChoice, this procedure performs the household perception of salinity and influence of climate change	Household, Landscape
UpdateHouseholdState	Update the modifications in household profiles annually	Household
Create-New-households	Create a new young household regulated by an empirical function of population growth	Household
Plot-Graphs	Draw various graphs of system performance indicators	Household, Landscape

Source: Author’ s own compilation

5.2.4.5 Operational LUDAS by integrating decision-making process in saline condition by using empirical data

The LUDAS model in this study case was specifically redesigned for the context of adaptation to soil salinity expansion in Fimela. Then for that, the decision-making routine at the individual level is modeled and integrated into the LUDAS model through different procedures that are farmers' perception of soil salinity expansion and adaptation choice.

5.2.4.5.1 Graphic and user interface

LUDAS's user interface is made up of the following components:

- User input (Land use map, Elevation map, Witness map...)
- Global (experimental) parameters: uses sliders to externally adjust the values of parameters to be evaluated in the model.
- Navigation window for digital land-use/cover maps: display the land-use/cover pattern exported at any period during the simulation to evaluate annual shifts.
- Time-series graphs of biophysical and human system performance indicators: These plots enable users to see real-time shifts in predetermined indicators, such as average annual crop yield.
- Monitors and particular time-series plots are included for more related indicator computations, such as the farm owners' number.

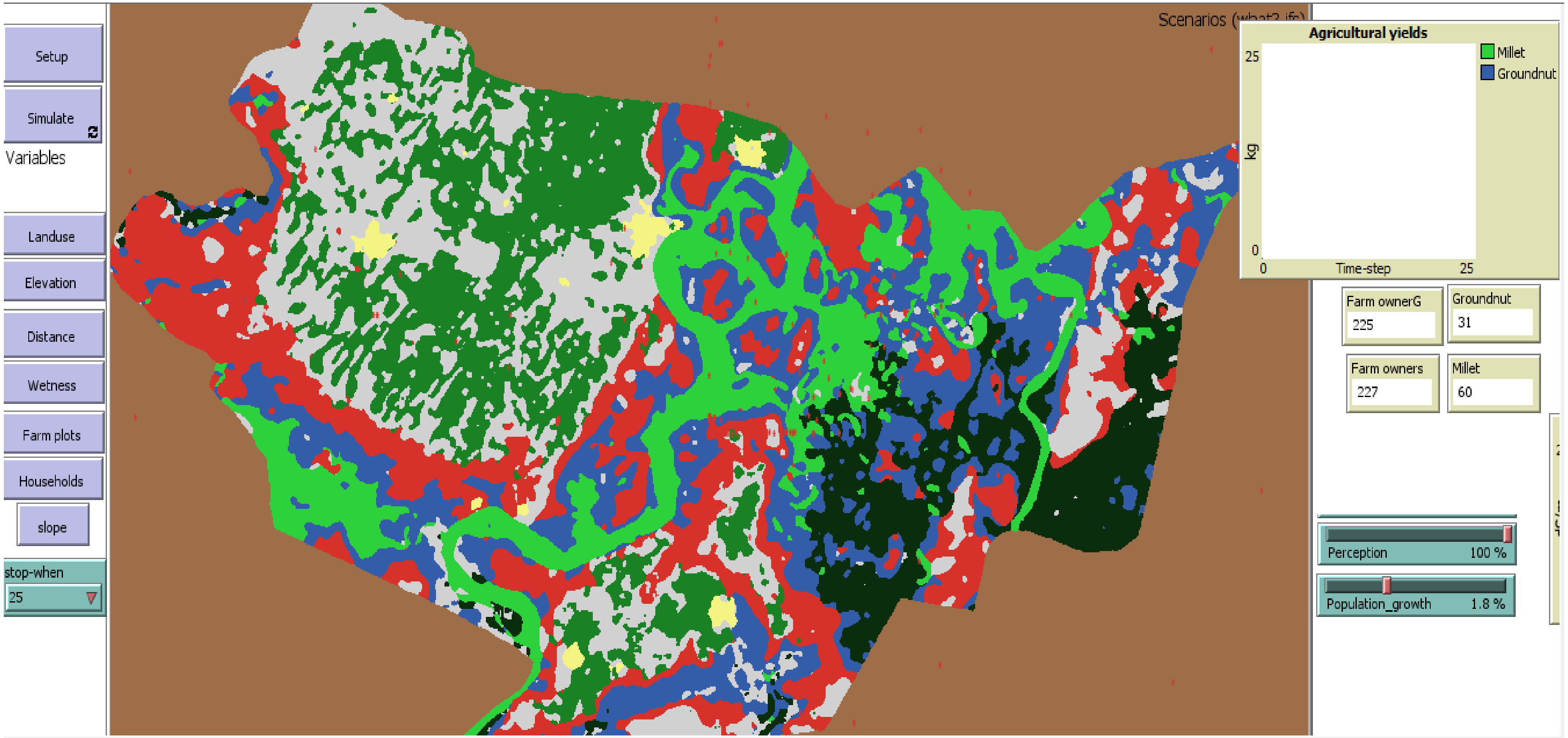


Figure 5.2: Operationalize simulated model graphic interface. *Source: Authors compilation with netlogo software.*

5.2.4.5.2 Scenarios

Three scenarios have been considered in this model:

(1) The baseline corresponds to the initial step without any influence

(2) Farmers have no perception of salinity expansion under climate change influence (No-PCS) and,

(3) Perception of salinity expansion under climate change impact (PCS).

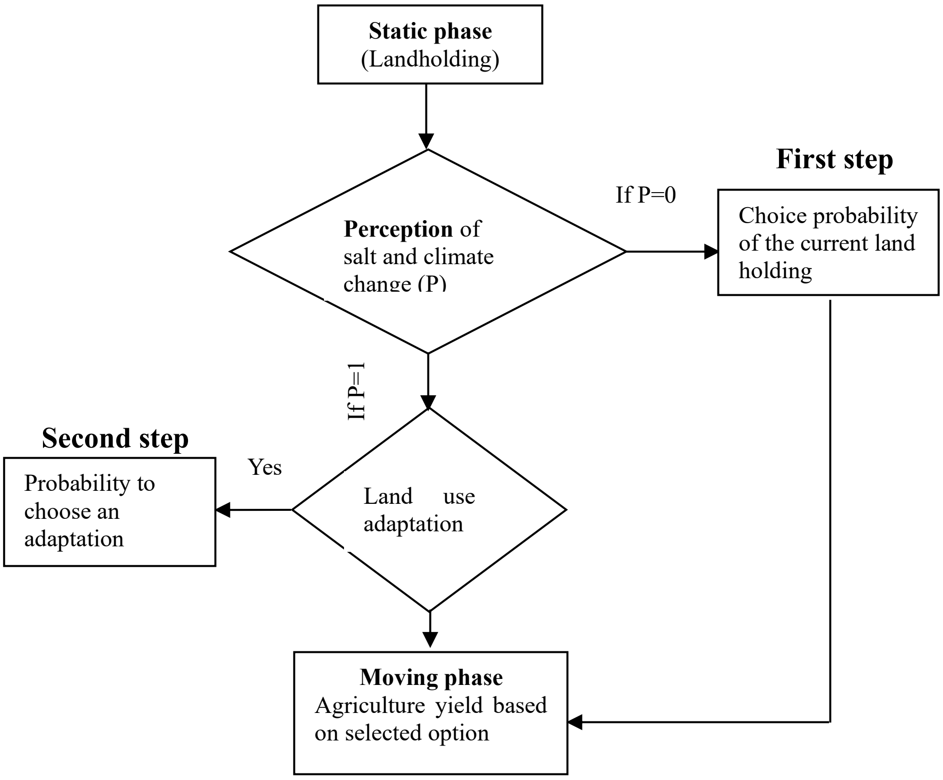


Figure 5.3: Schematic illustration of the decision-making routine stages integrated in the decision programme. Source: Author' s compilation.

The first step in simulating household decisions involved simulating farmers' perceptions of soil salinity threats, the second step involved simulating farmers' adaptation choices and the final result, agricultural yield, is defined according to the linear regression definition.

-This **first stage** in household decision-making was developed using the binary logistic regression analysis results (Roco et al., 2015a; Oguz & Assefa, 2014; Basbas et al., 2013; Deressa et al., 2011b), section 5.3.1.2.

The likelihood of a household perceiving a soil salinization expansion threat or not (Farmers-perception) is incorporated into the LUDAS model via a dummy variable with the value 1 (Yes) when the farmer perceives an increase in soil salinity threat, and the value 0 (No) otherwise.

When the farmer's perception value is 0, the household decision programme will skip the adaptation process and proceeds to the non-adaptation farm land choice procedure. The household decision programme will simulate the adaptation-choice procedure when the probability of farmers' perception is equivalent to 1.

-Based on the m-logit results, the model creates **the second step** sub-module.

The regression considered three major adaptation options: increasing fertilizer, reforestation, and no adaptation, section 5.3.2. When a household chooses an adaptation option, that option is carried out in the Farmland-choice procedure, particularly during the moving period. The perception of soil salinity threat is the primary factor influencing household adaptation choice.

Simulation: Using Net logo version 6.3, each scenario was run five times for 25-time steps (years). All scenarios began with a population of 164 households considering various initial maps. The performance of agricultural yields over the next 25 years was plotted as a time-series graph.

5.3 Results

5.3.1 Results of farmers’ perception sub-model

5.3.1.1 Descriptive results of comparing farmers' perceptions of climate parameters to meteorological data

The concerned station for the ANACIM data is Fatick, where the Fimela district belongs. Among the interviewees, more than 44% and 43% respectively agree and strongly agree about the decrease in rainfall amount over the last 20 years. About 48% and 42% perceived, respectively, a decrease and a strong decrease in rainfall frequency over the same period, in contrast to 4.2% and 2.1% who perceived an increase in rainfall frequency, **Figure 5.4**. Comparing this perception of farmers on rainfall change with the rainfall trend analysis recorded over the last 30 years that shows an increase in rainfall, **Figure 5.4**, farmers' perception of rainfall change in a long-term period does not conform to the climatological evidence. Then, there is no strong evidence that the rainfall pattern has decreased over the last years in the Fimela area; in contrast, the result shows a slight increase in the rainfall parameter. The finding is opposite of those of Ayanlade et al. (2017) who stipulate that farmers' perceptions of precipitation conform to historical meteorological data in southwestern Nigeria but conform to the findings of Simelton et al. (2013). This result shows that farmers' perception of climatic parameters and particularly of rainfall, has limits in the long term, as shown by Amadou et al. (2015)’s study, and may be explained by the fact that changes in rainfall are easily confused with changes in agricultural system sensitivity (Simelton et al., 2013).

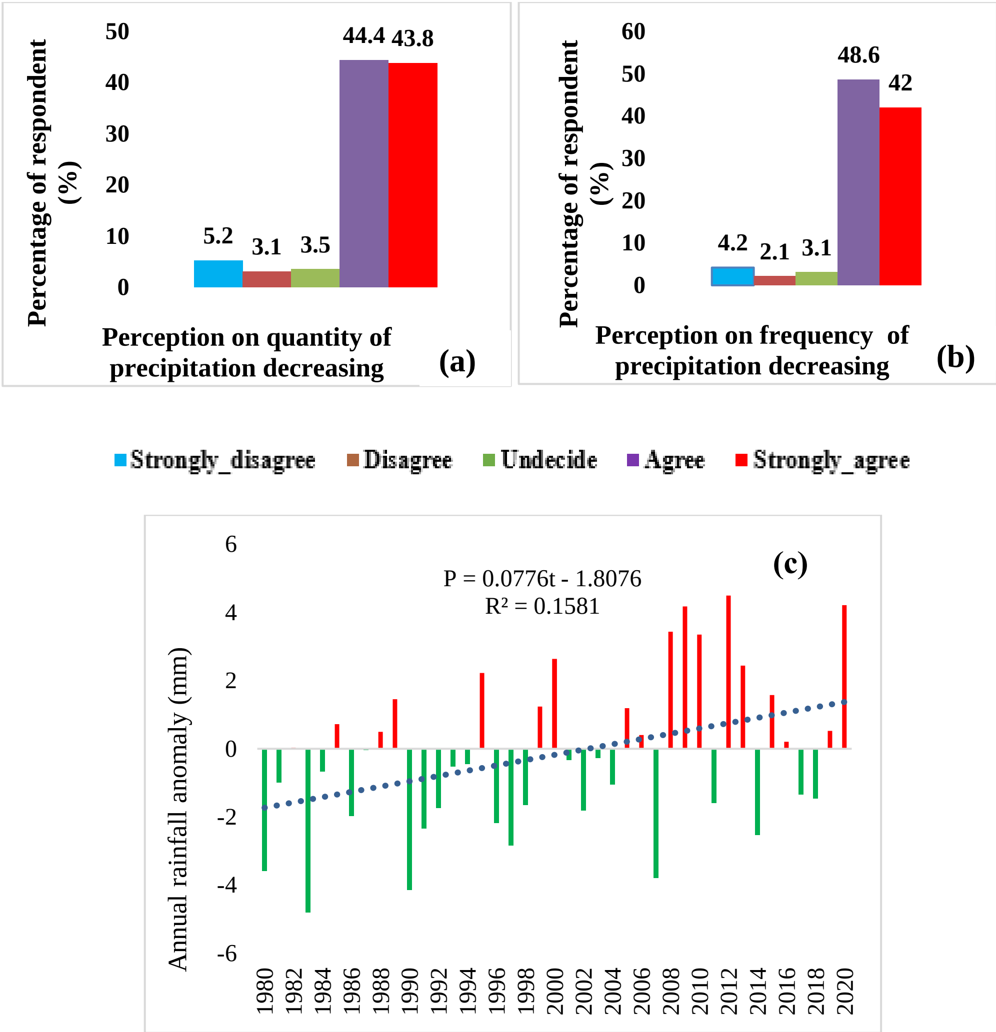
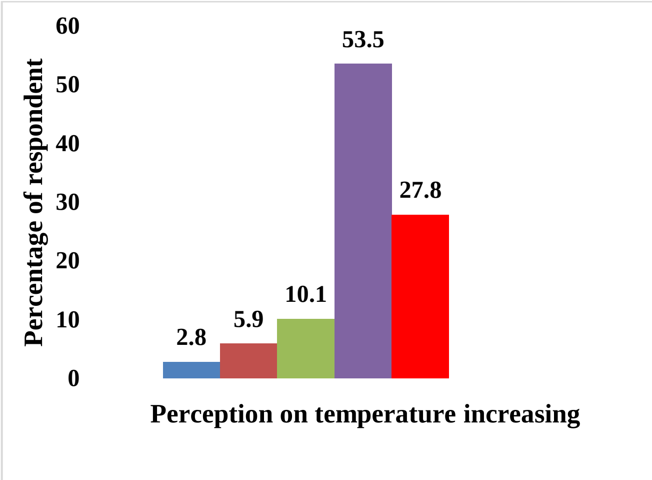


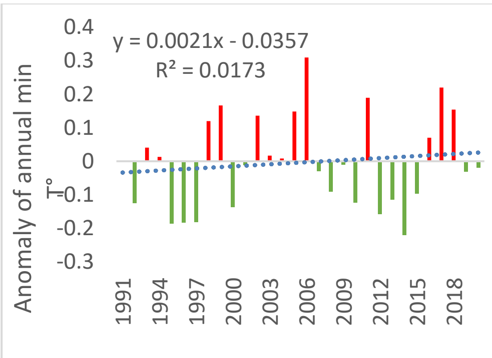
Figure 5.4: Farmers' perception of rainfall amount (a), rainfall frequency (b) and the trend of precipitation (c). Source: Author' s own Computation from Field Survey, 2021.

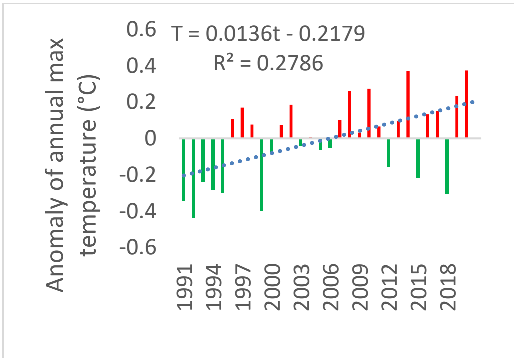
Concerning the temperature variable, most respondents, 53% and 27%, respectively agree and strongly agree about an increase, **Figure 5.5**. They perceived a strong increase in temperature during the last years, in contrast to 2.8% and 5.9%, who claimed that temperature has not increased. However, 10% of the respondents did not observe any temperature change. This observation follows the tendency of the temperature pattern over the last 30 years, which shows an increase in temperature. The findings are consistent with those of Rapholo and Diko-Makia, (2020), who compared farmers' perceptions of temperature increases to climatological data in South Africa. Nevertheless, the increase in the min temperature is very slight compared to the maximum temperature obtained with the climate data analysis.



(d)

Strongly_disagree Disagree Undecide Agree Strongly_agree





(e) f

Figure 5.5: Farmers' perception of minimum temperature (e) and maximum temperature (f). Source: Author's own Computation from Field Survey, 2021.

These results coincide with the trend results obtained with the annual anomaly indexes concerning the temperature parameters and not for rainfall parameters. This means that farmers' perception of climate change through rainfall decrease and temperature increase is not one hundred percent correct due to some other parameters that have not been fully accessible to farmers. This is in line with the results of Imran et al. (2020), who revealed that farmers' perceptions of rainfall do not correspond to historical meteorological data of rainfall in Pakistan, whereas their perceptions of temperature do correspond to the temperature trend of the meteorological data. First, this can be explained by climate change being a long-term change in atmospheric circumstances, whereas farmers respond to climate-related questions based on short-term experience. Secondly, they depend solely on their memories of atmospheric conditions with no assistance from any scientific devices, whereas climate change has been a slow process with a long-term shift in atmospheric conditions detectable only with meteorological devices (Hasan and Kumar, 2019).

5.3.1.2 Binary logistic results for farmers' perception determinants

Table 5.5 displays the binary logistic regression's results that reveal the significant determinant of farmers' perception. The regression results showed a significant likelihood ratio (p=0.001), indicating that the model strongly explains the farmers' perception of soil salinity.

Only four explanatory variables have a significant influence on farmers perceptions of soil salinity: perception of temperature (+), the household elevation (-), the information (-) they got about climate data in their area, and the climate change causing salinity perception (+). Farmers' perception of soil salinity expansion is also influenced by their beliefs about climate change having a positive relationship with it. It suggests that farmers' perceptions of "temperature increase" positively influence their perceptions of soil salinity expansion under climate change at the 5% level. This is explained by the fact that the most farmers perceive soil salinity as the most serious climate change-related issue, followed by rising temperatures and erratic rainfall (Islam et al., 2021). The same effect is observed with elevation, demonstrating that the lower the elevation, the better the perception. According to Bakr and Ali (2019) and Duan et al. (2022), there is a significant correlation between soil salinity and surface elevation. Besides, the result shows that receiving information and awareness about soil salinity expansion also decreases a good perception of it at a 1% level in this study. This may be explained by the fact that most farmers claimed not getting the information in formal manner but rather from their surroundings. Farmers who can link climate change to an increase in soil salinity are more likely to detect an increase in soil salinity at the 1% level. This is supported by the fact that climatic factors and soil salinity have a linear relationship, as seen in arid and semi-arid areas around the world where variations in temperature and precipitation significantly impact soil salinity (Khamidov et al., 2022).

The display results back up studies that show evidence of a rise in temperature with climate change occurring in the latest years, as opposed to rainfall. Most farmers in the research area perceive changes in rainfall and temperature patterns and believe that climate change is occurring due to these changes, as found by some studies such as Hasan and Kumar (2019) and Roco et al. (2015). Furthermore, farmers in Fimela reported increased soil salinity as a result of climate change, which occurred as a consequence of sea level rise, a decrease in rainfall, and an increase in temperature in their area, leading to the abandonment of cultivable areas mainly impacted by land rice (only 7.3% of the sampling is still farming rice), which is the most affected crop in the area.

Even though farmers' perception of temperature is consistent with the trends of the closest station's minimum and maximum meteorological temperature data, the assertion of a decrease in rainfall is not supported by the trend from historical rainfall data, which shows an overestimation of rainfall decrease in the area by farmers. In other words, rainfall in the area has not decreased significantly in terms of average quantity compared to farmers' assumptions, as found by Hasan and Kumar (2019). According to studies such as Kemausuor et al. (2011), farmers perceived a decrease in precipitation and an increase in temperature over a lengthy amount of time, more than ten years. This means that perceptions of climate change, particularly of rainfall patterns, and their effects may be skewed in the long run because farmers' perceptions of rainfall in long-run decline are based on their experiences with rainfall variability rather than average yearly rainfall amounts. This result is in contrast with Hasan and Kumar (2019)'s result, which confirmed that farmers' perception of rainfall change in Kalapara (Bangladesh) is aligned with meteorological data. This could explain why farmers' perceptions of rainfall differ from meteorological rainfall trends, which consider the amount of rainfall over time rather than the frequency, onset, and cessation dates as farmers do. This result can also be explained by the negative influence of the information variable in the binary regression.

It can be stated that farmers are not receiving the correct information on climate parameters, and this misinformation or lack of information can lead to farmers having incorrect perceptions, as is the case with rainfall. This lack of information may be due to an untrustworthy source of information since most farmers on salt-affected soils got their information from their parents and/or other neighboring farmers, as demonstrated by Omar et al. (2022).

Farmers' indigenous knowledge of how a lack of rainfall and higher temperatures can lead to an increase in soil salinity level has inspired this study to investigate how farmers' perceptions of soil salinity expansion are linked to their perceptions of rainfall decrease and temperature increase. The results in **Table 5.4** show that farmers' perception of rainfall does not affect their perception of an increase in soil salinity in their area, in contrast to their perception of a temperature increase. The same is true for their perception of climate change influencing soil salinity levels. This means that farmers attribute an increase in soil salinity to an increase in temperature rather than a change in rainfall patterns. This implies that farmers can link soil salinity expansion to climate change cause in their area. As for the elevation, the lower the household farm location, the higher its perception of soil salinity expansion.

Table 5.5: Binary logistic regression results for predicting farmers' perception of soil salinity

Variables	Coefficient	Standard error	Wald	Sig.	Exp(B)
h-age	-0.007	0.012	0.333	0.564	0.993
h-gender	0.742	0.483	2.363	0.124	2.101
h-rainfall quantity in the last 20 years	0.239	0.297	0.649	0.42	1.271
h-rainfall frequency in the last 20 years	-0.008	0.328	0.001	0.98	0.992
h-temperature increase in the last 20 years	0.332	0.162**	4.183	0.041	1.393
h-climate change cause salinity	1.474	0.317***	21.674	0.000	4.366
h-Information	-1.331	0.514***	6.706	0.01	0.264
P-Elevation	-0.142	0.059**	5.746	0.017	0.868
Intercept	-0.688	1.167	0.348	0.555	0.502

Source: Author' s own Computation from Field Survey, 2021.

The model as a whole has good predictive power with a value of 79.3%, **Table 5.6**. Then this model is good at predicting good farmers' perception of soil salinity expansion.

Table 5.6*:* Correct prediction table

From\ to	No	Yes	% Correct
No	24	48	33.3%
Yes	11	202	94.8%
Total	35	250	79.3%

Source: Author' s own Computation from Field Survey, 2021.

5.3.2 Multinomial logit's results for modelling adaptation choice

The results reflect a highly significant empirical model with p=0.000 and a Nagelkerke R-square equal to 0.804. The model was able to describe 80.4% of the total variance in farmers' adaptation against salinity choice using the selected independent variables. The whole model also has good predictive power with a value of 92.40%, see **Table 5.8**.

Table 5.7 shows that the choice of the adaptation type "Increasing fertilizer" is positively influenced by the following variables: (h-severity), (h-vulnerability), (h-self-efficacy), (h-confident-level), (h-social-influence), (h-village-influence), (h-extension-service) and (h-FBO-member). Most variables are represented by the socio-psychological factors defined in chapter 3, where the variables are defined as correctly predicting the different constructs validating this study's use of PMT theory. Farmers' access to extension services and affiliation with an FBO group results show that farmers with much connection network are more suggested in this adaptation finding in the climate change context. The (h-elevation) also negatively affects the "increase fertilizer" type but at 10%. However, for the "Reforestation" type, the same tendency is observed with the variables (h-self-efficacy), (h-confident-level), (h-social-influence), (h-village-influence) and (h-FBO-member) that are positively and significantly affecting the farmers' choice. The elevation is significantly and negatively affecting the adaptation choice. This means that when farmers are located in a low area, they are more tempted to adopt adaptation.

Table 5.7: M-logit results for modelling adaptation decision

	Increase-fertilizer			Reforestation type		
Variables	Coef.	Standard error	P-value	Coef.	Standard error	P-value
Intercept	-32.099	8.566***	0.000	-30.876	12.651**	0.015
Age	-0.032	0.029	0.265	-0.061	0.053	0.250
h-size	0.114	0.084	0.174	0.086	0.135	0.525
Millet-area(ha)	-0.070	0.504	0.890	0.123	0.956	0.897
Groundnut-area	-0.152	0.507	0.764	0.264	0.823	0.748
h-total-assets	-0.304	0.450	0.498	0.071	0.846	0.933
Severity (TA1)	0.810	0.422**	0.055	1.264	0.772	0.102
Vulnerability (TA2)	0.872	0.397**	0.028	0.144	0.752	0.849
Efficacy	2.761	0.730***	0.000	2.109	1.022**	0.039
Confident-level	3.141	0.794***	0.000	2.931	0.989***	0.003
Social influence	2.242	0.834***	0.007	0.130	1.082	0.905
Village influence	2.524	0.803***	0.002	3.746	1.100***	0.001
Extension services	1.935	0.924**	0.036	0.612	1.668	0.713
Farmers-organization	2.761	1.265**	0.029	5.491	1.800***	0.002
h-elevation	-0.288	0.160*	0.071	-0.652	0.246***	0.008

Likelihood test: 92.27, df=28; p=0.000, R^2 (Nagelkerke) =0.804, Cox et Snell = 0.570, McFadden =0.683. ***, ** and * shows significance level respectively for 1, 5, and 10 %.
Source: Author' s own Computation from Field Survey, 2021.

Table 5.8: Percentage of correct prediction

	Increase fertilizer	Reforestation	No adaptation	Percentage corrects
Increase-fertilizer	175	1	6	96.20%
Reforestation	4	1	1	16.70%
No adaptation	6	0	42	87.50%
Percentage global	78.40%	0.80%	20.80%	92.40%

Source: Author' s own Computation from Field Survey, 2021.

5.3.3 Land use/cover classification results:

From the LULC classification, it shows (16.79%) of cropland, (1.20%) of settlement, (9.52%) of mangroves, (20.5%) of forest, (14.45%) of water bodies, (18.78%) sabkha and, (18.74%) of salt marshes. The dominant class in the area is the forest class, as shown in the table below, and for this case, both forest and savannah areas have been considered in the same class, which is forest.

Table 5.9: Results for land cover/use surface in Fimela (2020)

Land use/cover	Descriptions	Surface (ha)	Percent age (%)
Crop lands	Crop land area mostly represented by millet and groundnut crop	5291.28	16.79025
Water bodies	Rivers and sea water	4555.35	14.455
Settlements	Houses, villages and others type of building	379.17	1.20318
Mangroves	Tropical plants adapted to wet soils, salt water and are periodically submerged by tides	2999.97	9.519483
Forest	Area with important trees cover	6463.38	20.50955
Sabkha	Coastal supratidal mudflat or sand flat in which saline minerals accumulate as results of semi-arid or arid climate	5918.42	18.78029
Salt-marshes	Coastal wetlands flooded and drained by salt water brought in by tides	5906.43	18.74224

Source: Author's own Computation from Field Survey, 2021.

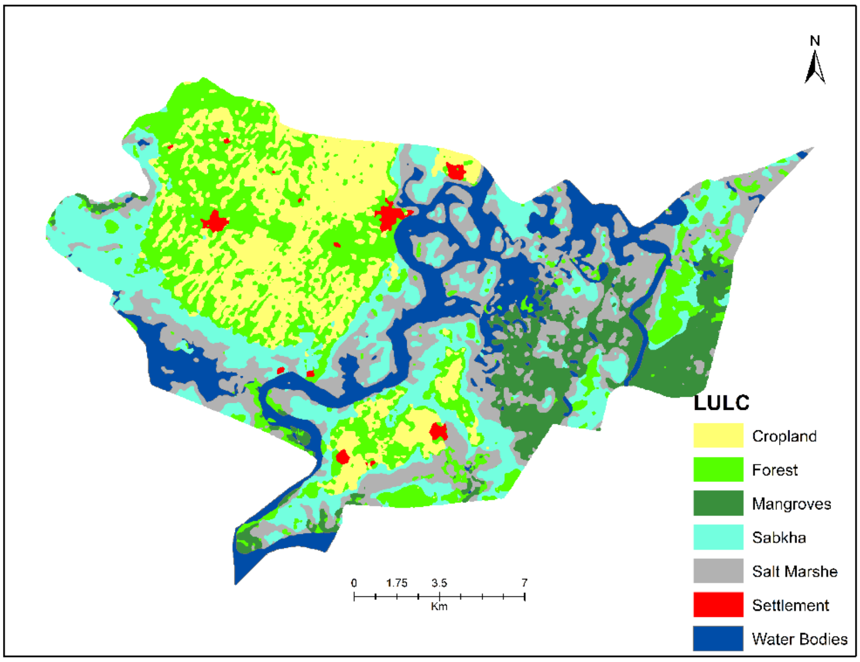
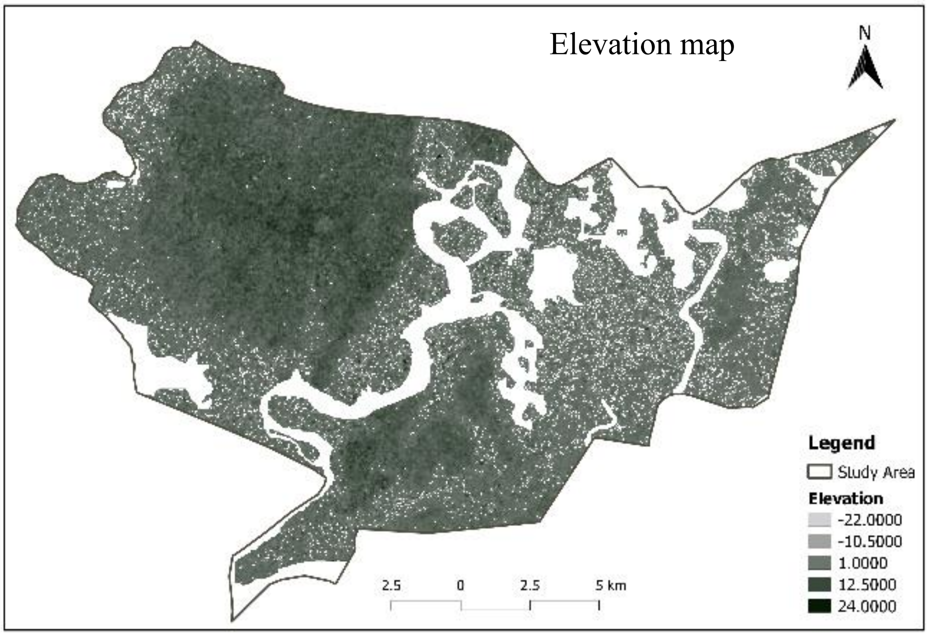


Figure 5.6: Land use/cover classification. Source: Author's own computation.

Some topographically indices of the area are considered in this study, as cited in some analyses, like the regressions. They are the digital elevation model (DEM), the distance from the river, and the slope, see **Figure 5.7**.

The DEM in the zone is comprised of between -22 to 24 meters and is reflecting a disparities spray around the area. The highest value of DEM is mainly located in the crop area zone, according to the LULC and DEM maps. The DEM is important in defining the crop yields sub-model since it is positively correlated to the EC of the area. The distance to the river grids is also reported in **Figure 5.7**. During surveys, farmers reported that their villages are far or near the river, which according to them is one of the main sources of soil salinity increase. So, their land use choice adaptation sub-model considers the distance from the river aspect in the regression. This variable is shown in **Figure 5.7** that, the distance from the river in the area is spread between the low value zero and the highest one, 6km.


Elevation map
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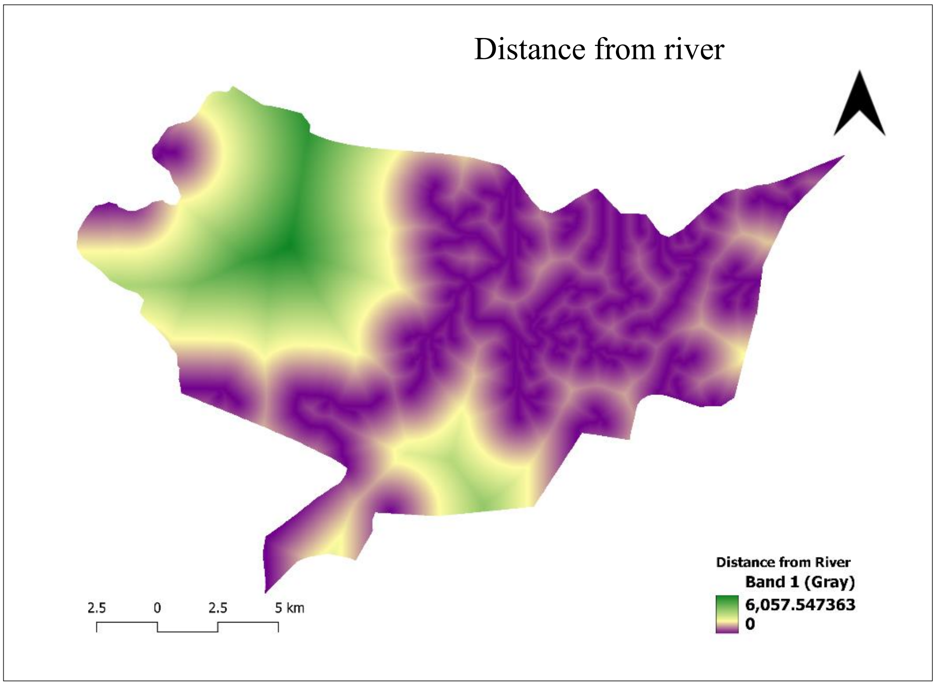
Distance from river
Distance from River
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0
2.5
5 km

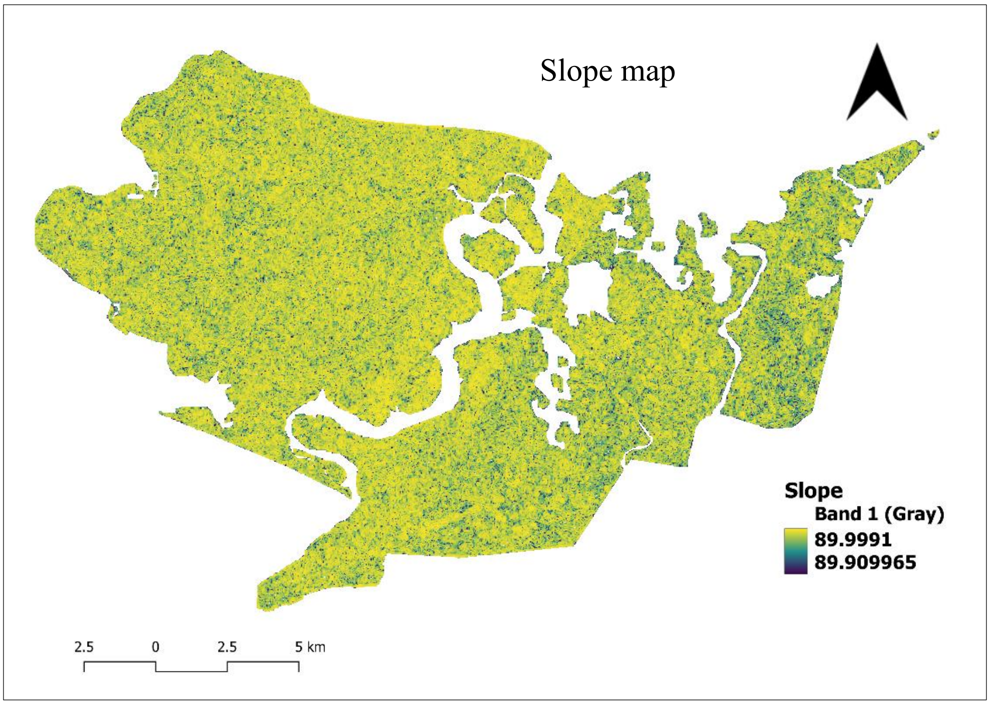


Figure 5.7: Map of elevation, distance to river and slope. Source: Author' s own Computation.

5.3.4 Log regression results for agricultural yields sub-model (Groundnut and millet)

The results of regression analysis for millet and groundnut crop yield are described in **Table 5.10**. The F-statistic is lower than 0.01, which means that the model is relevant in explaining the agricultural yield of the cited crop in the area. However, the coefficient of the determinant is lower than 0.5, as in some research fields, but it is still considered that the model is a good fit. This result is explained by the fact that most of the variables' data were collected through interviews rather than field measurements (Amadou, 2015; Le, 2005). So, in this case, the significant coefficients still represent the mean change in the output for one unit of change in the predictor variable when the other inputs remain constant.

For the millet, the farm size is the significant variable that explains the millet yield. A decrease of 0.87 units of farm size increases the millet yield by 1 unit.

This can be explained by the fact that the smaller the farm and the more farmer will be able to supply efficient input needs for millet harvesting depending on his budget. The same result is found in chapter 4.

For the groundnut, the same result has been found for the farm size. The total household assets and the chemical fertilizer are significant and positively affect the groundnut yields. Meaning an increase of 0.247 in household assets and 0.425 in chemical fertilizer, respectively, increase the groundnut yield for 1 unit. The elevation of the groundnut farm is also significant and negatively affects the groundnut yields with a decrease of 0.434 for a unit of groundnut yield.

Table 5.10: Result of agricultural yield sub-model regression

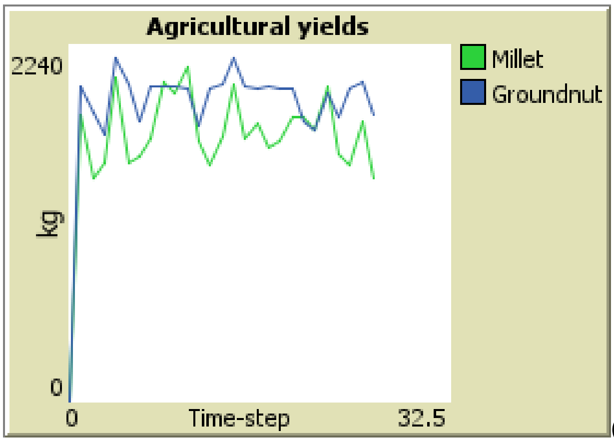
	Elasticities	Standard error	t-value	P-values
Millet yield (R^2=0.36, P= <0.006)				
Intercept	1484.778	5880.345	0.252	0.802
Ln(household-total-assets)	0.125	0.1	1.256	0.216
Ln (Chemical-fertilizer)	0.002	0.055	0.039	0.969
Ln (Size-Millet)	-0.877	0.208	-4.209***	0.000
Ln(h-size)	0.295	0.25	1.178	0.245
Ln (Farm-millet-elevation)	-0.171	0.306	-0.56	0.579
Ln (slope-Millet)	-329.518	1306.747	-0.252	0.802
Ln (Amount-of-Paid-labor)	0.186	0.154	1.21	0.233
Groundnut Yield (R^2=0.262; P=<0.000)				
Intercept	2201.203	2449.788	0.899	0.371
ln (Chemical-Fertilizer)	0.425	0.14	3.041***	0.003
ln (Size Groundnut-farm)	-0.325	0.138	-2.351**	0.021
Ln (Household-total-assets)	0.247	0.074	3.347***	0.001
Ln (Slope Groundnut)	-488.659	544.421	-0.898	0.372
Ln (Elevation Groundnut)	-0.434	0.199	-2.176**	0.032
Ln(h-size)	0.024	0.178	0.136	0.892

Statistically significant at 5% (**) and 10% (***). Source: Author' s own Computation from Field Survey, 2021.

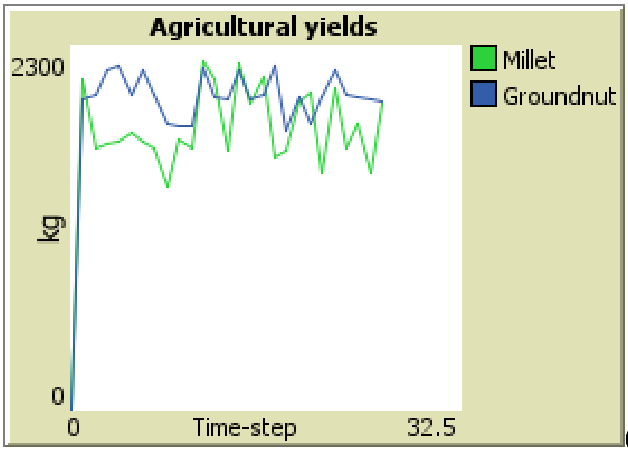
5.3.5 Simulation results

5.3.5.1 Implication of soil salinity threat and climate change perception on agricultural yields

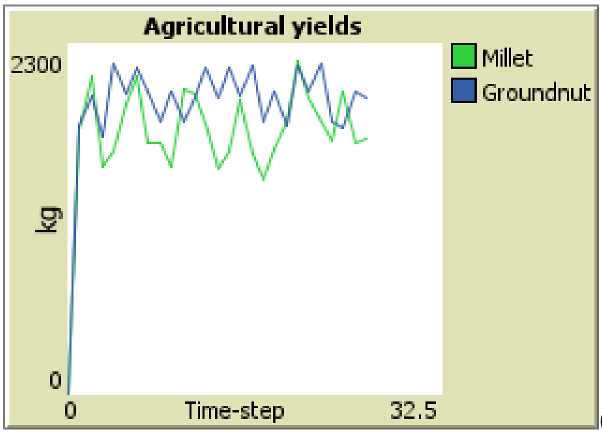
Figure 5.8 displays the simulation output for the 25 coming years. Data were extracted and analyzed from these results in the following section to answer the overall research questions and accomplish the study's objectives.



(a)



(b)



(c)

Figure 5.8: Result of agricultural yield sub-model regression. Source: Author' s own Computation.

Table 5.11 summarizes the simulated average yields of millet and groundnut crops under the defined scenarios (baseline, no-PCS, and PCS). Over the 25 years, the results for all scenarios indicate an overall increase in groundnut crop yield and a slight decrease in millet crop yield. The millet yield in the baseline scenario is greater than in the other scenarios but slightly lower than in the No-PCS scenario. The inverse is shown for groundnut yield, which is higher in the PCS scenario than in the others. As a result, both crops under consideration (millet and groundnut) were quite sensitive to the proposed scenarios, with better yields under PCS for the groundnut crop and a slight decrease for millet.

Table 5.11: Average annual millet and groundnut crop yield over the three scenarios

	Scenarios		
Crops	**Baseline**	**No-PCS**	**PCS**
Millet (kg/ha/year)	1773 ± 233	1771 ± 203	1763 ± 219
Groundnut (kg/ha/year)	1944± 128	1955± 137	2031± 148

NB: Values are mean ± SD of outcome variable for 5 simulation runs. Source: Author' s own Computation.

Using 95% confidence intervals, the average groundnut yield under the PCS scenario is significantly greater than the baseline and No-PCS scenarios **Table**

5.12 and **Figure 5.10.** There are slight yield differences between the scenarios for millet, but **Table 5.12** shows that the differences are not significant.

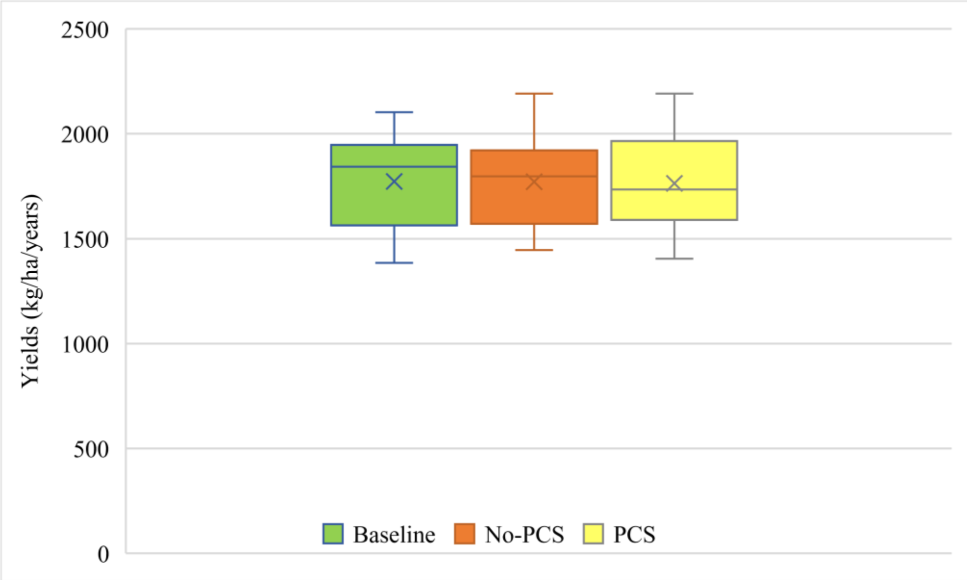


Figure 5.9: Simulated crop yields of millet. The bars are bounded by the values of the 95% confident level. Source: Author' s own Computation from Field Survey, 2021.

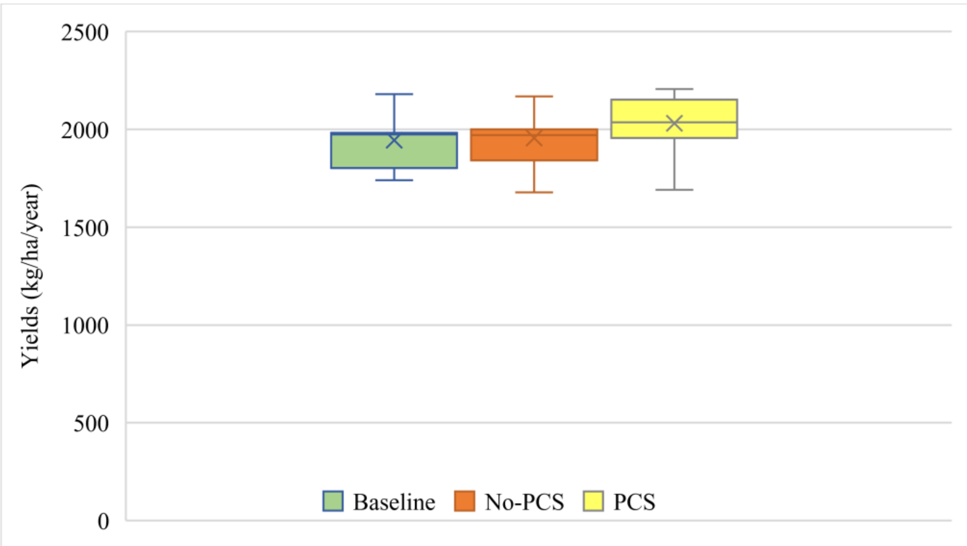


Figure 5.10: Simulated crop yields of groundnut. The bars are bounded by the values of the 95% confident level. Source: Author' s own Computation from Field Survey, 2021.

Table 5.12: Comparative analysis of the yields' average per main crop under the three scenarios using t-test

Scenarios-Comparative	Contrast	St-Dev.	t-Test	Significance
Millet				
Baseline *vs.* No-PCS	1.998	61.934	0.032	0.974
Baseline *vs.* PCS	9.361	64.063	0.146	0.884
No-PCS *vs.* PCS	-7.362	59.777	-0.123	0.902
Groundnut				
Baseline *vs.* No-PCS	-10.62	37.624	-0.282	0.779
Baseline *vs.* PCS	-86.934	39.157	-2.22	**0.031**
No-PCS *vs.* PCS	-76.316	40.455	-1.886	**0.065**

Source: Source: Author' s own Computation.

5.3.5.2 Discussion

The simulated average crop yields from the groundnut and millet are represented in **Figure 5.9** and **Figure 5.10.** The simulation results are supported by the result in Chapter 4, where the adoption of adaptation has no significant influence on millet yield but has a significant influence on groundnut yields.

So, in the long run, farmers' adoption of adaptation will still not affect millet crop production. The causes of this minor effect are discussed in Chapter 4. The opposite is true for groundnut. According to the LUDAS prediction in this context, farmers' perception of soil salinity expansion due to climate change has a significant positive effect on agricultural groundnut yield. This may be explained by the incorporation of the adoption sub-model in the model, and it is supported by the results in Chapter 4, where the adoption of adaptation strategies has a significant impact on groundnut yields. Thus, the farmer adaptation type remains efficient on groundnut crops and increases their productivity in the long run. This adoption of adaptation is made possible by farmers' accurate perception of soil salinity expansion as a consequence of climate change effects which is guided by different factors such as climate change's information access, see **Table 5.5**. Thus, how farmers perceive soil salinity expansion as one of the negative effects of climate change is important and influences their outcomes through their land use decision (adaptation). Thus, through perception, humans adjust to their environment through a learning process in which they assess their sensory impressions to give meaning to their environment and behave appropriately (Nguyen et al., 2016).

5.4 Conclusion

This section investigated how farmers' decision-making is formed in the context of soil salinity expansion under a changing climate using an agent-based model, and how this decision affects farmers' yield in the context of the main crops, groundnut, and millet. Three scenarios (Baseline, No-PCS, and PCS) were defined and used for simulation to assess how farmers' perceptions influenced the outcomes of their agricultural activities using differently defined sub-models. Sub-models on adaptation adoption, farmer perception, and crop yields have been included in the model to simulate yields over the next 25 years based on farmer behaviour to cope with soil salinity. The findings support previous findings and show that farmers who perceive a change in soil salinity expansion as a consequence of climate change have higher yields in groundnut. However, the difference between those who perceived soil salinity (PCS) and those who did not (No-PCS) is insignificant for millet crops, supporting the findings in Chapter 4, which stipulate that the type of adaptation used is ineffective on millet crops.

CHAPTER SIX

6. SYNTHESIS, CONCLUSION, AND RECOMMENDATIONS

This chapter summarizes the main findings, general conclusions, recommendations, and limitations obtained from the previous chapters.

6.1 Summary of findings

1) The main adaptation strategies adopted by the farmers against salinity in Fimela were “increased use of fertilizer” and “reforestation”.

2) Using the protection motivation theory and structural equation modelling approach, the socio-psychological factors that explain farmers' adaptation behaviour were identified. The results further indicate that threat appraisal, coping appraisal, and subjective norms are significant factors that influence farmers' intention to adopt adaptation measures against salinity. Contrary to expectation, maladaptive coping has no relationship with farmers’ intention to adapt against salinity in Fimela.

3) By estimating an endogenous switching regression model, we show that farmers' adoption of adaptation against soil salinity expansion or not is influenced by their household total assets, their millet farm size, also by their relatives, and their surrounding villages' opinions.

4) Farmers' adaptation positively impacts their groundnut yield and food security, whereas it does not significantly impact their millet yields. This insignificant impact on millet can be affiliated with the type of adaptation (increasing fertilizer), which is not very efficient above a certain level for millet crops.

5) The simulation result reveals that farmers' perception of soil salinity expansion threat influences agricultural yields through the adoption of adaptation to control soil salinity under climate change.

6) In this case study, the simulation results support the findings in Chapter 4, which stipulate that farmers' adoption of adaptation has no significant effect on millet yield but has a significant effect on groundnut yield in Fimela.

6.2 Conclusions

This study aimed to simulate the climate change adaptation decision-making of smallholder farmers in Sine Saloum's saline area in the Fimela district in Senegal. It explores the socio-psychological factors that influence farmers' adoption of adaptation to face soil salinity expansion and, the impact of this adoption of adaptation on farmers' groundnut and millet yields, and food security. So, three key conclusions have been derived from this study.

Firstly, the findings of objective 1 highlight the importance of evaluating farmers' threat appraisal, subjective norms, self-efficacy and response efficacy to implement coping policies against salinity expansion threats as a consequence of climate change. Hence, a causal effect exists between socio-psychological factors and farmer behaviour in adoption of adaptation to soil salinity expansion. Secondly, farmers use adaptation strategies such as "increasing fertilizer" and "reforestation" to deal with the negative effects of soil salinity expansion in Fimela. Despite this, the adoption of adaptation has a positive influence on groundnut yield and a negative effect on food security (positive effect on food insecurity) but no effect on millet crops. Then, a review of farmers' adaptation strategies to cope with salinity in Fimela becomes important since no significant effect has been particularly found on millet yield.

Finally, farmers' perceptions of a threat impact agricultural activity outcomes, directly or indirectly, via the definition of adaptation strategies. Understanding farmers' perceptions of a threat are critical for understanding adaptation strategies and their implications on agricultural yields. Analyses of the impact of climate change, such as soil salinity expansion, on agricultural land use, necessitate an understanding of a complex systems approach that includes both human and environmental dynamics. This study addresses this interdependence through a simulation based on agent-based modeling (LUDAS). The simulation results validate the previous objective's result (Chapter4). It demonstrates that in this case study, groundnut yield is influenced by farmers' perception through the adoption of adaptation, but not millet yield.

6.3 Policy recommendations

From this study, some recommendations have been provided to help decision-makers such as governments and NGOs and farmers improve adaptations used to cope with soil salinity expansion in the area.

1) Adaptation strategies may consider farmers' capacity to evaluate their efficacy and the efficacy of their responses. It would be beneficial if government or NGO that intervene in the area provide information on the threat of salinity expansion, its causes, and the long-term effects on farmers' livelihoods. This can be accomplished by investing in information

and knowledge about the threat, both in production and distribution, because how farmers assess a threat influences their adoption of adaptation strategies.

2) Policies that consider the influence of social parameters will also be beneficial, as farmers have a strong tendency to mimic their immediate surroundings. As a result, government's agencies and NGO that intervene in the area such as JED/EEDS should support a few pilot farmers in developing precise and effective strategies can inspire other farmers to fall into line through the village and social influence via farmer-to-farmer approaches, farmer field schools, and extension officer training.
3) Farmers' adaptation strategies to cope with salinity in Fimela should be reviewed by scientists' researchers since an insignificant effect on millet yield and an indirect negative impact on household food security have been discovered. It is critical to work with scientific researchers to develop good coping strategies that differ from existing farmer strategies and to look for a fluent channel to help impose it on farmers in a salinity threat area. This policy must be accompanied by providing or assisting farmers in acquiring more needed materials to cope with the expansion of salinity in their area by government or NGO's agencies, as these variable influences farmers' adaptation against soil salinity effects positively.

6.4 Limitations of the study and suggestions for future research

This research identified the impact of adopting adaptation strategies against soil salinity on farmers' yield and food security by considering whether a farmer adopts adaptation to soil salinity or not. This study could not consider each type of adaptation differently to analyze this impact. Thus, further studies should consider not only whether farmers have adopted adaptation strategies in saline conditions, but also the various types of adaptation. This will help to be more specific on which type of adaptation among the whole is indeed causing the results found with the endogenous switching regression.

The study used the LUDAS model to contribute to understanding farmers' adaptation to soil salinity in this study by considering a human-environment system. However, a human-environment system as a whole is hardly representative of a model since some parameters may be very difficult to capture. In this particular case, the study could not consider laboratory salt content data of each land use type to represent the whole environment as an agent in the model by interpolation. So, further research should consider this aspect in addition to a better representation of the human-environment system in the LUDAS simulation. This aspect can be captured by the Land Use Salinity Interaction model (LUSI) developed by (Thiam, 2019).

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APPENDIX

Appendix1: Questionnaire

WASCAL: Climate change and land use. KNUST Université (Kumasi, Ghana). I'm doing my Ph.D. on climate change and land use, and my research focuses on Climate variability and farmers' adaptation in saline areas.

Thank you in advance for taking the time to answer these questions. The result will contribute to understanding climate change impacts in your community. Your participation is voluntary, and rest assured that your answers will remain anonymous and be kept confidential.

Questionnaire No:
Name of investigator: Name of respondent:
Phone number: Village: Town:
GPS coordinate of household: **Latitude: ……………………….**
Longitude: ………………………………

A) Characteristics of respondent:

1. Age:
2. Sex: ☐ Male ☐ Female

3. Civil statute:

Single ☐ Married ☐ ☐ Widow
Divorced

4. Ethnicity Identity:

Serere ☐ Wolof ☐ Others ☐

5. Religious identity:

☐ Muslim ☐ Christian
Others ……………...

6. Level of Education:

Primary ☐ Secondary school ☐ University ☐ Arabe ☐
Non-school ☐

7. Principal activity:

Farmer ☐ Fisher ☐ Breeder ☐ Others ………… (*Check all relevant activities)*

9. Other activity: ……………
10. Household size: ……………………….

B) Farms' characteristics

1.

Parcel ID	Type of culture							Type of land acquisition
	Groundnut							
	Agri-cult. practice	Time of cul-ture	Sup (ha)	Number of bags	Sali-nity	Coord GPS	Dis-tance from sea	
1								
2								
3								
4								
5								

Parcel ID	Type of culture							Type of land acquisition
	Millet							
	Agri-cult. practice	Time of cul-ture	Sup (ha)	Number of bags	Sali-nity	Coord GPS	Dis-tance from sea	
1								
2								
3								
4								
5								

Par-cel ID	Type of culture							Type of land acquisition
	Rice							
	Agricult. practice	Time of cul-ture	Sup (ha)	Number of bags	Salinity	Coord GPS	Dis-tance from sea	
1								
2								
3								
4								
5								

(For salinity, put 1 if the land is saline and 2 if the land is not saline. Ask about the weight of each bag used to store the product. Land acquisition: 1 if heritage, 2 if buy, 3 if rent, 4 if borrow. For agricultural practice, put 1 if mon-oculture and 2 if culture mixt. For the time of culture, put 1 if full-time and 2 if half-time.

2. Distribution of farms' activity:

Period of farm preparation …………… Sowing period ………………. Harvest period …………

3. Information about the labour used:
4. Family labour ☐ Paid labour ☐ Assistance labour ☐

(*If several responses ticked them*)

If paid labour does exist, how much is it for all the season? ……………….. CFA

C) Institutional Characteristics

	1. Are you a member of the farmer-based organization (FBO)?	2. Do you have access to credit for your farm's activities?	3. Do you have access to an insurance service for your farm's activities?
Yes			
No			

If yes to 2), from which structure?

Bank ☐ Individual ☐

4. How accessible is the credit to you?

☐ Inaccessible at all ☐ Hardly accessible ☐ Fairly accessible
☐ Accessible ☐ Very accessible

If hardly accessible or hardly inaccessible, ask why?
……………………………………………………..

5. If yes to 3), how accessible are the insurance services to you?

☐ Inaccessible at all ☐ Hardly accessible ☐ Fairly accessible
☐ Accessible ☐ Very accessible

If hardly accessible or hardly inaccessible, ask why?
……………………………………………………..

6. Do you have easy access to agricultural extension services (as advice) for your farms' activities? Yes No
7. If yes to 6, then which kind of services?
……………………………………
8. If yes to question 6, from which organization?

☐ Government (ANCAR)

☐ Private (GMO or association)

D) Perception of climate change, salinity, adaptations, and socio-psychological factor

1. What worries you the most about your farming activity (the threats)?
Salinity expansion ☐ Other ☐ If others cite it……………………………………………………………
2. Do you believe in climate change and its consequences?

☐ Not at all ☐ Slightly ☐ Undecide
☐ Certainly ☐ Extremely

3. How do you perceive the expansion of land salinity in your area?

☐ Not severe at all ☐ Fairly severe ☐ Undecide
☐ Very severe ☐ Extremely severe

4. What do you think is/are the cause/s of salinity expansion? (*If multiple responses ticked them*)

☐ It's due to fate
☐ Due to rainfall decrease
☐ It's due to an increase in temperature
☐ It's due to sea level rise
☐ Others cause…

5. What do you think is/ are the consequences of salinity expansion? (*If multiple responses ticked them*)

☐ It has considerably reduced my land
☐ It has considerably reduced the quality of my productivity
☐ It does not impact my agricultural activity at all
☐ Other's consequences: ……………………...

6. Have you really noticed a change in the pattern of rainfall and temperature when you compare now to 10 years ago?

Yes ☐ No ☐

Questions on perception	**1. Strongly disagree**	**2. Disagree**	**3. Undec ide**	**4. Agree**	**5. Strongly agree**
7. Rainfall quantity has decreased this last 20 years ago					
8. Rainfall frequency has decreased this last 20 years ago					
9. Temperature has increased this last 20 years ago					
10. Climate change has caused salinity increased in the land over time					
11. Salinity expansion due to climate change has considerably decreased my productivity.					
12. Salinity expansion has negatively impacted life mood in the area					

13. Salinity expansion has increased poverty and unemployment in the village.					

Assessment of adaptations and psychological aspects

14. Are you engaged in adaptation against salinity expansion in your land?
Yes ☐ No ☐

15. If yes to 14), what is/ are the adaptation/s that you used to fight salinity

- ☐ I use peanut shell and millet residues on my land to deal with salinity
- ☐ I use a salt-tolerant crop variety
- ☐ I practice tree reforestation
- ☐ I take advantage of the dikes built by entities such as NGOs which stop the advance of salt in my fields.
- ☐ I increase the amount of fertilizer
- ☐ I practice fallow
- ☐ I abandon my cultivated land
- ☐ I migrate from my agricultural activity to another non-agricultural activity.
- ☐ I migrate outside the village in search of other activities
- ☐ Others: ……………………………………………………………

Response efficiency:

16. What motivated you in your choice of adaptation X against salinity?
……………………………………….

17. How would you rate the adaptation (X) you use in terms of effectiveness?
☐ Very ineffective ☐ Ineffective Neutral ☐ Effective ☐
☐ Very effective

18. The adaptation (X) you have adopted gives you very good results in terms of productivity
☐ Strongly disagree ☐ Disagree ☐ Undecide Agree ☐
☐ Strongly disagree

Response cost:

The adaptation (X) is very costly in terms of resources (monetary and time)
☐ Not costly at all ☐ Slightly costly Undecide ☐
☐ Costly ☐ Extremely costly

Adaptation strategies, in general, are too expensive in terms of time and effort (monetary and energy)
☐ Not costly at all ☐ Slightly costly ☐ Undecide
☐ Costly ☐ Extremely costly

Incentive

19. Do you receive from the government any assistances to fight salinity in your land or area? Yes ☐ No ☐
If yes, which kind of assistance? (*If multiple answers ticked them*)
☐ Financial ☐ Material ☐ Technical Assistance
Others………….

20. Does the government provide any disaster information about salinity?
☐ Never ☐ Rarely ☐ Sometime ☐ Always

If yes, which kind of warning information?
……………………………………………….

21. If yes to 19 et 20), does this assistance help you fight salinity expansion?

☐ Not at all ☐ Slightly ☐ Moderately
☐ Strongly ☐ Extremely

Subjective Norms:
If yes to 14, I adopt this adaptation strategy (X) because:

Questions	1. Strongly disagree	2.Disagree	3.Undecide	4.Agree	5.Strongly disagree
1.My friends, neighbours, and family are engaged in the adaptation, so I'm doing so					
2.Almost all the villages is/are making the same adaptation					
3.I need to adapt to salinization as my livelihood depends on my affected land					

Maladaptation: Those actions that have led to undesirable and ineffective results.

	1.Strongly disagree	2.Disagree	3.Undecide	4.Agree	5.Strongly agree
1. There is no need for any action to be taken to face salinity because these actions won't make any difference					
2.All issues are determined by fate and unchangeable by human					
3.I don't think I have the capability nor enough motivation and energy to fight the salinity					

1. Do you have any members of your household who have emigrated to the city? Yes ☐ No ☐
   If yes, give the reason for their immigration and the place where they migrated ………………………………………… Abroad
2. If yes to question 28, how many are they? ....
   If yes to question 28, give the number of male migrants ………… and female migrants ………………………

E) Livelihood assessment:

1. Household incomes

N° of a household member	Off-farm income (CFA) (out of scope)	Remittance Revenue (CFA) (money sent from abroad or from the city)

2. Do you have any members of your family who work outside agricultural activities? Yes ☐ No ☐

If yes, which activity is she/he doing: (*List all the activities even if there are several members of the household)*

3. Do you own any livestock in 2021? Yes ☐ No ☐

Type of asset	**Total Number**	**Quantity sold**	**Unit price (CFA)**
Sheep			
Goats			
Cow			
Pigs			
Poultry			
Others 1 2			

4. Do you own any physical assets in 2021? Yes ☐ No ☐

Physical assets	**Assets number**	**Unit cost (CFA)**
Bike		
Charrettes (Donkey or horse)		
Cars		
Television		
Tractor		
Moto Pomp		
Others (for example, houses, group electrogene…)		

5. Estimate the amount of your daily expenditure on food consumption ……………………… (CFA)

6. Estimate the amount of your daily consumption expenditure other than food ………. (CFA (CFA)

Items	Amounts (CFA)
Scholarity fees	…………………… /year or month (Circle the concerned)
Transport	……………………………/month
Amount of water bill and electricity/month	Water: ……………/month Electricity: ………………/month

7. Assessment of food security

N°	Questions	Responses	Codes
1	Faced with salinization, were you worried that your household did not have enough food?	0= No (If no, don't ask Q2) 1=Yes	_______
1.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
2	Faced with salinization, have members of your household not been able to eat the type of food you prefer due to a lack of resources?	0= No (If no, don't ask Q3) 1=yes	_______
2.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
3	Faced with salinization, has any member of your household had to eat a limited variety of food due to a lack of resources?	0= Non (If no, don't ask Q4) 1=Yes	_______
3.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
4	Faced with the phenomenon of salinization, have any members of your household had to eat foods that you really didn't want to eat due to a lack of resources to obtain other types of foods?	0= Non (If no, don't ask Q5) 1=Yes	_______
4.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
5	Faced with the phenomenon of salinization, did anyone in your household have to eat an insufficient amount of food than you needed because there was not enough food?	0= Non (If no, don't ask Q6) 1=Yes	_______
5.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
6	Faced with the phenomenon of salinization, did any member of your household have to eat fewer meals during the day because there was not enough food?	0= Non (If no, don't ask Q6) 1=yes	_______
6.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______

7	Faced with salinization, there was no food of any kind in your household due to the lack of resources to obtain food?	0= No (If no, don't ask Q8) 1=Yes	_______
7.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
8	Faced with the phenomenon of salinization, did members of your household go to sleep at night hungry because there was not enough food?	0= No (If no, don't ask Q9) 1=yes	_______
8.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______
9	Faced with the phenomenon of salinization, did members of your household go all day and night without eating anything because there was not enough food?	0= No (If no, don't respond to 9. a) 1=yes	_______
9.a	How many times does it happen?	1=Rarely 2=Sometimes 3=Often	_______

8. How much do you think salinity has affected your household income?
Strongly ☐ Slightly ☐ Not at all ☐

9. Have you changed your financial activities because of the salinity?
Yes ☐ No ☐

10. If yes to question 9), how did this change affect your income level?
☐ My income has increased ☐ My income decreased despite
It didn't change my income level at all

11. If yes to question 9), to which financially contributing activity (s) have you converted?......…………………………………...

12. A From 9), is this activity / s more profitable for you than the agricultural activities to which you are accustomed?
Yes ☐ No ☐

13. Have you noticed changes in the various assets you own over time due to the expansion of salinity?

A decrease ☐ An increase ☐ No change ☐

14. How many hectares of land do you estimate you have lost due to the expansion of soil salinity? ………………ha

15. After the adoption of adaptation X (mentioned in question 15), your activities and income experienced:

A decrease ☐ An increase ☐ No change ☐

Appendix2

COMMUNE DE FIMELA

N°	Villages names	Name of the village chiefs	Popula-tion	Total Num-ber of Households	Number of household sampled /vil-lage
1	BABOUCAR TOMBOU	Sidy DIARRA	561	56	8
2	DJILOR	Souleye Simon FAYE	915	96	20
3	FIMELA	Malang SARR	3000	300	45
4	KEUR SAMBA DIA	MAMADOU DIAO	3392	339	38
5	KOBONGOYE 1	Arona FALL	1103	110	16
6	KOBONGOYE 2	Djibril TOURE	207	21	3
7	MAR FAFACO	MOUSSA SARR	2833	283	41
8	MAR LOTHIE	Paul NDIO-GOYE	1798	180	22
9	MAR SOULOU	MAMADOU THIOR	485	49	7
10	MBISSEL	Maliame SAGNE	736	74	10
11	NDANGANE CAMPEMENT	Niokhor FAYE	1021	102	7
12	NDANGANE SAMBOU	Mamadou BOP	1770	177	4
13	NDIEDIENG	Birame DIOUF	514	51	7
14	SAMBA DI-ALLO	Bourama SANOKHO	528	53	8
15	SIMAL	Lang MARE	2438	244	28
16	YAYEME	Ngor BASSE	1346	135	24
TOTAL CM DE FIMELA		**16**	**22647**	**2270**	**288**

Source: NGO JED/EEDS, 2020

Appendix3

- **Saline soil from field 2021**

- **Rice farm affected by "tan" from field 2021**

- **Field Work 2021 (Farmer in his groundnut farm)**

- **Field survey 2021**