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LAND USE CHANGE, MODELLING OF SOIL SALINITY AND HOUSEHOLDS' DECISIONS UNDER CLIMATE CHANGE SCENARIOS IN THE COASTAL AGRICULTURAL AREA OF SENEGAL

BY

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DEVELOPMENT)

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DECLARATION

I hereby declare that this submission is my own work towards the PhD 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 which has been accepted for the award of any other degree of the University, except where due acknowledgment has been made in the text.

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ABSTRACT

Soil salinity remains one of the most severe environmental problems in the coastal agricultural areas in Senegal. It reduces crop yields thereby endangering smallholder farmers' livelihood. To support effective land management, especially in coastal areas where impacts of climate change have induced soil salinity and food insecurity, this study investigated the patterns and impacts of soil salinity in a coastal agricultural landscape by developing an Agent-Based Model (ABM) for Djilor District, Fatick Region, Senegal. Landsat images for 1984, 1994, 2007 and 2017 combined with normalised difference vegetation index (NDVI), elevation, wetness index and distance to the river were used to determine Land use-land cover and salinity changes. Land use classification and intensity analysis were applied to determine the time intervals during which the annual change area is relatively slow versus fast, and the variation of the categories' gains and losses during a time interval. Soil samples plots (at 0-30 cm depth) were collected according to different land use, soil and crop types to determine the salinity patterns. Households' survey data were collected based on 304 selected respondents to assess the perception and adaptation strategies of farmers. Land Use-Salinity Interaction (LUSI) was developed to explore the potential impacts of increased temperature and farmers' decisions on soil salinity dynamics. Salt content, crop yield and households' decisions sub models were incorporated in LUSI model. Three scenarios were simulated over a 20-year period, namely Baseline (current trend), 1 °C increase in temperature (Temp1) and 2 °C increase in temperature (Temp2). Eight LULC were identified in Djilor: mangrove, forests, savannah shrubs, croplands, bare lands, salt marshes, sabkha and water bodies. Forests and croplands constitute the major land use in terms of area. Croplands recorded the highest gain (17 %) throughout the period from 1984 and 2017, while forest registered the highest loss (12.5 %). The time interval 19841994 had the fastest annual area change. Regarding soil salinity, bare lands, fallow lands, rice plots and Fluvisols registered high values in salt content. Clay content, elevation and distance to river were the important factors associated with the increased salt content. In 1984, highly saline and moderately saline areas were the largest in extent 32.65 % and 38.9 %, respectively. In 2017, slightly saline areas increased to 39.69 %, while highly saline and moderately saline areas decreased to 20.85 % and 25.60 %, respectively. Sabkha and salt marshes cover had the largest salt-affected areas over time. Regarding the social response to salt content, local perception of soil salinity indicates a general increase of soil salinity in the area. Women group engaged in rice farming appeared to be more affected by soil salinity. To cope with the negative impact of soil salinity, the farmers' strategies are mainly the application of chemical fertilizer and manure, planting and conservation of trees, and installation of soil bunds. Simulation of soil salinity under current conditions showed an increasing trend of salinity over the next 20 years. The average EC was 6.48 dS/m and 9.77 dS/m for Temp1 and Temp2 scenarios, respectively for the period 2017-2036. Temp1 and Temp2 scenarios will contribute to increase the mean EC by 7.7 % and 15.8 % per year, respectively. Simulated salinity will also contribute to decrease crop yield. Rice crop registered the lowest yield over time with 228, 187, 149 kg ha^{-1} y^{-1} in BAS, Temp1 and Temp2, respectively, compared to maize, millet and groundnut. This study recommends the implementation of appropriate land management and mitigation strategies for preventing

climate change and its effects on salinity dynamics in the coastal regions of Senegal by policy makers and other stakeholders.

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LIST OF ABBREVIATIONS

	Agent Based Model
	Agence National Des Statistiques
ANOVA:	Analysis of variance
BAS:	Baseline
Ca:	Calcium
CEC:	Cation Exchange Capacity
CSE:	Centre de Suivi Ecologique
DEM:	Digital Elevation Model
EC:	Electrical Conductivity
ESP:	Exchangeable Sodium Percent
FAO:	Food and Agriculture Organization
GIS:	Geographical Information System
GPS:	Global Positioning System
IDRC :	Internationa Developement Research Center
INP :	Institut National de Pédologie
IPCC:	Intergovernmental Panel on Climate Change
ISRA :	Institut Sénégalaise de Recherche Agricole
K:	Potassium
LULCC:	Land Use-Land Cover Change
LUDAS:	Land-use Dynamics Simulator
LULC:	Land use-land cover
LUSI:	Land Use-Salinity Interaction
MAS:	Multi Agent System
Mg:	Magnesium
Na:	
NDSI:	
ABM:	
ANDS :	

	Sodium
	Normalized Difference Salinity Index
NDVI:	Normalized Difference Vegetation Index
NGOs:	Non-Governmental Organisations
ODD:	Overview, Design concept, and Details
ODD + D:	Overview, Design concept, Details and Decisions
OLS	Ordinary Least Squares
Panel-RE	Panel Estimator Random
PAPIL :	Projet d'Appui à la Petite Irrigation Local
PLD :	Plan de Développement Local
RBDS :	Reserve de Biosphère du Delta du Saloum
SAVI:	Soil-Adjusted Vegetation Index
SI:	Salinity Index
SPSS:	Statistical Package for Social Science
Temp1:	1-degree increase in temperature
Temp2:	2-degrees increase in temperature
TWI :	Topographic Wetness Index
UICN :	Union International pour la Conservation de la Nature
US:	United States
USD:	United States Dollars
USDA:	United States Department of Agriculture
UTM:	Universal Transverse Mercator
WASCAL:	West African Science Service Centre on Climate Change and Adapted Land Use
WRB:	World Reference Base

DEDICATION

I dedicate this PhD research work to my late mother, **Fatou Mbaye**, who unfortunately did not see the fruits of the seedling she planted. May the Almighty God accept her in His Paradise.

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CHAPTER 1: GENERAL INTRODUCTION

1.1. Background

The role of land in providing food and human security, building resilience to climate change and contributing to its mitigation is globally recognised (Nkonya *et al*., 2011). Despite this, land degradation is still affecting livelihoods and sustainable development. It may be caused by one or several factors, including land use and environmental factors such as salinization (Nkonya and Mirzabaev, 2016).

Land degradation due to soil salinity is one of the major and widespread environmental problem facing the world. It is the result of the accumulation of salt in land and water to an extent that causes degradation of vegetation and soil (Podmore, 2009). Salinization has great impact on soil fertility and crop production, particularly in arid and semi-arid areas where the climate conditions are harsh with insufficient rainfall and high evaporation rates. It has accelerate soil salinity processes, and thereby inducing food insecurity (Gorji *et al.*, 2015; Teh and Koh, 2016). Furthermore, soil salinity also affects other major soil degradation phenomena such as soil dispersion and increased soil erosion (Metternicht and Zinck, 2003; Rengasamy, 2006).

The extent of the effect of soil salinity is widespread. According to the Food and Agriculture Organisation of the United Nations (FAO) (2000), the global area of salt-affected soils including saline and sodic soils was estimated at 831 million hectares (Martinez-Beltran and Manzur, 2005; Rengasamy, 2006). Abrol *et al.* (1988) reported that 932 million ha in the world were salt affected areas, with 38.4% in Australia, 33.9% in Asia, 15.8% in the Americas, 8.6% in Africa, and 3.3% in Europe. Similarly, about 20% of the total irrigated land (230 million ha) worldwide is found to be highly affected by salinity. Salinization reduces the area of farmland by 1-2% per year and continues to increase (FAO, 2002). The issue of salinity will continue to expand due to the adverse impacts of climate change. Indeed, an increase in temperature coupled with the reduction of rainfall would increase the salt accumulation in the upper layers of soil and hence affect plant and crop growth (Dasgupta *et al.*, 2014; Marciniak *et al*., 2014; Ayed *et al*., 2015).

Two types of salinization processes are distinguished: primary salinization which is the natural process of parent material weathering and secondary salinization which is the result of human activities (Yadav, 2005; Podmore, 2009). These processes are the product of a complex interaction of various factors (e.g. groundwater quality, topography, irrigation, drainage, rainfall and temperature), which cause changes in both time and space, generally irreversible, leading to a lower production potential of the soil (Jabbar and Zhou, 2012). Another important factor associated with the variation of salinization is land-use history, which was neglected in previous studies (Zhang and Zhao, 2010). Land cover change results in the conversion of the vegetation appearance and function, which disturbs hydrological conditions, i.e. the balance between salinity and water, and in turn alter the land salinity pattern (George *et al.*, 1997).

The issue of soil salinity, processes, dynamics and impacts have been investigated through diverse approaches and at different scales (Schofield, 2003; Metternicht and Zinck, 2003). Despite all these attempts, soil salinity is still having limited database that can provide the true extent and characterization of salt-prone land resource. Limited predictive studies have been conducted in relation to soil salinity and climate change (Szabolcs, 1990; Schofield, 2003). The predicted climatic change will increase the saline areas mainly for two reasons:

i) The direct effect of climate on salt movement and the salt balance of soils through increasing temperature and aridity, and on the extent of coastal salinization due to the sea level rise; ii) The indirect effect on salt dynamics by changing the land use pattern e.g. by extending the area of irrigation as a consequence of the climate change (Szabolcs, 1990).

1.2. Problem Statement and Justification

Soil salinity has been one of the main problems for all coastal areas of the world generally due to inundation from sea level rise (Dasgupta *et al*., 2014; 2015). A recent study of Rintoul (2018) in the Southern Ocean showed a global increase of sea level rise that will consequently carry saline water and projects salt toward continental lands. Along the coastal area in Senegal, soil salinity constitutes the most complex and common soil degradation identified generally due to seawater intrusion. It was estimated that the seawater intrusion as a result of sea level rise, increased at a rate of about 1.3 $g^{-1} l^{-1} y^{-1}$ between 1950 and 1986 (Page and Citeau, 1990). Consequently, out of the 3.8 million ha of the cultivable land, 1.7 million ha are affected by salt at the national level (FAO and CSE, 2003). In fact, salinity affects almost all the eco geographic zones in Senegal. However, it is more present in the basin of Casamance with 73% of salt affected areas, 21% in Sine Saloum and 5% in the Niayes (INP and CSE, 2009).

In the groundnut basin which covers Kaolack and Fatick regions, soil salinity as a result of seawater intrusion from the Saloum River is one of the most serious long-term environmental problems (Faye and Maloszewski, 2005). In the agro-ecological zone of the groundnut basin, the salted soils extend to 201.237 ha, which represents 17.49% of the soil in this area (PAPIL, 2013). However, one of the main salt-affected areas in Senegal is located in Fatick region, coastal zone (UICN, 2013), that has 33% (221.441 ha) of the regional area being classified as highly salt affected (Chauvin, 2012). In this region, various natural and anthropogenic factors influence the wide extent of salt affected area. Indeed, considering the hydrological and geomorphological context, climatic variability (insufficient rainfall, high temperature and evaporation) prevailing in the area, the high vulnerability to soil salinity can be explained (Sadio,1991). Salinization also occurs due to some anthropogenic actions such as inappropriate farming practices, overgrazing, deforestation and other intensified agricultural activities (Legros, 2009).

Soil salinity in Fatick region has been investigated through various approaches. Most of these studies have paid much attention to salinization processes, salt balance and spatial extent, and mainly carried out in mangrove areas (Marius, 1985; Sadio, 1991; Montoroi, 1993). Findings from all these studies showed that soil salinization in Fatick results from various mechanisms including saltwater intrusion and capillary rise of salts from shallow groundwater. Salinity mainly affects the shallow groundwater resources, large areas of arable land and the ecosystem services provided by mangroves ecosystem which plays a vital role to the majority of the local communities (Faye and Maloszewski, 2005).

This situation is particularly worrying since the area has an agricultural vocation which occupies 73% of the population (ANDS, 2013). Indeed, the consequences of this increase in salinity are, among others, the abandonment of rice cultivation, declining soil fertility, yield reduction and consequently food insecurity and poverty in Fatick region (Sarrouy, 2010; ISRA, 2012; Sambou, 2016). Agricultural losses caused by salinity are estimated to be substantial and expected to increase, particularly in coastal regions where the potential impacts of climate change include potential flooding from sea level rise, temperature and rainfall changes (Metternicht and Zinck, 2003; Ahmed and Hamed, 2012; IPCC, 2018). So, if measures to fight against this salinity phenomenon are not taken, a very large part of cultivable surface of this region will be transformed into saline soils, thus endangering the populations survival and livelihoods. Therefore, in order to cope with and adapt to the increasing trend of soil salinity and enhance the restoration of salt affected cropping area for promoting sustainable agriculture, there is the need to have better understanding and assessment of soil salinity dynamics and impacts in the agricultural landscape. This is where dynamic models such as multi-agent based (MAS) model can play an important role and offers a way of incorporating biophysical and human systems in a saline landscape. Thus, the MAS model met exactly the purpose of this study, since it provides insights on soil salinity related to temperature and human systems in an agricultural landscape. In addition, various Agent Based Models (ABMs) have been developed to explore land use dynamics. However very few of them have tackled the soil salinity subject.

Moreover, mapping, monitoring, and prediction of salinization have been widely investigated through a synergy of approaches involving remote sensing and GIS, field and laboratory data, the use of models and geostatistical techniques (Furby, 2010; Juan *et al.*, 2011; Payne *et al.*, 2014; Nawar *et al.*, 2014). However, case studies with full data integration are still the exception. These methods of assessing soil salinity rarely integrate different components of soil salinization. They often focus on single issues such as surface salinity while ignoring other dimensions of soil salinization (e.g. vertical salinity process). Indeed, few of them incorporate farmers' decision in assessing soil salinity, which is one of the main important aspects of this study.

1.3. Aim and Research Objectives

1.3.1. Aim

This study aimed at investigating the patterns and impacts of soil salinity in agricultural land use using a multi agent-based model.

1.3.2. Specific objectives

The specific objectives were to:

- Determine soil salinity patterns and its determinants in a coastal agricultural landscape,
- Assess changes in land use and soil salinity over the period from1984 to 2017,
- Assess household perception of soil salinity and their adaptation strategies and,
- Develop a Land Use-Salinity Interaction (LUSI) model for exploring potential impacts of temperature scenarios and human decisions on salinity dynamics.

1.4. Research Questions

Based on the specific objectives, the following research questions were posed:

- How do soil salinity patterns vary in different land use, soil and crop types?
- What factors influence soil salinity in a coastal agricultural landscape?
- How have land use and soil salinity changed over the period from 1984 to 2017?
- How will the increase in temperature and the household decisions affect the extent of soil salinity in the next 20 years?

1.5. Presentation of the Study Area

1.5.1. Location and Size

The study was carried out in Djilor district, Fatick region, Senegal. It is located in the west central part of Senegal between latitude 13°54 and 14° 04' N and longitude 16°12 and 16°20' W (Figure 1.1). It covers an area of 444 km^2 and is watered by the Saloum River and its tributary, the Sine river. It is about 40 km from the sea and situated within the protected area of the Saloum Delta Biosphere Reserve (RBDS), which combines the characteristics of a marine, estuarine and lacustrine landscape. Administratively, Djilor district is subdivided into three agro-ecological zones and composed of 44 villages and eight hamlets: i) Kamatane: located in the northern part, it groups fourteen (14) villages; (ii) Djilor, the central part, it composes fourteen (14) villages; (iii) Keur-Cheikhou is situated in the south-west and composed by sixteen (16) villages. Djilor has extensive arable land which

has enabled the development of agriculture that mobilizes 73 % of rural households (ANDS, 2013). However, the sector remains vulnerable and is confronted with several constraints such as soil salinity. Soil salinity proce ss has been noticed in many parts of the study area, mainly due to seawater intrusion from the Saloum River system and evaporation (Faye *et al*., 2005) that has great impact on soil fertility and crop production and therefore endangering population survival (Sambou *et al.*, 2016).

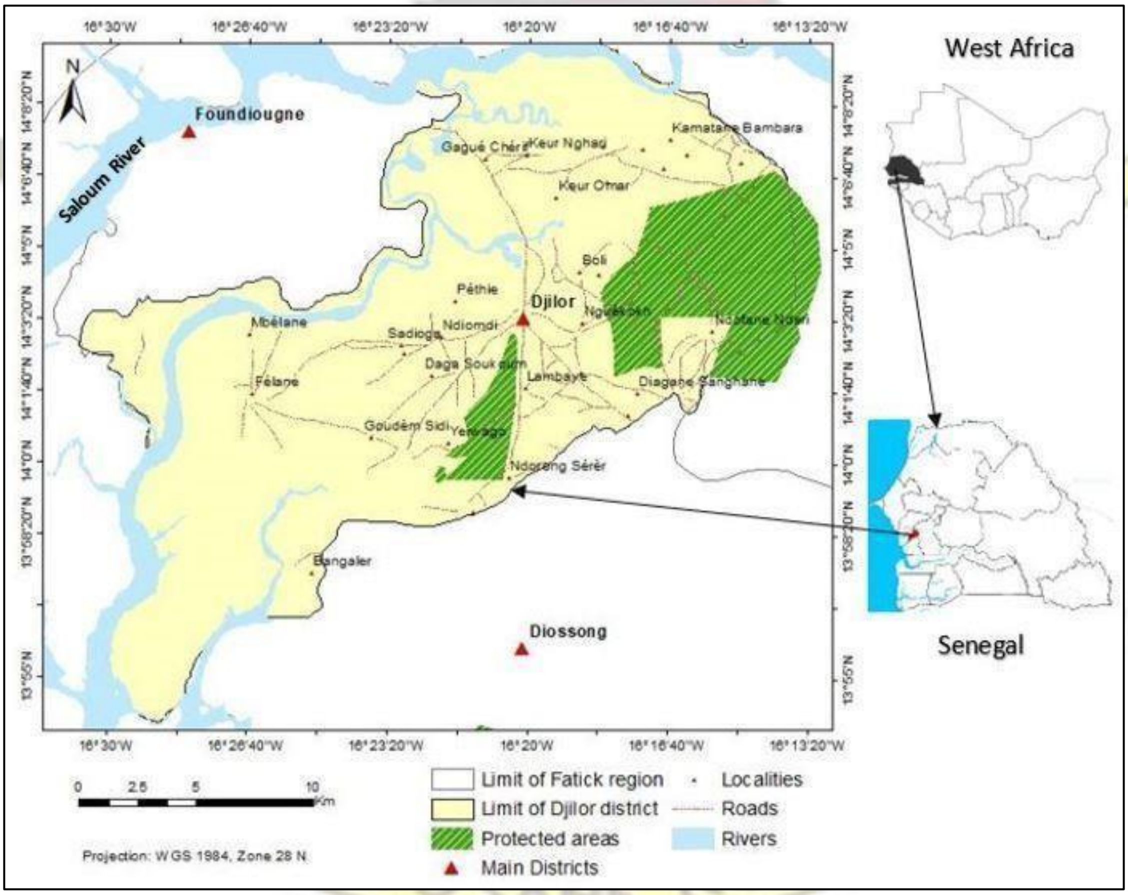

Figure 1.1: Location of study area (Djilor district)

1.5.2. Geology

The geology of Djilor corresponds to one of the Saloum basin of which it is an integral part.

According to Diop (1978), Saloum basin is located in the Continental Terminal and has Quaternary Sediments. In terms of geomorphology, the alternation of wet and dry periods of the Quaternary has deeply shaped the landscape and resulted in its current configuration. The different episodes of climatic events in the area have contributed in the formation of various geomorphologic units which are encompassed in two broad areas: the estuarine and the continental zones. The coastal strands, mangroves, salts marches and tidal flats, terraces uplands and depressions are the main geomorphological units of the area (Diop, 1978 and Marius, 1985). The tidal channels and the topography present in the region have facilitated the degradation of the environment, especially the intrusion of saltwater into agricultural land.

1.5.3. Soil

Based on the soil map (1/500,000) collected from the National Pedology Institute of Senegal (INP) and the FAO classification, three dominant soils characterise the area: Lixisols (tropical ferruginous soils), Gleysols (hydromorphic soils), and Fluvisols (halomorphic soils) (Figure 1.2). Lixisols are weathered soils with sub surface accumulation of low activity clays, mostly developed in drier areas. Gleysols are saturated soils with groundwater within 50 cm from the soil surface and have poor internal drainage. Fluvisols are generally recent soils in alluvial, marine or lacustrine deposits (FAO, 2001; Spaargaren, 2007). A significant variation is observed within these soils in Djilor in terms of texture, water and organic matter content, depth and other characteristics. The tropical ferruginous soils composed by the leached tropical ferruginous soils, commonly known as “*Deck- Dior*” soils in Djilor, are estimated at 17798 ha or 30% of the land area. Slightly leached ferruginous soils, also known as “Dior ”, soils, cover 12% (7084 ha) of total land area. The ferruginous soils are often situated in upland and more suitable for millet and groundnut crops. However, they are also subjected to degradation because of their sensitivity to water and wind erosion and inappropriate agricultural practices. Hydromorphic soils, locally called '*'Deck soils''*,

cover 5184 ha or 9% of the study area. They are located at the lowland and are rich in minerals and organic matter. Then, halomorphic soils known as saline soils and acidified saline soils called "*tann*". They are well represented in the commune since the drough t of 1970. Today these salty soils and acids continue to expand and increasingly encroach on croplands.

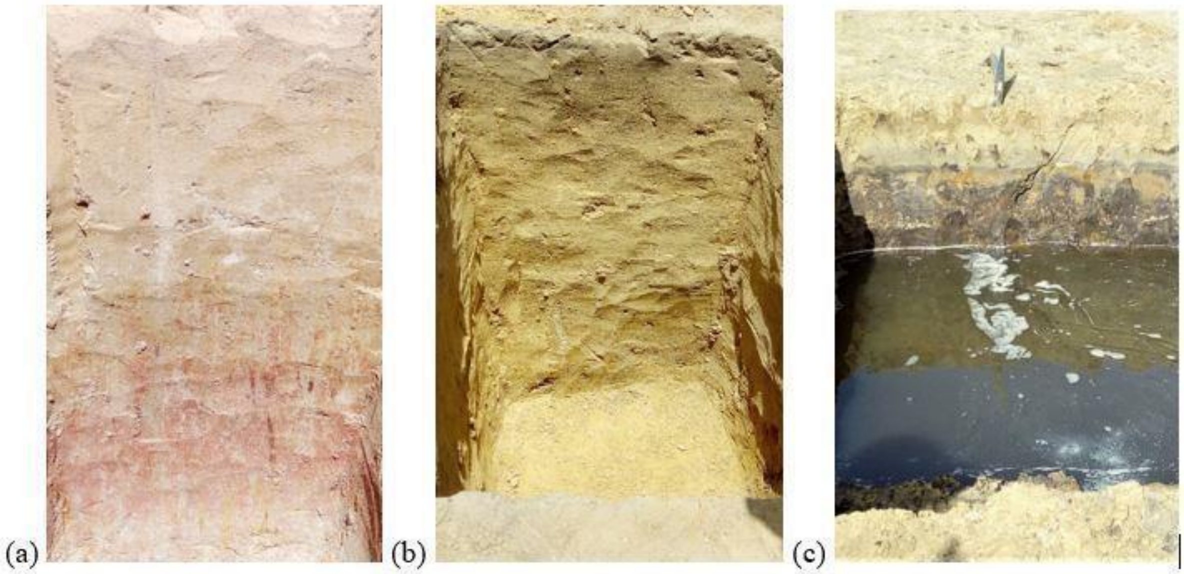

Figure 1.2: Soil type profiles : Fluvisol (a), Lixisol (b), Gleysol (c)

1.5.4. Vegetation

The vegetation cover of Djilor is mainly represented by shrub savannah composed of *Faidherbia albida (Kadd), Acacia seyal (Sourour), Adansonia digitata (Gouye), Cordyla pinnata (Dimb),* etc. The herbaceous layer is dominated by *Leptodania astata, Acacia opticifolia, Sida sp, Andropogon gayanus.* About 2100 ha of Djilor area fall under different protected area and composed of diverse ecosystems of mangrove, forest, cropland, fallow, and plantation (PLD, 2009). The classified forests of *Vélor* (1214 ha) and Djilor (900 ha) and community forests of *Djiffa (*300 ha) and *Ngargo* (377 ha) are the main forest formation of the area. In addition, invasive halophytes plants such as *Tamarix senegalensis* have occupied most of the saline areas. Also, Djilor is characterised by a high mangrove area covering 312 (ha).

1.5.5. Climate Conditions and Hydrography

Djilor is in the Sudan -Sahelian zone, characterised by an annual mean rainfall of 546 mm based on data from 1965 to 2016 collected from the Senegal National Meteorological Agency. The climate is composed by two distinct seasons: a rainy season of five (5) month from June to October and a dry season of seven (7) months from November to May. The annual rainfall has considerably fluctuated from 1970 to 2016 with a major decrease during the period from 1970 to 1990 followed by a slight increase in annual rainfall from 2008 to 2016 (Figure 1.3).

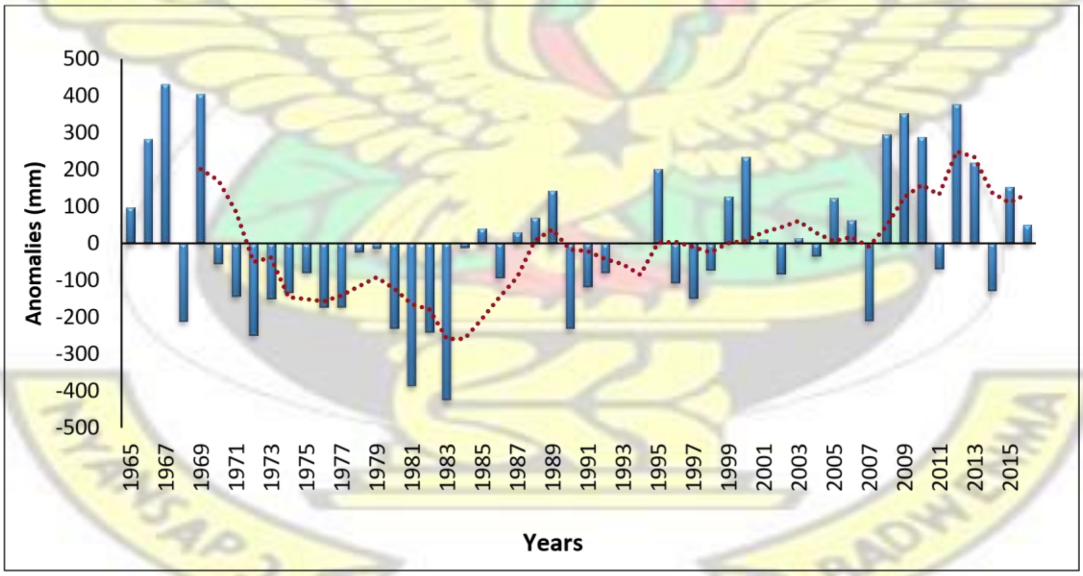

Figure 1.3: Mean deviation of annual rainfall of Fatick Station from 1965 to 2016

Based on the available temperature data from 1991 to 2016 at Fatick station, the area is characterised by an average annual temperature ranging from 28 to 31 °C. The maximum temperature is noticed in April with about 39.55 °C. During cold periods (January to December), temperature can drop below 20.7 °C. From 1991 to 1996, the analysis of temperature shows a decrease in temperature (Figure 1.4). However, from 1997, an increase in temperature is observed even though some years recorded a slight decrease.

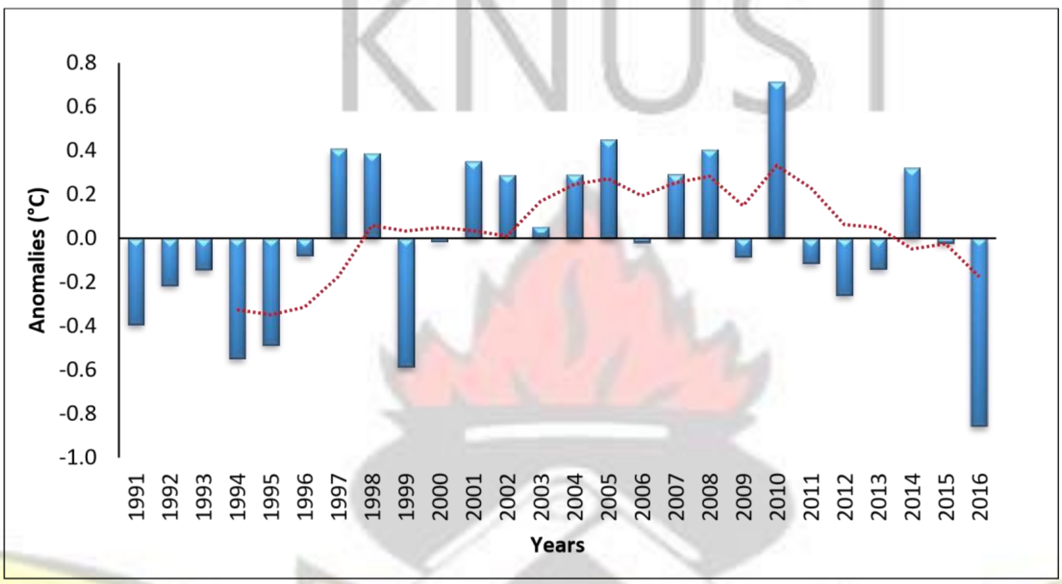

Figure 1.4: Mean deviation of annual temperature of Fatick Station from 1991 to 2016

The hydrographic network of the study area is relatively dense. The district is crossed by the sea arm of Saloum River and 16 marigolds that separate it from the local communities of *Thiomby* and *Mbellacadiao.* There are about twenty (20) valleys in the district including the one of *Mbam* which is more than 300 ha, the *Ndour-Ndour* valley which covers an area of 200 ha, the valley of *Boly Serere* and *Mbassis* which are respectively have 150 ha each.

Since the drought events of 1971, the whole of Senegal and especially the Fatick region, is characterised by a great irregularity of annual rainfall and temperature from one year to another, and this has accelerated the salinizati on process as well as reduced the water resource stocks, which constitute an important factor for the agricultural system and communities' livelihoods.

1.5.6. Human Population and Socio-economic Activities

The population of Djilor is estimated at 28, 606 people and had a population density of about 34.7 inhabitants per km² in 2013. The ethnic composition of the district is rather heterogeneous with a predominance of *Sereres*, which account for almost 60% of the population. This situation is explained by the geographical position of the local community which is at the heart of the ancient kingdom of *Sine*. There are other ethnic groups such as the *Pulaar* (25%), the *Wolofs* (10%) and other minorities such as *Diolas*, *Socés*, and *Bambara*. Agriculture is the main economic activity of the population as confirmed by 85% interviewed household heads, followed by pastoralism and other activities such as fisheries. The importance of agriculture explains the high concern of the populations in soil conservation and soil salinity management. The main staple foods and crop production in the study area are generally cereal based crops such as rice, millet, groundnut, maize, and sorghum, as well as root crops, fruits and vegetables. Millet and groundnut cultivation are mainly cultivated by men, while rice and maize are generally cultivated by female. A large proportion of this production is for consumption. However, contrary to millet, part of groundnuts may be intended for commercial purpose. Due to the soil salinity issue, households agreed that crop production and food availability have considerably reduced. Rice cultivation particularly has become more and more difficult because of soil salinity which affected most of the valleys (rice plots) and constitutes therefore a redoubtable issue for the local population and their food security.

1.6. Outline of the Thesis

The thesis is structured into seven (7) chapters. **Chapter 1** presents the general introduction including the problem statement, the objectives and the corresponding research questions.

It also briefly gives an overview of the study area. **Chapter 2** provides the literature review on the concepts related to soil salinity processes and its different methods of assessment including remote sensing and Multi-agent-based modelling. **Chapter 3** addresses specific objective 1, which focuses on soil salinity variability under different land use, soil and crop types in the area as well as assessing the determinant factors associated with the increase of soil salinity in Djilor. **Chapter 4** deals with specific objective 2. It estimates the changes in LULC types and soil salinity over the area. **Chapter 5 covers** specific objective 3. In this chapter, the household's perception of soil salinity dynamics and land use decisions are determined as well as salinity effects on farmers' livelihood and adaptation strategies. **Chapter 6** addresses the specific objective 4, which focuses on simulating salinity dynamics under different temperature scenarios. In this chapter, an agent-based simulation model (i.e. Land Use-Salinity Interaction model) was developed by combining simplified bio-physical processes affecting soil salinity and farmer decisions to mitigate its negative impact in a coastal agricultural landscape. Finally, c**hapter 7** presents a summary of the research findings, the conclusions and the relevant recommendations from the study.

1.7. Research Limitations

Some limitations were recorded in this study which were generally related to the multidimensional approach of evaluating soil salinity.

Firstly, the unavailability of soil data in the area for the past years was a major limitation in this study. For instance, using past measured EC data as ground truth for soil salinity mapping could provide better results of soil salinity change.

Secondly, the soil salinity dynamic model was based on assumption that 1 °C increase in temperature would increase the salt content by 0.249 dS/m, which could be a source of bias in predicting soil salinity.

Thirdly, the simulation of salinity extent was only based on temperature. Climate factors such as sea level rise and rainfall which could give a complete analysis of soil salinity-based climate change were not explicitly considered in this study.

Also, the validation of LUSI model was also a challenge. MAS model validation is currently debatable. However, certain methods of validation such as comparing simulated and observed data (Bousquet and Le Page, 2004), sensitivity analysis (Schouten, 2013), and using Role Playing Games theory (Villamor *et al.*, 2010; Amadou *et al*, 2018) are mostly applied. In this study, only the simulated versus observed data were used to validate the model.

Finally, LUSI model did not take into account the economics aspects of soil salinity, which methodologically, can participate in the validation and calibration of economic agent-based models (Troost, 2014).

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CHAPTER 2 : LITERATURE REVIEW

2.1. Introduction

This Chapter presents the review and theory of previous studies on the issue of soil salinity processes and dynamic in relation with land use-land cover and climate changes. Soil salinity management as well as its different methods of assessment including remote sensing and multi-agent-based modelling are also discussed in this Chapter.

2.2. Concepts and Definitions

2.2.1. Salinity/Sodicity

Soil salinity is a soil chemical degradation that consists of an accumulation of free salts in the soil that leads to deterioration of soils and vegetation (Arslan and Demir, 2013). Saltaffected soils are generally correlated with salts such as sodium chloride (*NaCl*), sodium sulphate (Na_2SO4), calcium chloride ($CaCl_2$) and magnesium chloride ($MgCl_2$). However, sodium chloride is one of the major salt contaminants in most of the saline soils (Munns *et al.*, 2002; Mansour and Salama, 2004). The resulting problems of salinity may be very different, depending on the geochemical processes involved in the development of salinization. For instance, as an important category of salt-affected soils, sodic soils are characterized by an excess level of sodium ions (Na^+) in the soil solution as well as in the cation exchange complex, exhibiting unique structural problem as a result of certain physical processes (slaking, swelling, and dispersion of clay) and specific conditions (e.g. surface crusting) (Ahmad *et al.*, 2011). Generally, in sodic soils, the high concentration of sodium (Na^+) displaces other cations such as calcium (Ca^{2+}) and magnesium (Mg^{2+}) and persists bound to clay particles causing significant structural soil degradation. A high proportion of exchangeable sodium attached to clay mineral exchange sites weakens the bonds between soil particles when the soil is wetted. As a result, the soil particles with increased dispersibility becomes more susceptible to erosion by water and wind (Paix *et al*., 2011). When drying, sodic soils become dense, cloddy and structureless because of the destruction of natural aggregation. At the soil surface, dispersed clay can act as adhesive, forming relatively dense crusts that impede seedling rooting and emergence (Daliakopoulos *et al*., 2016).

Moreover, based on the origin of salts, several studies have classified salinization into two types: 1) primary salinization, and 2) secondary salinization (Yadav *et al.*, 2011). Primary salinization is developed from the accumulation of salts in the soil or water over long periods of time, through natural processes including physical or chemical weathering and transport from parent material, geological deposits or groundwater (Figure 2.1) *(*Daliakopoulos *et al.*, 2016). According to Zhu (2001), primary salinization occurs generally in sea salt marshes or areas in which salt is already a part of the soil composition, and any plants that grow there are adapted to the soil properties. Taiz and Zeiger (2002) stated that the main source of salts in the soil is the weathering of parent materials in the exposed layer of the earth's crust as well as seawater since it contains about 500 mol/m^3 NaCl. Weathering processes break down rocks and release soluble salts of various types and therefore cause soil salinization. Salinization caused by seawater results from the deposition of salt carried in wind and rain (Munns *et al*., 2002).

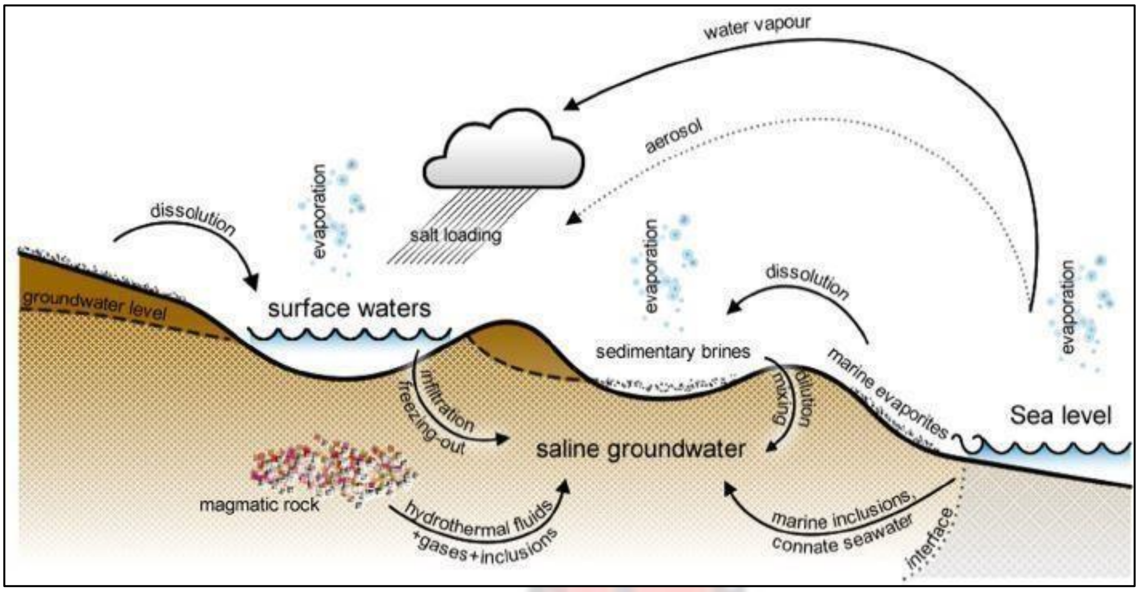


Figure 2.1: Primary salinity mechanisms (Daliakopoulos *et al*., 2016)

Contrary to primary salinization, secondary salinization is induced by human intervention such as mismanagement of irrigation systems (e.g. irrigation with saline water, poor drainage), land clearing, and large levels of salt in the effluent from intensive agriculture and industrial wastewater (Boivin and Brusq, 1985; Daliakopoulos *et al.*, 2016) (Figure 2.2). The connection between soil salinity caused by land use practices and its effect on soil productivity is fundamental to almost all published definitions of secondary salinization. Most importantly the central points of all the definitions are based on poor irrigation and drainage, inappropriate farming practices, overgrazing, deforestation and other intensified agricultural activities (Legros, 2009). In addition, secondary salinity occurs through seawater intrusion that is expected to be aggravated by climate change which is predicted to bring an increase in sea level rise, decrease in precipitation and rising temperatures (Yeo *et al.*, 1999; Carolinas Integrated Sciences, 2012).

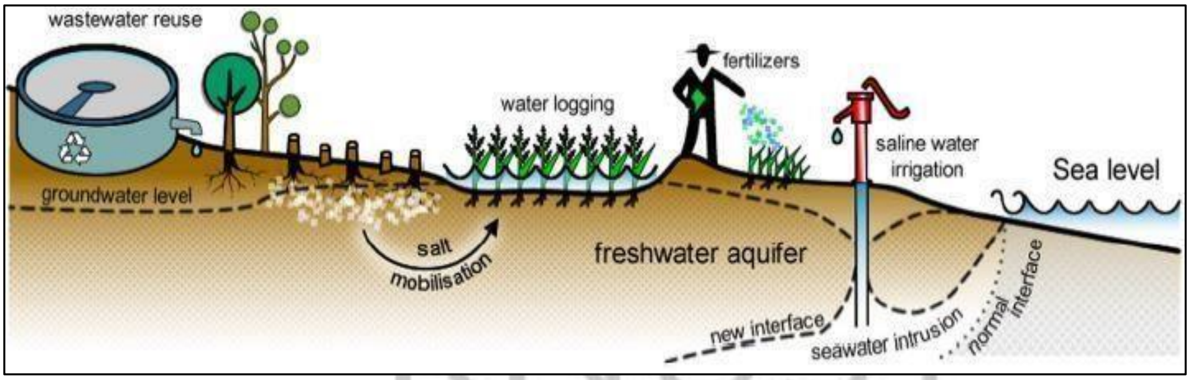


Figure 2.2: Secondary salinity mechanisms (Daliakopoulos *et al*., 2016)

In both cases (i.e. primary salinization and secondary salinization) , the main responsible factors are the concentration and the relative composition of salts in the surface and groundwater, and the changes they may suffer in soil solution (Sentis, 1996). However, it is sometimes difficult to categorise salt -affected areas issue as one or the other type because secondary salinization is often primary salinization accelerated by human activity. Many areas that now exhibit secondary salinization show considerable evidence of having been affected by primary salinization in the past (USDA, 2011).

2.2.2. Soil Salinity and Climate Change

Soil conditions depend on several climatic parameters, including rainfall, temperature, and humidity. Therefore, any change in climatic parameters will affect soil properties, crop production and consequently endangering communities livelihoods (Ashour and Al -najar, 2012). In the last century, in the Sahelian region of Africa, climate change has led to considerable changes in sea level, precipitation and temperature characteristics with negative effects on agricultural sectors and consequently on crops as well as expanded impoverish and degraded soils (IPCC, 2007). In arid and semi-arid lands temperature and rainfall play a very important role in the pedogenesis of saline and sodic soils (Hendry and Buckland, 1990). The study of Szabolcs (1990) was one of the first findings showing the implications of impact of climate change induced (i) temperature increase, (ii) sea level rise and (iii) irrigation water shortage on the soil salinization. For instance, in soil salinity process, as a consequence of extreme temperatures, high evaporation from the groundwater triggered the accumulation of salt in soil surface and crop's root zone by capillary rise (Austin *et al.,* 2010; Yu *et al*., 2014). Moreover, increasing sea level rise and insufficient rainfall due to global climate change have also had a great impact on salinization process and particularly on salt intrusion in coastal areas (Baten *et al*., 2015). In fact, due to sea level rise, seawater inundates coastal lowlands and deposits salts on the land surface (Teh and Koh, 2016; Sow *et al.*, 2016). According to Habiba *et al. (* 2014), climate-induced factors such as sea-level rise is one of the most pressing cause of salinity intrusion in coastal areas with tide through the rivers and estuaries. As for rainfall, it is considered as the main natural source for recharging groundwater. Therefore, in areas where rainfall is much higher than the rate of evaporation, salts are carried back to the ocean by surface and groundwater flows and do not accumulate (Faye *et al.,* 2005; Podmore, 2009), suggesting that insufficient rainfall reduces the availability of freshwater discharge and occasionally increase salt that would have been leached from the topsoil (Miller *et al*., 2005).

2.2.3. Soil Salinity Related to Land Use-Land Cover Change

Land use-land cover change (LULCC) is recognised as a major driver of global environmental change with continuous deforestation, urbanisation, modification and intensification of agricultural land. As such LULCC have induced significant effects on soil degradation including soil salinity, soil erosion and organic matter depletion (Sharma *et al.*, 2011). Soil salinity especially has been accelerated by human intervention through LULCC as well as land management practices (Zhang and Zhao, 2010). Many studies have recorded the environmental effects of soil salinity due to natural as well as human-induced Land useland cover change (LULCC). It includes studies on effects of soil salinity such as soil fertility and decreasing crop yield (Sylla, 1994; Wiegand *et al.*, 1996), agriculture and vegetation degradation or change in the type of plant species (Sambou, 1991; Abdul Qados, 2011; Sambou *et al.*, 2016). It is recognised that land cover dynamics, in particular, shifts in the vegetation cover and extent of the salt marshes may have considerably contributed to expand salt-affected areas and anticipated further environmental degradation (Masoud and Koike, 2004). On the other hand, soil salinity becomes a Land use-land cover issue when it inhibits plant growth, causes the death of nearby trees and therefore contributes to the changes and transitions among land use types (Allbed *et al*, 2017).

2.2.4. Soil Salinity Impacts and Management

2.2.4.1. Salinity Impacts

Soil salinity has adverse effects on various sectors, ecosystems and consequently on people livelihoods (Habiba *et al.*, 2014; Baten *et al.*, 2015). The agricultural sector constitutes one of the most sensitive sectors to the risks and effects of salinity (Dobermann *et al*., 2013). This problem is expected to be aggravated by climate change which is predicted to bring about increases in temperature and sea level rise (Baten *et al.*, 2015). Salinity has profound effects on soil productivity due to unavailability of freshwater and soil degradation (Ayed *et al.*, 2015). It reduces soil quality, limits the growing of crops, and constrains agricultural productivity. Similarly, salinity causes browning of rice fields and consequently reduces rice production (Yeo *et al*., 1999; Ali, 2006; Nhan *et al*., 2010). In West Africa, around 650,000 ha of rice land is threatened by salinization, particularly within the arid or semi-arid region where rainfed rice production is not feasible (Africa Rice Center, 2007). This is mainly because rice plots are mostly located in lowlands and therefore are most exposed to seawater inundation and salt accumulation. Briefly, soil salinization results in significant limitations to agricultural crop production and, therefore, negatively affects food security. The salinity induces losses of yields within dry territories which can undermine the quality of life for local people and aggravate damage caused by land degradation and climate change. Worldwide, the annual loss of agricultural productivity is estimated to be US$ 31 million, while the financial loss due to land abandonment following soil salinization and lack of water for leaching salt from the soil is estimated at US$ 12 million (World Bank, 2009). In addition, salinization also poses a major environmental hazard by degrading the quality of water, vegetation change and decreasing wildlife diversity (Bhatt *et al*., 2008). Salt has two major effects on plants: osmotic stress and ionic toxicity, both of which affect all major plant processes (Baten *et al.*, 2015). Indeed, salinity renders less water available to plants in the root zone by increasing the osmotic pressure of the soil solution and thus prevents the plants to get enough water. High concentration of salt may also prove toxic to the plants when concentrations of salts are imbalanced inside plant cells, thus inhibit cellular metabolism and processes. In fact, salinity constitutes one of the causes of vegetation change and deforestation (Sambou *et al.*, 2016).

2.2.4.2. Salinity Management

Sustainable land management solutions for the problem of soil salinity largely depend on water availability, climatic conditions, land use types under threat, the current extent and rate of the threat, and the availability of resources (capital, inputs) (Panagea *et al*., 2016). In fact, various strategies and technologies have been implemented to manage and prevent salinity effects over the world. A brief account of such methodologies towards soil salinity and water management is presented in Table 2.1.

These different measures result from the intervention of many stakeholders including researchers, communities, governments, NGOs and other concerned organisations.

However, the adoption of sustainable land management practices usually depends on financial, technical, socio-economic and biophysical factors (Illukpitiya and Gopalakrishnan, 2004). Moreover, the successful approach of combining various techniques of salt removal to restore large salt affected areas also demands both economic and technical needs. In developing countries, lack of funds and investment to support land amelioration in saline areas are one of the main factors that limit the rehabilitation of salt affected areas. However, in Senegal, many tentative soil salinity management practices (e.g. reforestation with halotolerant species such as *Acacia senegal*, *Eucalyptus sp*, *Tamarix aphila*, *Melaleuca leucadendron*, and *Prosopis juliflora*; construction of dam anti -salt, amendment of soils) were undertaken to reduce salinity effects on agricultural land and small farmers livelihoods. Despite all these attempts, soil salinity is still expanding and constitutes one of the serious environmental problems in Senegal.

Table 2.1: List of some management practices and technologies for saline soils

Management practices	Main benefits	Sources

Introduction of salinity tolerant plants (Halophyte plants) and tolerant crop varieties	Decrease salt accumulation, improve vegetation cover, decrease evaporation, conserve soil water content, improve crop production	Ahmed and Hamed (2012); *Qureshi et al.* (2007), Qadir *et al.* (2007)

Use of compost, manure and organic soil amendments	Improve soil quality nutrients	Miller *et al*. (2005); Kashenge-Killenga *et al.*, (2014)
Use of inorganic amendments	Increase soil nutrients, reduce irrigation water application, improve crop production	Srivastava *et al*.(2014); Ahmad *et al*.(2011)
Mulching with leaves /crops debris	Improve soil quality structure decrease of evaporation, conserve soil water content	Lanyon (2011) ; Fall (2017)
Mechanical removal of salt surface and salt crust	Decrease soil salt accumulation	Qadir *et al*. (1999) ; Inoue, 2012)
Leaching and surface flashing	Decrease soil salt accumulation, Increase drainage	Lanyon (2011); Qadir et *al.* (1999)

2.3. Soil Salinity Assessment

The complexity and difficulty to assess soil salinity remains a major challenge due to its highly dynamic process, causing identification constraints derived from the proper behaviour of the salt features, spectrally, spatially and temporally (Metternicht and Zinck, 2003). However, various methods have been used to monitor and evaluate salt content.

2.3.1. Soil Salinity Indicators

structure, conserve soil water content increase soil Indicators are measured parameters that provide understanding and information about the state of an object or phenomenon. According to Pellant *et al.* (2005), indicators are components of a system whose characteristics (e.g. presence or absence, quantity, distribution) are used as an index of an attribute that is too difficult or expensive to quantify. Using indicators is becoming increasingly important tools for assessing the environmental problem and disseminating findings to decision makers and the public (Reed *et al.,* 2006). In the context of this study, a salinity indicator is a sign or symptom suggesting how the soil is experiencing the impacts of salinity and therefore showing whether soil salinity is occurring in the area or not. The use of indicators in assessing soil salinity is informed by the complex nature of the processes of salinization which makes it impossible to measure in simple units. Studying salinity indicators include a combination of various physical and chemical properties of the soil that can best represent environmental and human-induced changes in soil salinity. Common measurable indicators of soil salinity are electrical conductivity (EC), exchangeable sodium percentage (ESP), deterioration of soil structure and soil surface crusting (Metternicht and Zinck, 2016).

2.3.2. Remote Sensing Approach

Remote sensing is one of the key tools in monitoring local, regional, and global environmental issues. More recently, much attention has been paid to spatial analysis due to the merging of geographic information system (GIS) and satellite images for environmental research and applications (Halder, 2013). Remote sensing data and techniques are particularly efficient for the identification and mapping of salt-related surface features (Matinfar *et al*., 2013). They have been progressively applied to monitor and map soil salinity since 1960 when black-and-white and colour aerial photographs are used to delineate salt-affected soils (Saleh, 2017). Currently, a variety of remote sensing data has been developed and used to delineate salt affected areas, including video images, infrared thermography, visible and infrared multispectral and microwave images (Metternicht and Zinck, 2003). Advances in digital photography and high-resolution satellite imagery continue to improve the speed, portability, and cost-effectiveness of detecting salinity. Allbed *et al.* (2014a) and Gao *et al.* (2016) have demonstrated the value and importance of remote sensing techniques in soil salinity studies. In fact, the presence of salts at the terrain surface can be detected from remotely sensed data either directly on bare soils, with salt efflorescence and crust, or indirectly through vegetation types and growth as these are controlled or affected by salinity (Mougenot, 1993). There are many satellites and sensors, which are useful in detecting and monitoring saline soils. Among them include LANDSAT, SPOT, IKONOS, IRS, and Terra-ASTER with resolution ranging from medium to high as well as hyperspectral sensors (Azabdaftari *et al*., 2016). However, several limitations of remote sensing application on soil salinity assessment were reported by previous studies. First, most of the sensors scan only the soil surface, while the entire soil profile is involved in salinity process and should be considered for better assessment of salinity extent (Farifteh *et al.*, 2006). Secondly, many environmental conditions or soil characteristics have an influence on reflectance or on the signals gathered by the sensor and may therefore cause a spectral confusion which masks the difference in salinity degrees (Metternicht and Zink, 1997). Such factors include soil moisture content and roughness, salt content, texture and mineralogy (Howari, 2003). Generally, reflectance increases with high quantity of salts crust at the land surface, and decreases with high moisture, the presence of ferric oxides and inclusion of clay, and therefore make salts difficult to identify (Mougenot *et al*., 1993). This may explain why most of the published investigations based on remote sensing distinguish only two to three classes of soil salinity. Usually, moderately to highly saline areas are easily detected, while low salinity levels and the initial stages of salinization are more difficult to discern. In addition, quantitative results of soil salinity from remote sensing applications are not easily achieved without the combination of auxiliary data such as groundwater depth, topography and soil data can be difficult to obtain, especially in arid areas (Zhu *et al.*, 2001; Metternicht and Zinck, 2003). Therefore, monitoring salinity changes from past to present years faces the difficulty that, in general, there is no ground-truth information available for past situations. Thus, validating historical remote sensing data involves uncertainties. All these limitation highlight the necessity of using further data and techniques, in combination with remote sensing to monitor soil salinity (Farifteh et *al.*, 2006).

2.3.3. Modelling Approach

Several models have been developed and applied to investigate and predict salt affected areas. They were developed according to the level of complexity, data requirements, the scale of application, the way salinity processes are represented, and the types of output information they display. Among them, SALTMOD (Madyaka, 2008), regression-based model (Lesch *et al*., 1995), SALMOD (Armour and Viljoen, 2002), SWAP (Mansouri *et al*., 2008), and HYDRUS (Rahman *et al*., 2016) have been relevant and useful to soil salinity modelling and mapping. Most of them predict the salt movement and accumulation on soil based on biophysical factors while ignoring the social dimension of soil salinity. As Farifteh e*t al.* (2006) proposed, there is the need to build an integrated approach that combines social data, geophysical survey and solute transport modelling to assess and map salt-affected soils. There have been many attempts to tackle this complex methodological approach, each with its own strengths and weaknesses. However, multi-agent system (MAS) models may be a promising approach in modelling soil salinity as recently demonstrated by Asseng *et al.* (2007).

2.3.4. Multi-Agent System (MAS) Models

The use of MAS model for tackling natural resources and environmental management issues has been steadily growing (Bousquet *et al.*, 1999). It has been recognized as a useful tool for building a sound theoretical framework to deal with the complexity of LULCC and to more efficiently support environmental decision-making processes (Bousquet and Page, 2004; Ligtenberg *et al.*, 2004). It has the capacity to combine biophysical and social data embedded in the modelled system (Bousquet and Page, 2004; Ligtenberg *et al.*, 2004; Villamor *et al*., 2011). Bonabeau (2002) described MAS model as a system of agents and the relationship between them. According to Gilbert (2007) MAS model is a computational procedure that permits a researcher to create, analyse and experiment with models composed of agents that relate within an environment. Similarly, Parker *et al*. (2003) highlighted the increasing interest of Agent-Based Model (ABM) in investigating various adaptation measures scenarios and evaluating new policy in land use.

In a Land use-land cover change (LULCC) context, agents can include land owners, farmers, collectives, migrants, management agencies, and/or policy-making bodies, all of whom make decisions or take actions that affect land-use patterns and processes (Asseng *et al.*, 2010). By simulating the individual actions of many diverse actors and measuring the resulting system behaviour and outcomes over time (e.g. the changes in patterns of land cover), ABM can be useful tools for studying the effects on land-use/land cover. Furthermore, experimentation with this kind of model can improve the understanding of how the interaction between landscape characteristics and the preferences and behaviours of agents might influence ecological functions and diversity.

The classic method to assess the soil salinity in Senegal was based on Electrical Conductivity (EC) measurements of the soil, which is usually correlated with other soil properties such as soil texture, Cation Exchange Capacity (CEC), pH, drainage conditions and organic matter level (Sambou *et al.*, 2016; Chauvin, 2012). In terms of spatial distribution, the salt content were usually displayed throughout maps and transect plots by using remote sensing and GIS techniques. However, none of the previous studies in the area had used an agent-based model tool to assess and simulate soil salinity dynamic in coastal region of Senegal.

CHAPTER 3 : SOIL SALINITY PATTERN AND ITS DETERMINANTS IN COASTAL AGRICULTURAL LANDSCAPE

3.1. Introduction

Salinization is the result of many disturbances. In regards to the two types of salinization described in Chapter 2, salinity occurs as natural and/or human-induced processes (George *et al*., 1997; Yadav *et al*., 2011). However, the salinization issue may further increase as a result of other sources by natural factors such as landform, land use types as well as soil types or by other anthropogenic variables such as land management practices (Schofield *et al*., 2001; Fang *et al*., 2005a; Northey *et al*., 2006; Zhang and Zhao, 2010; Acosta et *al*., 2011). These are important factors determining salinity hazard and risk for various landscapes and therefore contribute to the increasing effect of salinity in the agriculture sector.

Fatick region as part of the Saloum river delta is characterised by a high extent of salinity which may vary based on many environmental factors such as tidal flow, land use type, soil type and topographical land positions. Despite plans, studies and strategies undertaken by different stakeholders (e.g. Senegalese government, researchers and NGOs), information on such factors affecting the variation and increase of soil salinity as well as their interaction particularly in coastal agricultural areas remain limited. Filling this information gap is crucial for minimizing the negative impacts of salinization especially for local smallholder farmers in Djilor as well as for the whole coastal region of Senegal as one of the least developed countries. Thus, the objective was to characterise the soil salinity pattern under different land uses, soil and crop types and determine the factors associated with soil salinity in a coastal agricultural landscape that may affect smallholder farmers' livelihood.

3.2. Methodology

3.2.1. Data Collection

3.2.1.1. Soil Samples Design and Data Collection

Fieldwork was conducted from March to June 2017 for soil samples collection. In this study, a multi-stage sampling was applied to select the villages where soil samples were to be collected (Belay, 2014). Based on the information obtained from Djilor Agriculture and Rural Development office (CADL) and field investigation, Djilor district is divided into two zones, saline and non-saline. Thus, in the first stage, the 44 villages of the study area were stratified into two strata based on their location. For the second stage, 10 villages were selected from each zone, giving a total of twenty (20) villages identified. They were purposely selected representing the whole study area based on the following criteria:

i) their location within the district, *ii)* their proximity to the sea, *iii)* the extent of soil salinity, *iv)* the existence of land management practices, *v)* agriculture as dominant economic activities, *vi)* the presence of some projects working on the issue of soil degradation.

From that, 15 sample plots were randomly selected within different categories of land use, soil types and topography, in each village. Five soil sub-samples were collected in each sample plot unit by augering at 0-30 cm depth to make one composite soil sample (Dahal and Routray, 2011). Only the topsoil with a soil depth of 0-30 cm was considered because the topsoil is the most important component in farm plots, and generally subject to various fluctuations that induce salt accumulation (*Li et al.*, 2011; Yu *et al*., 2014). Thus, a total of 304 composite soil samples were collected over the study area (Figure 3.2). For each sample plot, the location was georeferenced using a Global Positioning System (GPS) and its land use and soil types were recorded. The land use type of each plot was identified based on the field observation and on the existing land use maps from the Centre of Ecological Monitoring (CSE) in Senegal with 30 m x 30 m resolution. Four major land use types of the plots were identified: grassland, annual crop land, bare land and fallow land. Also, the crop type of each plot was recorded during the soil survey with the assistance of the plot owners.
Four major crops were identified: rice, maize, millet and groundnut.

In addition, the characterisation of soil types of the study area, a total of twenty-four (24) soil profile pits (1.5 x 1) with one metre (m) soil depth were also dug according to the toposequence (Figure 3.2). About 8 toposequence transects were purposely chosen. Each toposequence composed of three (3) sampling pits installed at the major geomorphological units (i.e. low slope, middle slope and upper slope). Three soil samples were taken per pit at three depth: 0-30 cm; 30-60 cm and 60-100 cm. One metre soil pit depth was considered in this study since it constituted the maximum root depths for most of the trees and plants in the area. The pits were georeferenced and described. Genetic horizons of the profile and soil type were characterised according to the guideline of WRB/FAO (2014).

Figure 3.1: Soil sampling by auguring (a) and sample pits (b)

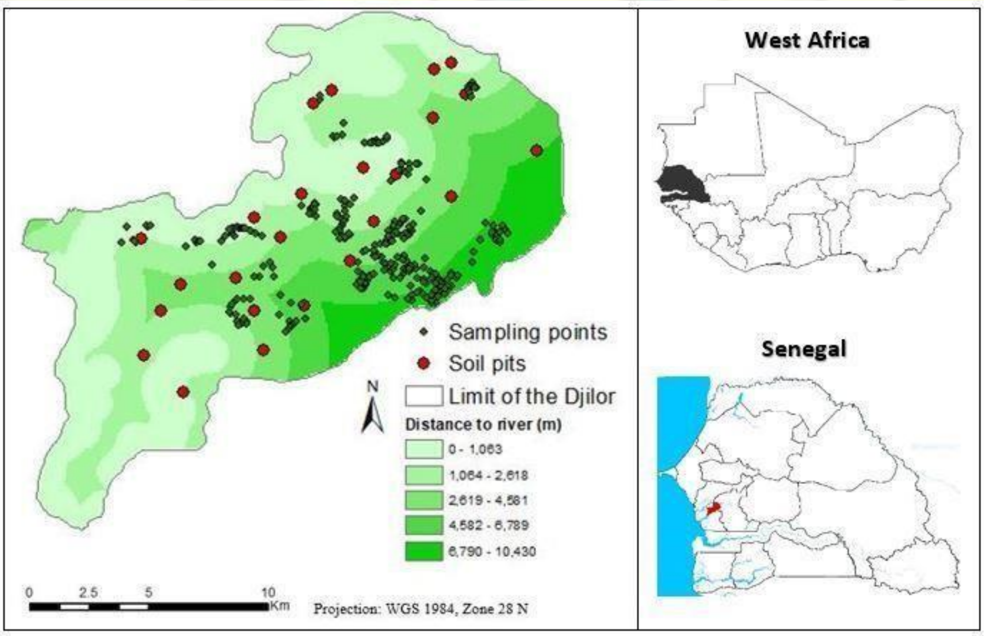


Figure 3.2: Location of the soil samples points

3.2.1.2. Laboratory Analysis of Soil Samples

Collected soil samples were taken to the soil laboratory to determine soil parameters such as electrical conductivity (EC), pH, exchangeable base (i.e. calcium, sodium, potassium, magnesium), cation exchange capacity (CEC) and particle size (i.e. sand, silt and clay).

These elements are important indicators of soil conditions and specifically the soil salinity mechanism.

Electrical Conductivity (EC)

The electrical conductivity (EC) of the soil is one of the chemical parameters that inform best about the evolution of salt content in the soil. It was determined through a suspension of 1/5 soil water ratio where 30 g of air-dry soil was mixed with 150 ml of distilled water, boiled and left to stand for cooling. It is determined by an electrical conductivity meter.

Soil pH

There are two main types of pH that can be distinguished: pH_{water} and pH_{kcl}. First, to determine pH_{water} of the soil, the suspension was at 1 / 2.5 with 20 g of sample added to 50 ml of distilled, boiled and cooled. The pH_{kcl} was obtained after addition of 3.75 g of *KCl*.

The pH is determined using a pH meter.

Exchangeable Bases and CEC

The exchangeable bases are mainly potassium (K^{+}), sodium (Na^{+}), calcium (Ca^{2+}) and magnesium (Mg^{2+}), which determine the type of salt in the soil solution. They are determined by atomic absorption for the metal cations (Ca^{2+} and Mg^{2+}) and by flame photometry for the sodium-potassium cations (Na^{+} and K^{+}). For sodium-potassium determination, a known sample weight was put into a conical flask and 50 ml of ammonium acetate extraction solution was added and shaken on a mechanical shaker for 2 hours and then filtered through filter paper, potassium and sodium were measured directly on the Flame Photometer. As for calcium and magnesium measurements, 5 g of air-dried soil sample was put in a 150-ml conical flask and 25 ml of neutral normal ammonium acetate solution was added. The solution was shaken on a mechanical shaker for 5 minutes and filtered through a filter paper. An aliquot (5 ml) of potassium hydroxide solution was pipetted and 5 ml of 16 % NaOH solution were added. A spectrophotometer with 630 nm wavelength was used to determine calcium and magnesium.

Particle Size

It was determined by using the Robinson pipette method. The determination of the percentage of the particles belonging to each fraction is based on the destruction of the aggregates by dispersion of the colloids flocculated using sodium hexa-metaphosphate. Fine fractions (clays and silts) were affected by sedimentation measurements, while coarse fractions (coarse, medium and fine sands) were isolated by sieving on standardized sieves. The soils were classified into different textural classes using the USDA textural triangle. The different types of clay content may differently affect salt accumulation in the soil, however, in this study, the type of clay was not determined; only the clay content was considered.

Exchangeable Sodium Percentage (ESP)

Exchangeable Sodium Percentage (ESP), another soil parameter that characterises soil Sodicity was also calculated. ESP is the sodium adsorbed on soil particles and it is calculated as indicated in Equation 3.1 (Tejada *et al*., 2006). Accordingly, sodic soil has an ESP greater than 15 %.

$$ESP = \frac{Na^{+}}{CEC} \times 100 \qquad (3.1)$$

3.2.1.3. Biophysical Data

Topographical characteristics, soil properties and other biophysical characteristics of the study area including distance to the river, groundwater depth and topographic wetness index were the main biophysical inputs used in this study (Figure 3.3).

Topographical Characteristics

Coastal areas are complex depositional environments, exhibiting considerable spatial heterogeneity in sedimentological and hydrological characteristics, often at very local scales (Sawczyński and Kaczmarek, 2015). Such spatial variability generally results from fundamental topographical characteristics, which also influence soil salinity. Thus, landform attributes such as slope, elevation as well as topographic wetness index (TWI) generated from Digital Elevation Model (DEM) (i.e. 30 m x 30 m resolution) were considered in this study. DEM was collected from the Directorate of Geographic and Cartographic Services in Senegal. Elevation and TWI especially are generally related to information on topography, soil types, and drainage systems, which effectively affect the salt content (among other soil attributes). TWI is mostly used to quantify the control of local topography on hydrological processes and delineates the spatial distribution of soil moisture (Quinn *et al.*, 1995), which is also an important factor in salinity process. It was computed as follow:

$$TWI = Ln\ (a\ tan\beta) \quad (3.2)$$

Where in terms of a raster DEM, *a* = the upslope area, per unit contour length, contributing flow to a pixel; t*anß* = the local slope angle acting on a cell.

Distance to the River and Groundwater Depth Maps

The relationship between soil salinity, distance to the river and groundwater depth has been reported by various authors. Qian *et al.* (2017) have recently shown the importance of distance analysis in salt accumulation. Therefore, the distance Euclidian tool in ArcGIS was used to generate the map of the distance to the river. As well, groundwater depth data were used. They were generated from a total of 26 sample wells collected during the dry season by the Local Small-Scale Irrigation Project (PAPIL, 2013), and soil map of the study area was collected from the National Institute of Pedology of Senegal.

The spatial analysis tool in ArcGIS was used to extract the values of the biophysical factors for each sampled plot. The elevation in the study area ranges from 0 to 20 m and a maximum slope of 0.5%, while the groundwater depth ranges between 0.5 and 8 m. It was observed that the lower values of elevation were along the river and within the lowlands and therefore constitute a good predictor for salt accumulation. The distance to the river of the sample points varied from 0 to 10.5 km. The higher wetness value reflects a higher degree of water saturation. The highest wetness recorded was 16.18 and the lowest was 6.3.

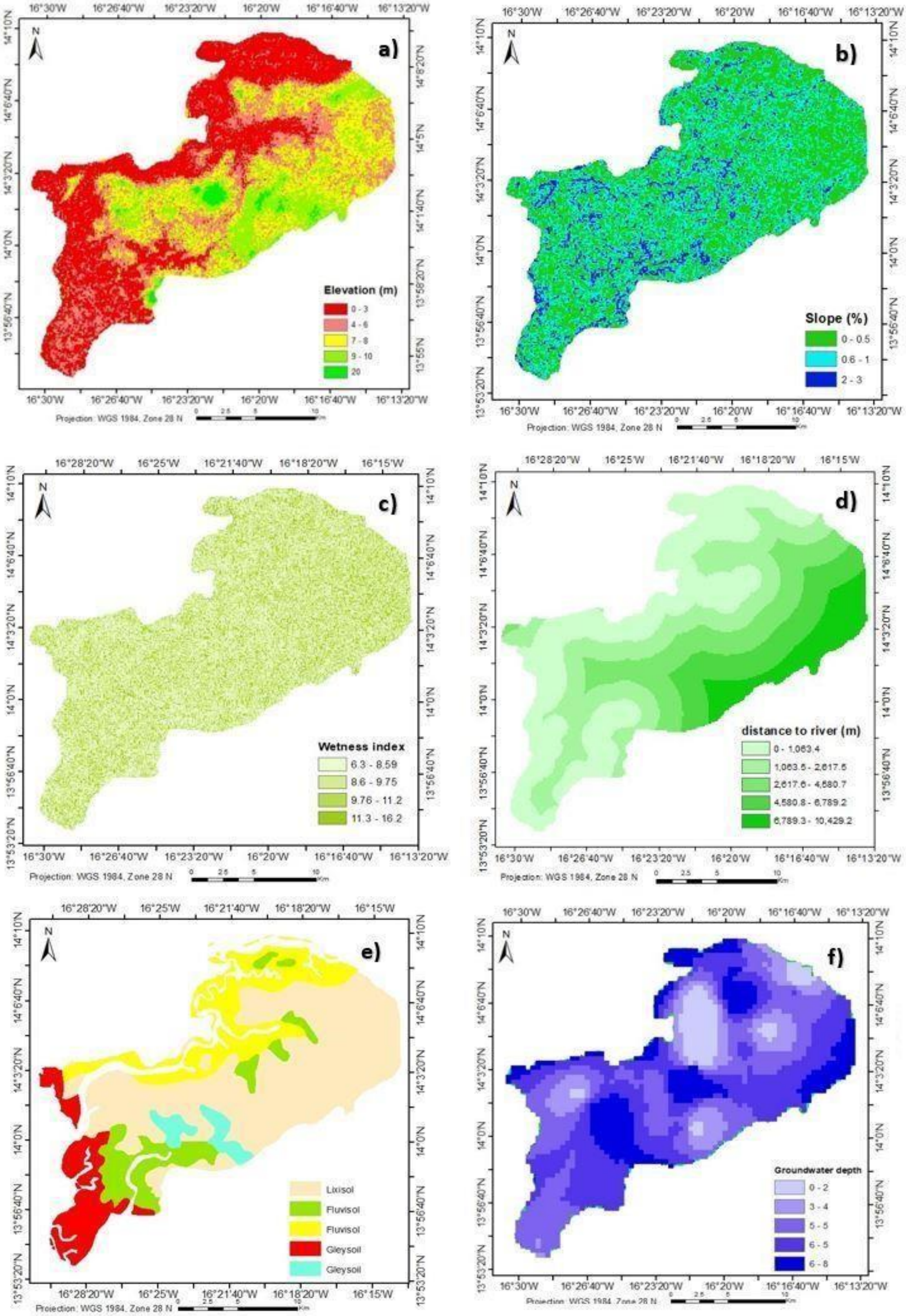


Figure 3.3: Elevation (a); slope (b), wetness index (c), distance to river (d), soil type (e); groundwater depth (f) maps of Djilor district

3.2.2. Data Analysis

Most of the sample sites were explored and compared using simple statistical analysis methods. One-way analysis of variance (ANOVA at $p=0.05$) was performed on soil samples from each area to determine the statistical significance and compare soil salinity distribution according to land use types, soil groups and crop types. The factors associated with soil salinity problem were determined using regression analysis. Factors having the highest impact on salinity content were measured using the coefficients size of standardised variables (Villamor *et al.*, 2014). The statistical analyses (including multi-collinearity and variance inflation factors tests) were performed using STATA 15 software.

3.3. Results

3.3.1. Soil Characteristics

Table 3.1 presents the results of laboratory analysis of soil physico-chemical properties used to determine the soil characteristics in the study area. The results reveal a great soil properties gradient as a function of the topographical positions (low slope, middle slope and upper slope) and soil depth (0-30 cm, 30-60 cm and 60-100 cm). The pH and EC values show a clear variability along the soil profile and from a land position to another as shown by the outputs of the correspondence analysis (Figure 3.4). In fact, the variation of EC along the soil profile is more associated with low slope position, while pH variation shows a close association with the upper slope.

Table 3.1: Mean values of soil properties under different topographical positions in the Djilor district.

Depth (cm)	EC (dS/m)	pH	Ca^{2+}	Mg^{2+}	K^{+}	Na^{+}	CEC	ESP (%)	Texture
Low slope									
0-30	8.0	5.30	2.87	0.21	0.58	4.40	4.42	223.5	SC
30-60	6.6	5.06	2.65	0.21	0.44	4.35	4.58	175.4	CL
60-100	5.1	4.36	1.75	0.64	0.49	3.96	3.19	127.3	CL
Middle slope									
0-30	4.6	5.81	1.78	0.42	0.12	0.77	3.46	29.6	S
30-60	3.4	5.98	1.68	0.51	0.13	0.65	3.85	16.1	SL
60-100	3.3	6.20	1.56	0.32	0.16	0.94	5.96	22.5	SL
Upper slope									
0-30	1.7	4.83	2.10	0.22	0.10	0.62	5.38	7.41	S
30-60	1.9	5.12	2.07	0.27	0.09	0.81	5.40	11.00	S
60-100	3.3	5.21	2.02	0.17	0.10	1.19	9.45	8.35	SL

Note*: S=sandy; SC= sandy clay, SL= sandy loam; CL= clay loam*

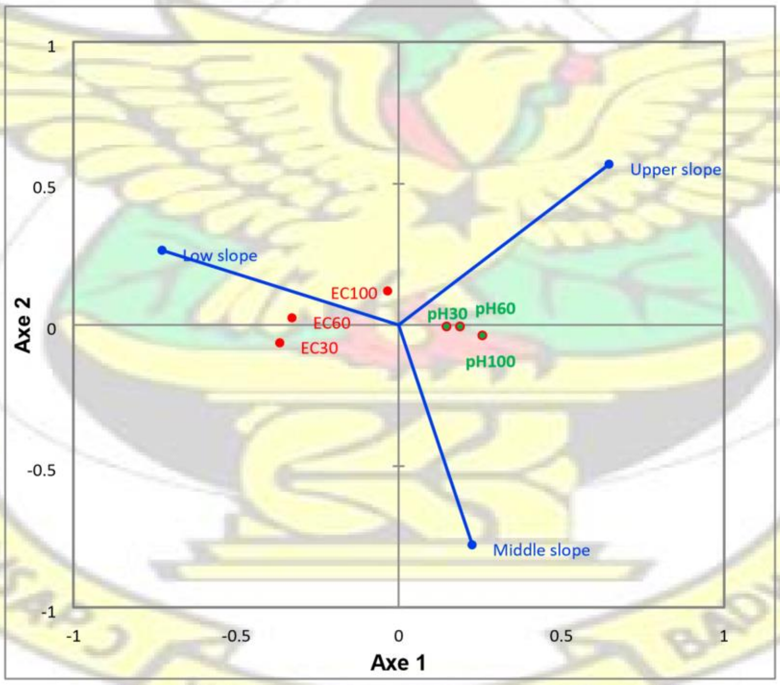


Figure 3.4: Relationship between pH, EC and topographical positions

In most of the soil pits (upper and middle slopes), pH values increase generally with soil depth, suggesting that the superficial soil horizon (0-30 cm) is more acidic than the deep ones.

However, some exceptions were observed in low slope soils. In these soils, the deepest horizons registered the lowest average pH values and is, therefore, more acidic than the soil surface. However, the trend of acidity in topsoil (0-30 cm) is upper slope > low slope > middle slope. Suggesting that, in topsoil, the upper slope soils (pH = 4.83) are generally more acidic than the middle slope (pH = 5.81) and low slope soils (pH = 5.30).

Similarly, the gradient of EC also follows the depth rule. In fact, the mean salt content tends to decrease downward in most of the sample pits (upper and middle slopes). In low slope, for instance, the topsoil (mean EC = 8 dS/ m) is more saline than the subsoil (i.e. 30-60 cm and 60-100 cm), which registered an average EC value of 5.6 and 5.31 dS/m, respectively. However, this trend of the salt content is not always observed especially in the upper slope, where EC increases downward with 1.68 dS/m, 1.86 dS/m and 2.29 dS/m in 0-30 cm, 3060 cm and 60-100 cm soil depths, respectively. The highest salt content in all the depth was recorded in low slope soils. Thus, the corresponding trend of salinity in the toposequence was low slope > middle slope > upper slope. In addition, soils in low slope showed the highest ESP with 223.5 %, 194.7 %, and 127.3 % respectively in 0-30 cm, 30-60 cm and 60-100 cm depth, and are therefore sodic soils (with ESP > 15%). This concurs with the dominance of the sodium-potassium facies in the Piper diagram (Figure 3.5), where the majority of the cations of the soil samples are located in the pole sodium-potassium (Na + K). Consequently, low slope soils dominated by these facies recorded the highest EC values.

Soil texture also varied in relation to topography and was classified as sandy, sandy loam, sandy clay and clay loam. The low slope soils recorded the high clay content with texture predominantly sandy clay in the topsoil and clay loam in the deepest horizons. As for the texture in the middle and upper slopes, they were generally sandy to sandy loam at all depth.

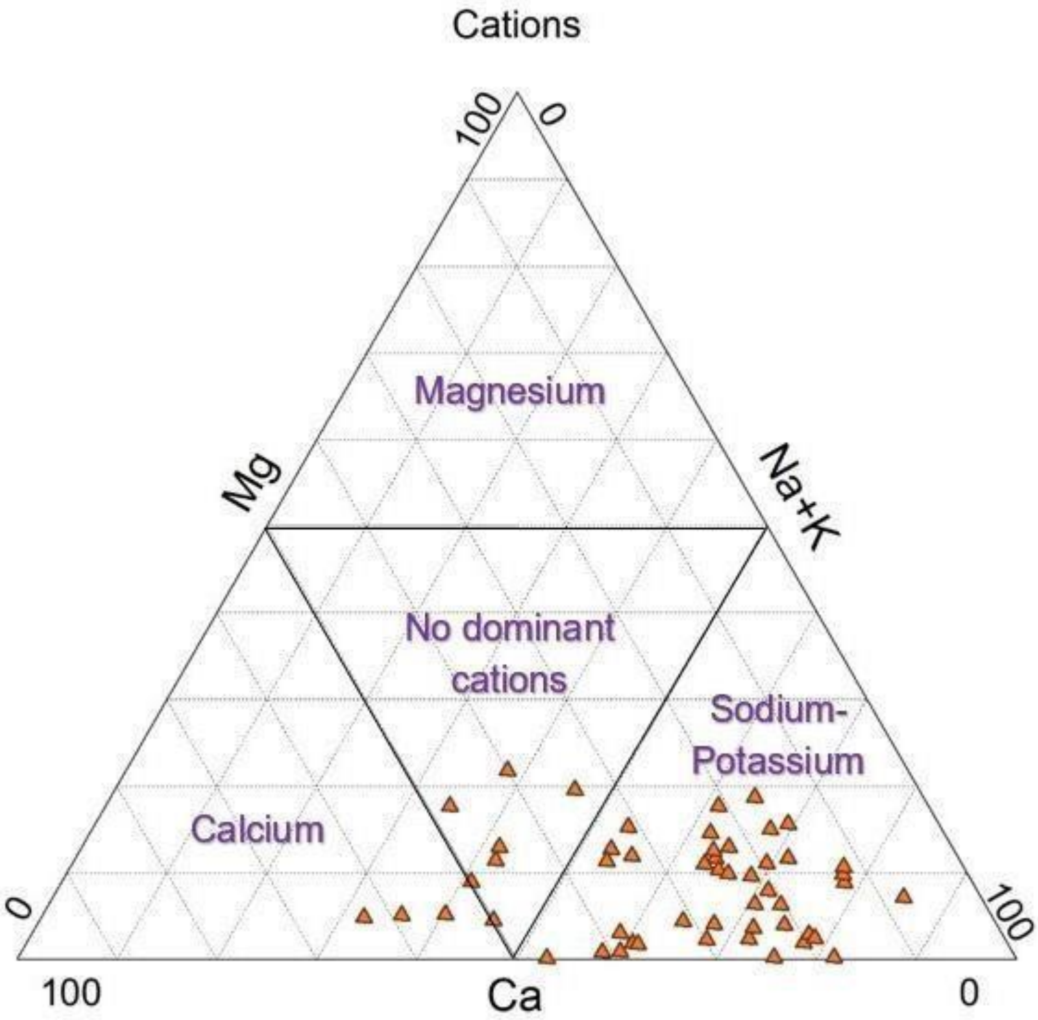


Figure 3.5: Piper diagram of the soil cations in Djilor

3.3.2. Distribution of Salinity under Different Land Uses, Soil and Crop Types

Figure 3.6 and Table 3.2 show that salt content varies significantly under different land uses (grassland, annual crop land, bare land and fallow), soil types (Fluvisols, Gleysols and Lixisols) and crop types (rice, maize, millet and groundnut) ($p = 0.000$). For land use types, bare land (8.46 dS/m) and land under fallow (8 dS/m) registered the highest mean values of EC, while cropland showed the lowest EC value (6.13 dS/m). Additionally, fallow and bare land showed the highest upper quartile (10 dS/m), suggesting that 25% of both lands have salt content greater than 10 dS/m (Figure 3.6a). So, the general trend of salt content in agriculture landscape is bare land > fallow > grassland > annual crop. Similarly, salt content differs from the three dominant soil groups in the area. Fluvisols are mostly saline soils with the highest mean EC value (8 dS/m) compared to Gleysols (mean EC = 6.36 dS/m) and Lixisols, which are generally moderately or slightly saline soils (mean EC = 5.11 dS/m). Likewise, in terms of crop types, rice plots registered the highest salinity (9 dS/m) followed by maize (7.45 dS/m), millet (6.96 dS/m), and groundnut plots (6.67 dS/m) (Table 3.2).

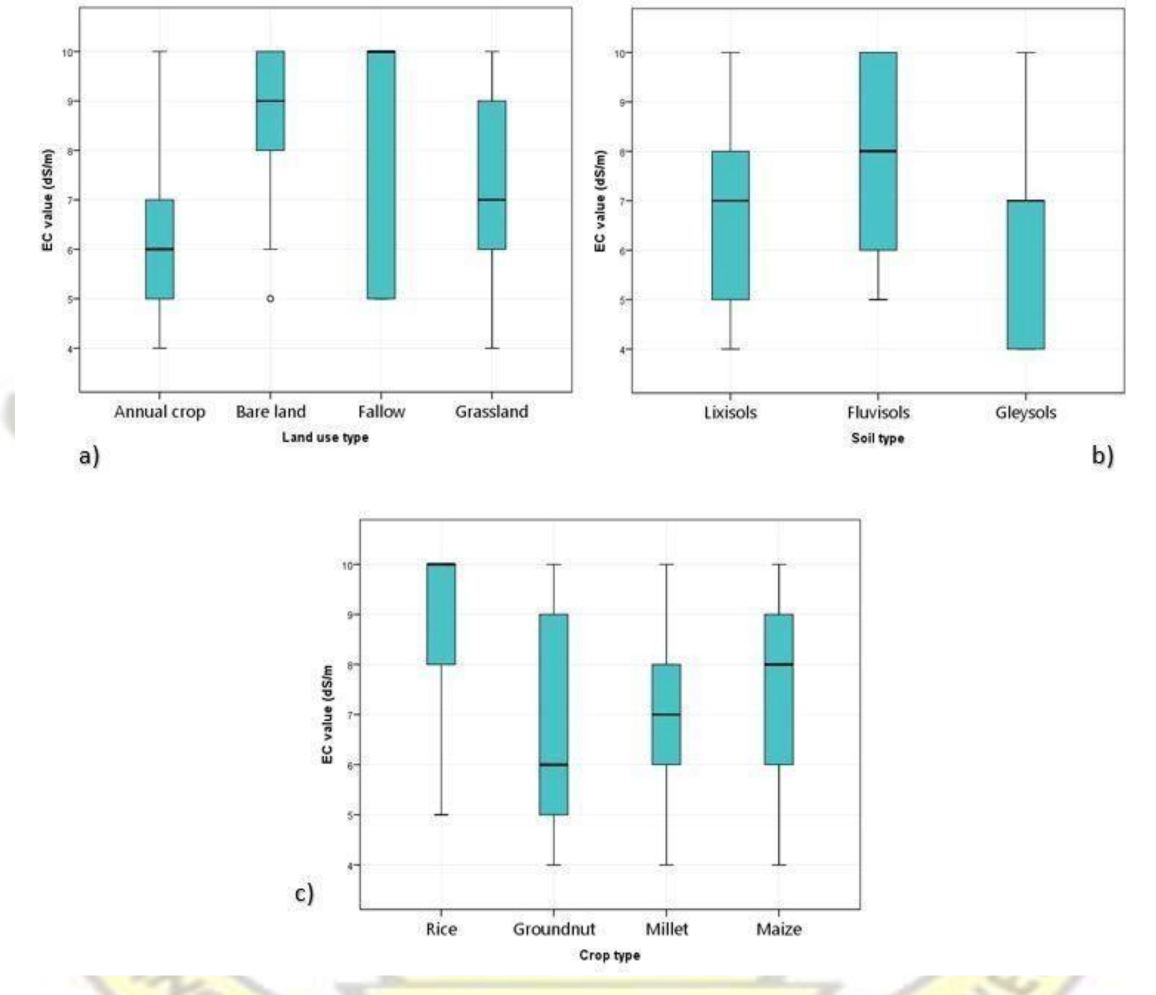


Figure 3.6: Soil salinity variation in different land use (a), soil type (b), and crop type (c) in a coastal agricultural area in Djilor district

Table 3.2: Some descriptive statistics of soil salinity in each land use, soil and crop types

	Mean ± StdDev. (ds/m)	Min.	Max.	Skewness	Kurtosis
Land use types	**ANOVA*** (p=0.000 at 95% CI)**				
Annual crop	6.13 ± 1.849	4	10	0.701	-0.184
Grassland	7.18 ± 1.881	4	10	0.020	-1.077
Fallow	8.00 ± 2.739	5	10	-0.609	-3.333
Bare land	8.47 ± 1.391	5	10	-1.006	0.723
Soil types	**ANOVA*** (p=0.000 at 95% CI)**				
Lixisols	5.8 ± 1.941	4	10	-0.046	-1.328
Fluvisols	7.97 ± 1.740	5	10	-0.173	-1.503
Gleysols	6.36 ± 1.891	4	10	0.302	-0.520
Crop types	**ANOVA***(p=0.000 at 95% CI)**				
Rice	9.00 ± 1.477	5	10	-1.390	1.211
Groundnut	6.67 ± 1.993	4	10	0.433	-1.082
Millet	6.96 ± 1.751	4	10	-0.060	-0.958
Maize	7.45 ± 2.179	3	10	-1.254	-0.102

***Note**: StdDev = Standard deviation; Min = minimum; Max = maximum; Skewness=coefficient of Skewness, Kurtosis= coefficient of Kurtosis, ANOVA = analysis of variance, ***=statistical significance at the 0.05 level; CI=confident interval.*

3.3.3. Soil Salinity Determinants

Table 3.3 summarizes the factors associated with the increase of salt accumulation in the study area. Among the significant variables associated with the increasing salt content include elevation, clay content, pH, distance to river and Fluvisols. Clay content is the only variable positively correlated with salt content (p = 0.000, Coef. = 0.12), suggesting that salinity increases with increasing clay particles in the soil. In contrast, elevation shows a significant negative relationship with measured salt content ($p < 0.05$; Coef. = - 0.215) suggesting that the lower the elevation of the area, the higher the salinity. Similar tendency was assessed with the distance from the river ($p = 0.000$, Coef. = -0.000), showing that the nearer the farm plots to the river, the higher the plots' salt content. Again, soil pH and Fluvisols were also found significantly related to salt content. Among these significant variables, clay content, distance to river and elevation were assessed to have the highest impact with respectively 39%, 20% and 18% (measured in coefficients size of standardized variables) (Figure 3.7). However, contrary to expectation, groundwater depth was not significantly related to salt content in the study area ($p > 0.05$).

Table 3.3: Factors associated with soil salinity in Djilor district

Explanatory Variables	**Coef.**	**Std. Err.**	**P_value**	**95% CI**	
Distance to river (m)	-0.000	0.000	**0.000**	0.000	0.000
Elevation (m)	-0.215	0.026	**0.000**	-0.267	-0.163
Clay context (%)	0.129	0.009	**0.000**	0.110	0.147
Soil pH	-0.203	0.079	**0.011**	-0.360	-0.047
Groundwater (m)	0.117	0.066	0.075	-0.012	0.247
Fluvisols	-1.208	0.232	**0.000**	-1.665	-0.751
Gleysols	-0.233	0.260	0.371	-0.745	0.279
Lixisols	-0.057	0.198	0.773	-0.447	0.333

Note*: n = 304, R-squared = 0.87, Prob > F = 0.000, P_value = statistical significance at the 0.05 level, Soil type= dummy variable: 1 = Lixisols, 2 = Fluvisols and 3 = Gleysols, CI=confident interval, Coef. = Coefficient; Std. Err. = Standard Error*

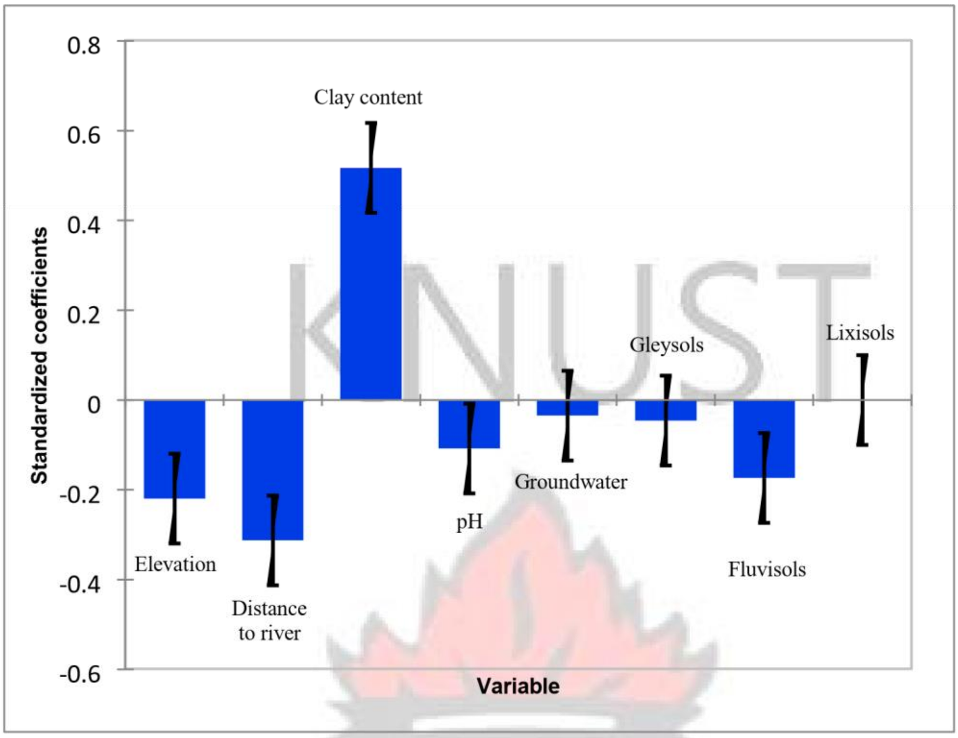


Figure 3.7: Effects of some biophysical factors on salt content

3.4. Discussion

3.4.1. Soil Salinity Distribution

It was observed that the highest pH and EC values were found in topsoil and on lower slope soils of the study area. This result is in line with the study of Van Asten *et al.* (2003) who reported that EC and pH in topsoil increased from the upper slopes to the middle and lower slopes. In addition, high values of ESP and Na were observed in lower slopes in particular. These results confirm the presence of saline and acidic sulphate soils in the study area, which were earlier investigated by Sadio (1991) in Saloum (western Senegal). As pH and EC showed a great horizontal gradient, it seems to suggest that salt from groundwater movement is minimal in the area. Furthermore, salinization and acidification prevailing in the study area may also explain the poor soil nutrients recorded. In fact, these two processes increase the availability of certain toxic elements (heavy metals) naturally or artificially present in soils particularly aluminium and manganese, which affect the assimilation of the soils nutrients as well as the presence of microorganisms that contribute to the structuration of the soil (Allen *et al*., 2011).

The statistical and laboratory analyses of the soil samples also showed a variation of salt content in relation to land use, soil and crop types. Rice plots were the most affected among the crop types. Similar findings were observed in Senegal by Sambou *et al.* (2015) who reported that the abandoned rice fields constitute most of the salt-affected areas. Related studies showed that rice is sensitive to salt through their geomorphological position (lowland) and edaphic need (generally silt clay) (Barbiéro *et al.*, 2001; Nhan e*t al.*, 2010). Thus, rice is more exposed to saltwater intrusion as compared to groundnut and millet fields. Among the soil types, Fluvisols have the highest salt content. The same finding was observed by Fang *et al.* (2005b) that salt content in Fluvisols was significantly higher than in Gleysols. In Senegal, Fluvisols belong to the saline acidic sulphate soils locally known as "*tann*" which are usually found on low areas subject to tidal flooding, and mostly confined to lacustrine and marine deposits (Sadio and Mensvoort, 1993).

3.4.2. Determinants of Increased Soil Salinity in Coastal Agricultural Area

Soil salinity in the study area is associated with various biophysical factors. Clay content was positively associated with the salt content in agricultural areas because of its high ionic capacity to retain high amounts of salts (Busenberg and Clemency, 1973). This finding corroborates with the studies of Zhao *et al.* (2016) in Heihe River, Northwestern China and Yu *et al. (* 2014) in the coastal zone of the Yellow River Delta, China, which both indicated that soil texture significantly affects salt content variation and therefore constitutes a good predictor for soil salinity. The distance to the river and elevation are obvious factors associated with the increased soil salinity in the area, which was observed in other studies as determinants for soil salinity (Yahiaoui *et al*., 2015; Qian *et al.*, 2017). The distance to the river has an important effect on soil salinity extent because of the sea water intrusion (Rossa *et al.*, 2011). As a coastal area, salt affected areas in Djilor were mostly related to the inundation from sea level rise. This finding confirms that salt accumulation in coastal agricultural landscape is principally due to seawater tides flood, depositing salts on the land surface (Sow *et al.*, 2016; Fall, 2017). Also, as previously documented by Marius (1985), wind constitute an important factor in salinity processes in the study area; it generally transports salt particles from the sabkha to the uplands and this phenomena justify the high values of EC recorded in topsoil.

Consequently, the groundwater depth did not show as a significant factor for soil salinity. Our finding contrasts with most of the studies that had reported as a highly significant factor affecting salt content (Grabau, 2012; Triki *et al*., 2017). This is because the study area is a coastal zone where most of the salts come from seawater intrusion through inundation and less available groundwater due to capillary rise. The strong horizontal variation of the salt content reported from the laboratory analysis also concurs with this hypothesis. However, the non-significant relationship of groundwater depth with soil salinity may be due to the low variability of groundwater depth of the sampled plots ranging from 1 to 5 m and the small number of groundwater sample points.

3.5. Conclusions

This chapter investigated the soil condition through salinity content distribution in different agricultural covers and topographical positions. Also, the factors associated with the increasing trend of soil salinity in the study area were also identified. In most of the pits, salt content decreased with an increase in soil depth, which indicated that topsoil registered the highest EC value. As well, soils in the lower slope were more saline than the ones in the middle and upper positions and were dominated by the presence of sodic soils (ESP > 15%).

Land use, soil and crop types affected the patterns of salt in the study area. Fallow land, bare land, rice plots and Fluvisols registered higher salt content. The analysis of the relationship between measured soil salinity and some environmental factors showed that salt content was significantly associated with elevation, clay content, distance to the river and pH. Clay content, distance to river and elevation were assessed to have the highest impact on salinity increase with respectively 39%, 20% and 18%. Soil salinity had no correlation with groundwater depth suggesting that the accumulation of salt in coastal agricultural lands was not significantly related to capillarity rise from groundwater contrary to most of the studies. This statement is supported by the strong horizontal variation of EC and pH given by the analysis of laboratory results, which suggested that salt movement from groundwater flow is minimal in the area. So, in Djilor as a coastal area, soil salinization is mostly caused by inundation and deposits of salt from the seawater intrusion. The results reflect the severe soil salinity and acidity issues prevailing in Djilor, which constitute the main drivers of soil degradation and threats of food security for the local communities. As key soil health indicators, this diagnostic of soil EC, ESP and pH remains useful for monitoring soil salinization in response to climate change impacts. Also, the findings of this study provide a baseline understanding of soil salinity in Djilor and may help decision makers and smallholder farmers to improve soil salinity management and their livelihoods. As sea level rise is projected to increase in the future, it is recommended to further investigate the future soil salinity pattern in the region (including other land uses such as the mangrove areas).

CHAPTER 4 : DYNAMICS OF LAND USE-LAND COVER AND SOIL SALINITY IN DJILOR DISTRICT BETWEEN 1984 AND 2017

4.1. Introduction

Soil salinity is becoming a serious problem throughout the world with nearly 831 million hectares of salt-affected land (Legros, 2009). Mainly in semi-arid and arid areas, soil salinity is one of the common environmental issues that affect agricultural production and sustainable utilization of land resources (Metternicht and Zinck, 2003). Most of the semiarid and arid areas are located in sub-Saharan Africa, where low rainfall and high temperature have accelerated soil salinity dynamics (Sakadevan and Nguyen, 2010). At the same time, land use/ land cover changes also contribute significantly to soil salinity. It is recognised that land cover dynamics, in particular, shifts in the vegetation cover and extent of the salt marshes may have considerably contributed to expand salt affected areas and anticipate further environmental degradation (Masoud and Koike, 2004). Further, intensive use of natural resources in areas where local communities depend on land, expansion of agricultural lands and excessive logging or deforestation are such practices that aggravate environmental degradation (Masoud and Koike, 2004). Moreover, soil salinity becomes a land use-land cover (LULC) issue when it inhibits plant growth, causing the death of nearby trees and therefore contributing to the changes and transitions among land use types (Allbed *et al.*, 2017).

Moreover, soil salinity is continuously increasing due to the adverse effects of climate change (i.e. sea level rise), and thus making it difficult to monitor and mitigate. From this view, long-term and permanent monitoring of the land use dynamics might be considered as an essential step for the understanding of soil salinity change and effects on various ecosystems.

By providing temporal and spatial data, remote sensing has an important and efficient role in detecting and monitoring land use and soil salinity changes (Metternicht and Zinck, 2003; Matinfar *et al.*, 2013). Thus, as an essential approach in assessing spatial patterns of soil salinity and LULC with an adequate understanding of landscape features and imaging systems, remote sensing data help in the analysis of soil salinity dynamics and its relative effects. In recent years, various salinity and vegetation indices such as normalized difference vegetation index (NDVI), normalised difference salinity index (NDSI), salinity index (SI) and soil-adjusted vegetation index (SAVI) have been used in remote sensing to delineate salt-affected areas (Zhang *et al.*, 2011; Taghadosi and Hasanlou, 2017; Yossif, 2017; Allbed *et al.*, 2017). By integrating multi-temporal imagery with biophysical data, these remote sensing indices and soil properties may provide an accurate estimation of soil salinity changes. In this study, Landsat imagery data was chosen as the major source as it is the world's longest continuously acquired collection of space-based land remote sensing data (Wu *et al*., 2008) and has shown accurate results in LULC change (Narmada *et al.*, 2015; Allbed *et al.,* 2017; Emad and Emad, 2017).

In Senegal, many land use-land cover change studies used remote sensing technique (Sylla, 1994; Wiegand *et al.*, 1996; Parton *et al.*, 2004; Abdul Qados, 2011; Sambou *et al*., 2015; Faye *et al.*, 2016; Sambou *et al.*, 2016; Barry *et al.*, 2017). Remarkable land use change patterns have been detected over the past years. These changes include loss of mangrove and forested areas, expansion of agricultural lands and salt marshes, shift of islands, and loss of traditional rice fields mainly due to inappropriate land management (i.e. illegal tree logging), frequent flooding and drought, and soil degradation (i.e. salinity and erosion). However, soil salinity changes analysis and its impact on other land uses are always missing in many of these studies. Apparently, the Saloum river region, particularly Djilor district, as a coastal area, has suffered from soil salinity process as a result of seawater intrusion, insufficient rainfall and increased temperature since the drought of 1970 (Sadio and Mensvoort, 1993; Sambou *et al.*, 2016). The salt accumulation process, in this zone, has led to the formation of saline soils, which are unsuitable for agricultural production. Hence, complementing land use change assessment with soil salinity analysis may provide important information to identify land management practices that help to cope with the negative impacts of soil salinity increase. For that purpose, this chapter investigates the soil salinity dynamics along with land use changes during the period between 1984 and 2017 in Djilor district. This includes:

1) Assessment of the land use changes using remote sensing as well as its interval level change;
2) Builds a soil salinity predictor system for soil salinity change analysis.

4.2. Methodology

4.2.1. Estimation of Land use-land cover Change (LULCC)

4.2.1.1. Data Source and Pre-processing

Four Landsat images for the years 1984, 1994, 2007, and 2017 were downloaded from the United States Geological Survey and used to derive the patterns of land use-land cover (LULC) in Djilor. These images were acquired during the dry season between March and April to enable a clear distinction of features, especially salt surface features (Lhissou and Chokmani, 2014). All the pre-processing and processing of images were made using ERDAS IMAGINE 14. The images were all geo-referenced to UTM WGS 1984 projection system. To train and validate the classified maps, a set of 164 points were collected by random sampling to represent the different LULC types. Furthermore, supplementary fieldbased data were collected using GPS sensor in features that were more difficult to separate (Faye *et al.*, 2016). Fieldwork was performed from April to September 2017 to collect information on historical LULC and validate the classified images using visual interpretation with google earth historical images and local knowledge from key informants in the study area.

4.2.1.2. Data Processing

A supervised classification was applied. The signature and the number of classes for the supervised classification were developed based on field investigation and the existing LULC classification map collected from the Centre de Suivi Ecologique (the Centre of Environmental Monitoring). Eight main categories were classified and defined (Table 4.1). The accuracy assessment of the classification was checked by computing the confusion matrix, the overall accuracy, and the Kappa coefficient for each year as well as the errors of omission and commission. To minimise classification errors due to image registration, all the classified maps were subjected to 3x3 pixels filtering to have a good homogeneity. The classified images were exported to ArcGIS for enhancement and mapping of LULC types for each year. Stepwise, a post-classification comparison was used for Land use /land cover change (LULCC) detection.

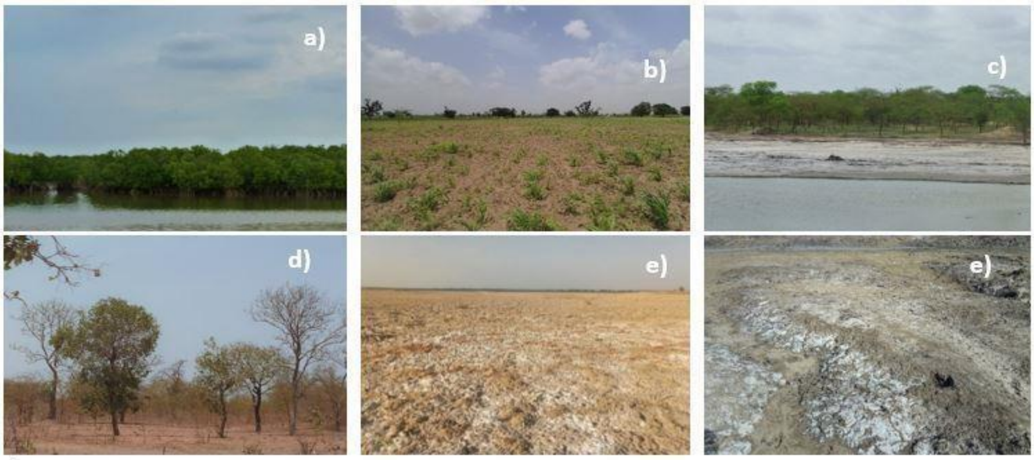


Figure 4.1: Land use-land cover types in Djilor: a) mangove; b) cropland, c) savannahs and water bodies, d) Forest, e) Sabkha (*tann*), f) salt mashes

Table 4.1: Description of the LULC types

Value	LULC	Description
1	Mangrove	Mangrove and estuaries with aquatic vegetation dominated by *Rhizophora racemosa*, *Rhizophora*

		mangle and *Avicennia Africana*
2	Savannah/shrubs	Vegetation composed of tree savannahs, shrubs and grasslands. Generally, tree height is lower than 5 m
3	Forests	Woodland or protected areas with tree height higher than 5 m
4	Salt mashes	Soil salt marshes, corresponding to the tidal areas and generally submerged. They are bordered by sabkhas and occur along the coast
5	Sabkha	Local term for tann, which soils are with salt crust on surface. Salt flat soils, characterized by very poor vegetation cover composed mainly of halophytes
6	Water bodies	Rivers, reservoirs and lagoons
7	Bare lands	Abandoned areas, settlements
8	Croplands	Cereal crops and vegetables crops (e.g. rice, millet, maize and groundnut)

Once the land classification was established, the intensity analysis was applied (Aldwaik and Pontius, 2012). The interval and category levels were particularly applied to determine the time intervals during which the annual change area is relatively slow versus fast, and the variation of the categories' gains and losses during a time interval, respectively. Interval and category level analyses were calculated using the fallowing Equations.

Equations 4.1 and 4.2 give the uniform intensity (U) across time extent (Y_1, Y_T) and the annual change (S_t) for each time interval (Y_t, Y_{t+1}), respectively. If $S_t > U$, then the change is fast for (Y_t, Y_{t+1}), if $S_t < U$, then the change is low for (Y_t, Y_{t+1}), and if $S_t = U$ for all time interval, then the annual change is stationary. The categories level was computed to determines the variation of the categories' gains and losses during a time interval.

$$U = \frac{(change\ area\ during\ all\ inteval)\ 100}{(duration\ \ of\ all\ interval) domain\ area} = \frac{\sum_{t=1}^{T-1} \{\sum_{j=1}^{J}[(\sum_{i=1}^{J} C_{tjj}) - C_{tjj}]\}\ 100}{(Y_T - Y_1)\sum_{j=1}^{J}\sum_{i=1}^{J} C_{1_{ij}}} \quad (4.1)$$

$$S^t = \frac{(change\ area\ during\ [Y}{(} \quad (4.2)$$

$$duration\ \ of\ \ [Y_t, Y_{t+1}])domain^t, Y_t^{+1}])\ \ area100$$

$$= \frac{\sum_{j=1}^{J}[(\sum_{i=1}^{J} C_{tij}) - C_{tjj}]\ 100}{(Y_{t+1} - Y_t)\sum_{j=1}\sum_{i=1} C_{tij}} JJ$$

Where U = the uniform annual change during extent $[Y_t, Y_T]$;

S_t = the annual change during interval $[Y_t, Y_{t+1}]$;

T = Number of time points, which equals 4 for this study; Y_t = Year at time point t;

t = Index for the initial time point of interval $[Y_t, Y_{t+1}]$, where t ranges from 1 to $T - 1$; J = Number of categories; i = Index for a category at an interval's initial time point; j = Index for a category at an interval's final time point;

C_{tij} = Number of pixels that transition from category i to category j during interval $[Y_t, Y_{t+1}]$.

Equations 4.3 and 4.4 were used to calculate the change in term of loss (L_{ij}) and gain (G_{ij}) for the four time intervals (Villamor *et al.*, 2013; Badabate *et al.*, 2017).

$$L_{ij} = (P_i - P_{ii}) \left(\frac{P_j}{\sum_{j=1} P_j}\right) \quad 4.3)$$

$$G_{ij} = (P_j - P_{jj}) \left(\frac{P_i}{\sum_{i=1} P_i}\right) \quad (4.4)$$

Where *Lij* is the proportion of loss from category *i* to *j* under random processes of loss; *Pii* is the proportion of the category *i* that showed persistence between the two times;

Gij is the proportion of gain from category *i* to *j*,

Pj is the proportion of the landscape in category *j* in the final time;

Pjj is the observed persistent proportion of the category *j*;

P*i* is the total area of category *i* at initial time.

4.2.2. Estimation of Soil Salinity Change

4.2.2.1. Data Collection and Analysis

In order to assess the spatial soil salinity change as well as predicting the salt content at different locations of the study area over the period 1984-2017, a total of 304 soil samples were combined with biophysical characteristics such as elevation, distance to river, wetness index as well as remote sensing indices (NDVI), salinity index (SI) and Normalized difference salinity index (NDSI) derived from Landsat image 2017. These indices were chosen because they have given better correlation in salt-affected areas analysis and constitute good indicators for salinity classification and quantification (Poenaru *et al.*, 2015). They were recently used in various regions to predict soil salinity distribution (Zhang *et al.*, 2011; Taghadosi and Hasanlou, 2017; Yossif, 2017; Allbed *et al.*, 2017) and computed as shown in Table 4.2. The spatial analysis tool in ArcGIS was used to extract NDVI, NDSI and SI values corresponding to each EC sampled point in the field. The description and calculation of the biophysical factors (e.g. elevation, distance to river, wetness index) are presented in Chapter 3. These are important indicators which may help to accurately highlight areas of salinization potential (Eklund, 1998). Then, a regression analysis was applied where remote sensing indices and biophysical characteristics are independent variables whereas EC (salt content) value of soil samples is the dependent variable. The classification of salinity level was based on the global standard salinity ranges (Azabdaftari *et al.*, 2016). From that, four salinity classes (non -saline, slightly saline, moderately saline and highly saline) were considered in mapping salinity level (see Section 4.3.2 of this Chapter).

Table 4.2: Remote sensing indices

Index name	**Formula**	**Source**
Normalized differential vegetation index (NDVI)	$\frac{Band\ 4 - Band\ 3}{Band\ 3 + Band\ 4}$	Tripathi *et al.*, 1997
Normalized difference salinity index (NDSI)	$\frac{Band\ 3 - Band\ 4}{Band\ 3 + Band\ 4}$	Asfaw *et al.*, 2016
Salinity index (SI)	$\sqrt{Band\ 3 \times Band\ 4}$	Dehni and Lounis, 2012

Figure 4.2 summarizes the different processes and data used for LULC and soil salinity change analysis.

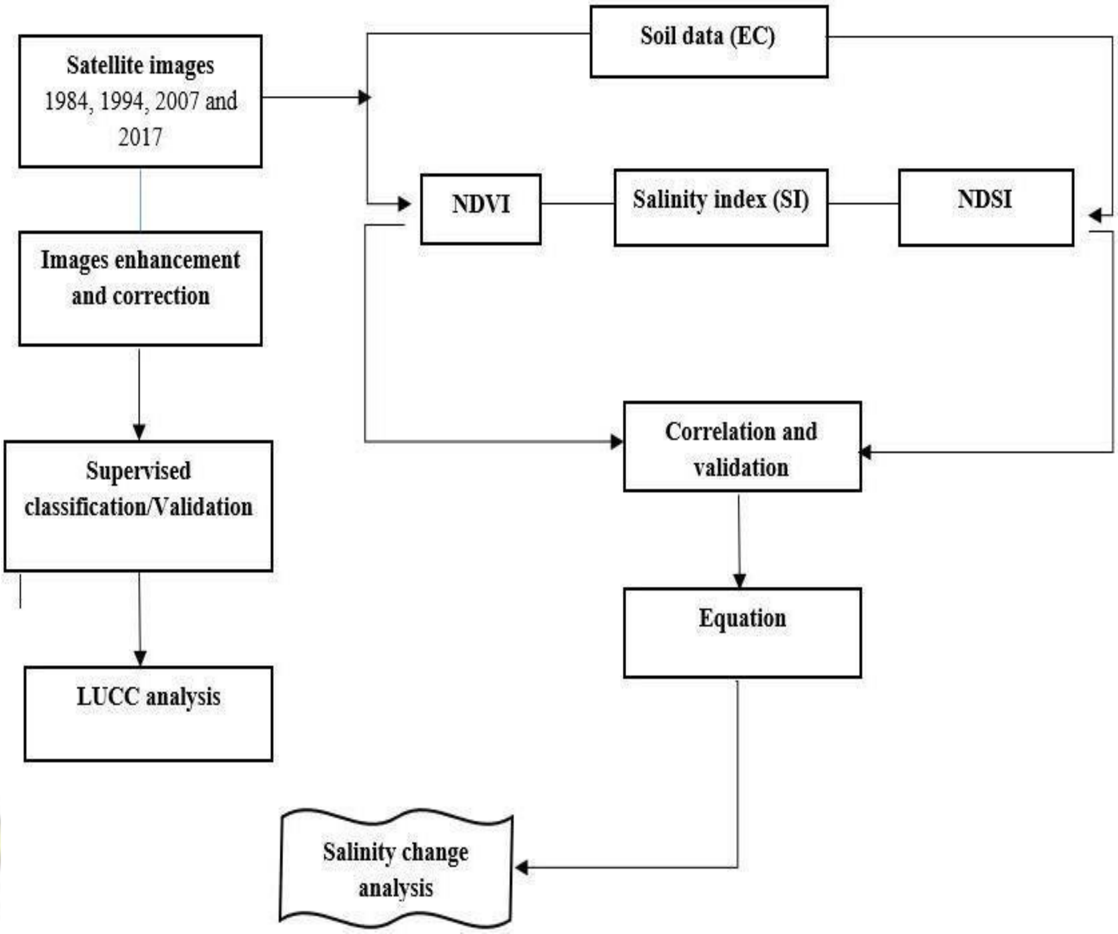


Figure 4.2: Flowchart of LULC and salinity changes detection

To obtain the statistics of salt affected areas under each land use type, the LULC and the soil salinity maps of Djilor were overlaid. The coverage of saline areas per land use type was determined in hectares and then derived in percentage.

4.2.2.2. Regression Model Validation

Various statistical methods have been used for model validation, which are mostly based on comparing measured and predicted values (Marcus and Elias, 1998). In this study, the validation and the assessment of the regression model performance were made by considering the coefficient of determination (R^2), the root mean square error (RMSE) and the t-test of slope (Adu-Bredu *et al*., 2008) as well as comparing the observed and predicted values (Pineiro *et al.*, 2008). These methods have been widely used for regression model validation. R^2 measures the goodness of fit of a model and gives the proportion of variance in the dependent variable that can be accounted for by the regression model. As for the root mean square error (RMSE), it evaluates the indices of the model precision with the ideal value being zero. The t-statistic for the significance of the slope aims to determine if the regression equation is usable. If the slope is significantly different from zero, then the regression model can be applied to predict the dependent variable (which is the salt content of this study) for any value of the independent variable.

4.2.3. Calibration of Salinity Dynamics Sub-model

Soil salinity is a source of many disturbances. The large contribution of sea level rise and rainfall on soil salinity in this region has been acknowledged but, its impact is ignored in this model for simplicity purposes and for the lack of data. Therefore, in this study, it was specially considered, and model salinity dynamics was based on increased temperature through a simple agent-based model. The salinity sub-model used in this study was previously developed in the coastal area of Bangladesh by Dasgupta *et al*. (2015), where measured salt content (EC) increased by 0.249 dS/m for each 1 °C increase in temperature. The author presented different characteristics of coastal ecosystems (rivers and estuaries), flooding, tidal influence and sea level rise. As a coastal area, the study site presents approximately similar characteristics in terms of biophysical characteristics and salinization processes.

Six (6) different method estimators were used by Dasgupta *et al.* (2015) to determine the effects of climate change on soil salinity. Three of these method estimators (spatial econometric estimator, OLS and Panel RE) were preselected for calibration. They were chosen because, in addition to climate change aspect, they also considered elevation which is a determinant factor of increased salinity in Djilor as shown in Chapter 3.

4.3. Results

4.3.1. Land use-land cover Change over the Period 1984-2017

Figures 4.3 and 4.4 represent respectively the LULC maps of years 1984, 1994, 2007 and 2017 and their respective changes, showing general changes on Land use-land cover in the area. Croplands, forests and bare lands constitute the most represented land cover types over time while water bodies and savannahs/shrubs occupied the lower covers in the area. Forests represented 18.3 % in 1984 and decreased to 13.9 %, 9.7 %, and 9.1% in 1994, 2007 and 2017, respectively. As well, Savannah/shrubs decreased from 9.2 % in 1984 to 7.2 % and in 1994 and 2007, respectively. However, it was noticed that a slight increase in savannah cover occurred between 2007 and 2017 from 4.3 % to 8.9 %. Croplands are the most represented in the area with 20 %, 18.4%, 25.8 and 29.9 % in 1984, 1994, 2007 and 2017, respectively. It was noticed that an increasing trend of croplands over time happened, but slight decrease was registered during the first period (1984-1994). The sabkha occupied 14.4% of the total area in 1984 but decreased to 11.7 % in 1994 and 10.6% in 2007 and gained 1.5% in 2017. The bare lands had almost doubled between 1984 (13.9%) and 1994 (23.3%) but decreased significantly to 11.9% in 2017.

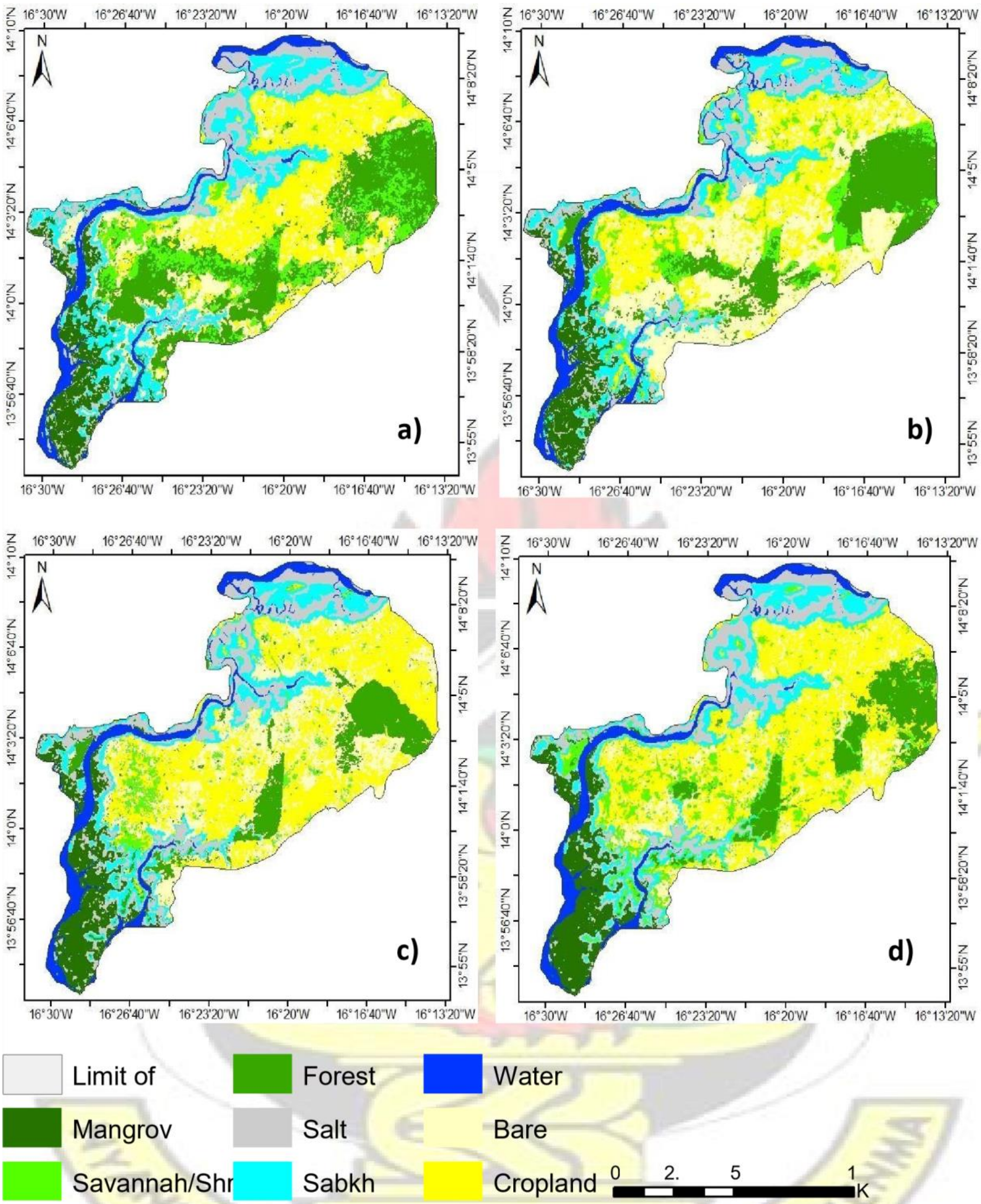


Figure 4.3: Historical Land use-land cover types in Djilor for the year 1984 (a), 1994 (b), 2007 (c) and 2017 (d)

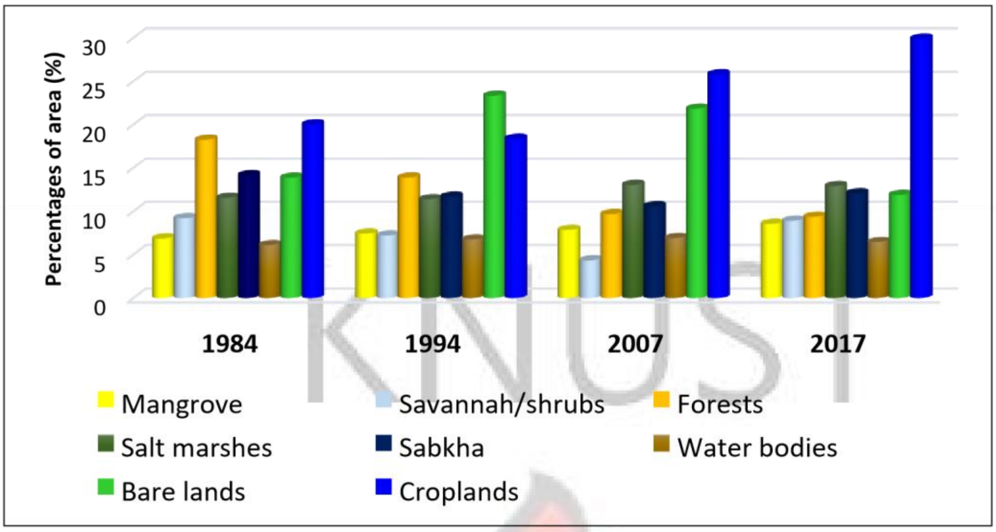
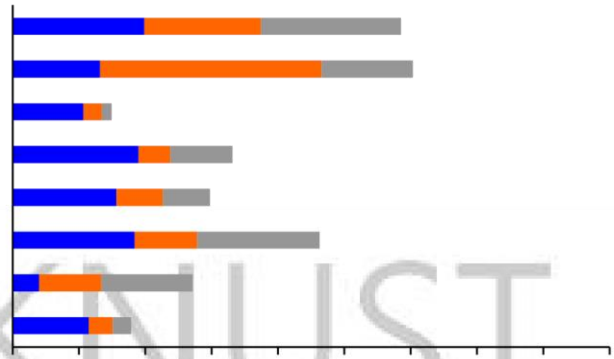


Figure 4.4: Major Land use-land cover area in 1984, 1994, 2007 and 2017 in Djilor

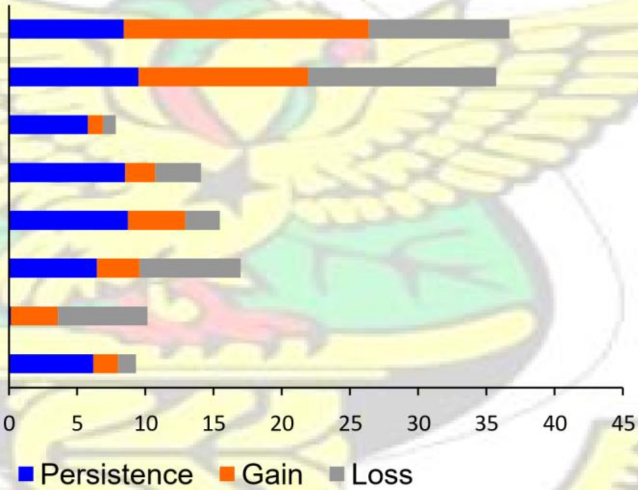
Figure 4.5 presents the gains, losses and persistence of the different LULC types for fourtime intervals (a) 1984–1994; (b) 1994–2007; (c) 2007–2017; and (d) the overall period 1984–2017.

During the first-time interval (1984-1994), bare lands registered the highest gain (16.7 %) followed by croplands (8.8 %). In contrast, Forests and croplands had more losses compared to gains. During the second time interval (1994-2007), croplands had the highest gain (18 %) followed by bare lands (12.4 %). In contrast, bare lands had the highest losses (13.8 %) followed by cropland (10.3 %). Within this time interval, Forest decreased its covers by up to 6.4 % as compared to the first-time interval. During the later time interval (2007-2017), croplands experienced the largest gain (14.5 %) followed by savannah (6.6 %). Contrarily, bare lands had the highest loss followed by croplands (9.7 %).

1984-1994



Cropland
Bareland
Water
Sabkha
Salt mashes
Forests
Savannah/Shrubs
Mangrove



0 5 10 15 20 25 30 35 40 45

Persistence Gain Loss

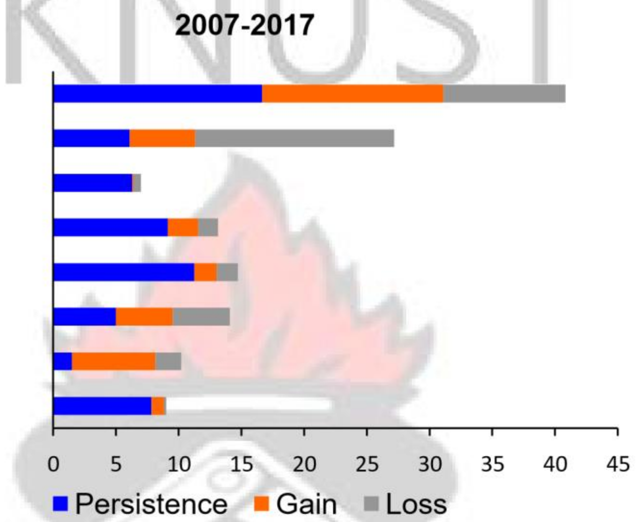
a)

1994-2007

Bareland
Water
Cropland
Sabkha
Salt mashes Forests

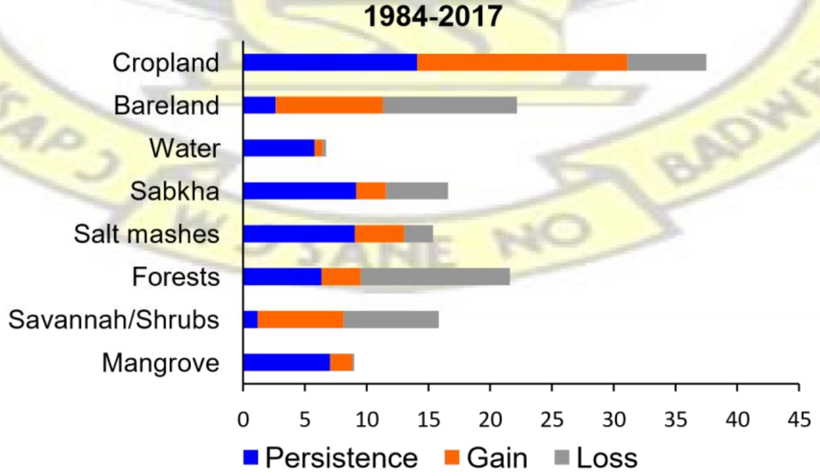
Savannah/Shrubs
Mangrove

b)



Cropland
Bareland
Water
Sabkha
Salt mashes
Forests
Savannah/Shrubs
Mangrove

c)



d)

Figure 4.5: Land use-land cover change persistence, gains and losses for four-time periods a) 1984-1994, b) 1994-2007, c) 2007-2017 and d) 1984-2017

faster than the annual area change during 1994 -2007 and 2007-2017. Most change in that first-time interval was allocated to forest loss compared to the second and last periods where both croplands and bare lands respectively gained and lost.

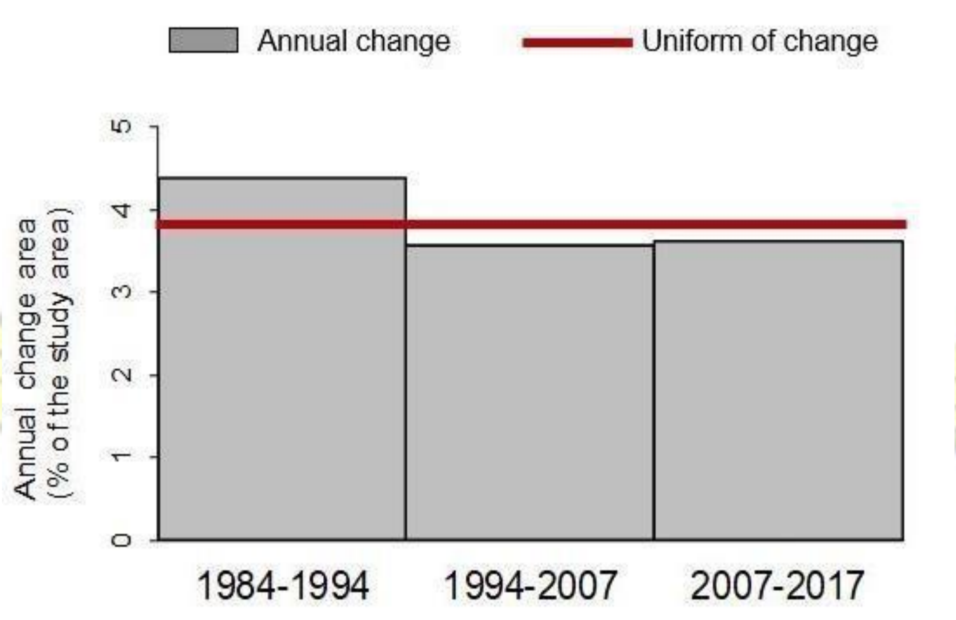


Figure 4.6: Interval level change intensity as an annual percent of the study

The reliability of these different statistics has been confirmed by the accuracy assessment via the Kappa and the overall accuracy. Table 4.3 (a, b) shows an overall accuracy of 86.58 %, 88.13 %, 97.22 %, and 99.68 %, respectively for the years 1984, 1994, 2007 and 2017. In addition to the Kappa coefficients ranging between 0.86 and 0.99, this result of the accuracy assessment is enough and satisfactory to validate the classified maps. In fact, the In terms of interval level, Figure 4.6 shows that the annual area change during 1984-1994 is mangroves, salt marshes and Sabkha were the most accurately classified LULC over time, while forest and savannah registered some classification errors mostly due to the confusion between them.

Table 4.3 (a): Accuracy assessment of the classified LULC maps (1984, 1994, 2007 and 2017)

Land use-land cover types	Ground Truth (Pixels)								Accuracy assessment			
	Mangroves	Savannah	Forests	Salt marshes	Sabkha	Water bodies	Bare lands	Croplands	Prod. Acc. (%)	Users Acc. (%)	Ov. Acc. (%)	Kappa
1984 classified data												
Mangroves	123	0	0	0	0	0	0	0	100	100	**86.58**	**0.85**
Savannah	0	102	110	0	0	0	0	0	73.91	48.11		
Forests	0	18	196	0	0	0	0	0	64.05	88.29		
Salt marshes	0	0	0	152	0	0	0	0	86.36	100		
Sabkha	0	0	0	24	128	0	0	0	100	84.21		
Water bodies	0	0	0	0	0	163	0	0	100	100		
Bare lands	0	18	0	0	0	0	107	0	100	85.60		

	Croplands	0	0	0	0	0	0	0	177	95.68	100		

1994 classified data													
	Mangroves	124	0	0	0	0	0	0	0	100	100	**88.13**	**0.86**
	Savannah	0	32	84	0	0	0	0	40	30.48	20.51		
	Forests	0	0	265	0	0	0	0	0	75.50	97.79		
	Salt marshes	0	0	0	133	0	0	0	0	100	100		
	Sabkha	0	0	0	0	217	0	0	0	100	100		
	Water bodies	0	0	0	0	0	372	0	0	100	100		
	Bare lands	0	1	0	0	0	0	132	2	100	96.35		
	Croplands	0	66	0	0	0	0	0	218	83.85	76.76		
2007 classified data													
	Mangroves	105	0	0	0	0	0	0	0	100	100	**97.22**	**0.97**
	Savannah	0	122	0	0	0	0	0	1	100	99.19		
	Forests	0	0	337	0	0	0	12	0	94.40	96.56		

	Salt marshes	0	0	0	119	0	0	0	0	100	100		
	Sabkha	0	0	0	0	150	0	0	0	95.54	100		
	Water bodies	0	0	0	0	0	271	0	0	100	100		
	Bare lands	0	0	17	0	2	0	130	0	91.55	87.25		
	Croplands	0	0	3	0	5	0	0	165	99.40	95.40		

Table 4.3 (b): Accuracy assessment of the classified LULC maps (1984, 1994, 2007 and 2017)

Land use-Land cover types		Ground Truth (Pixels)								Accuracy assessment			
		Mangroves	Savannah	Forests	Salt marshes	Sabkha	Water bodies	Bare lands	Croplands	Prod. Acc. (%)	Users Acc. (%)	Ov. Acc. (%)	Kappa
2017 classified data													
	Mangroves	136	0	0	0	0	0	0	0	100	100	**99.68**	**0.99**
	Savannah	0	158	0	0	0	0	0	0	100	100		
	Forests	0	0	174	0	0	0	0	0	100	100		
	Salt marshes	0	0	0	179	0	0	0	0	100	100		
	Sabkha	0	0	0	0	139	0	0	0	100	100		
	Water bodies	0	0	0	0	0	173	0	0	100	100		
	Bare lands	0	0	0	0	0	0	136	3	99.27	97.84		
	Croplands	0	0	0	0	0	0	1	174	98.31	99.43		

4.3.2. Soil Salinity Change over the Period 1984-2017

4.3.2.1. Soil Salinity Predictor Model

Table 4.4 shows the different factors used to build the soil salinity predictor model in the area. Among them, distance to the river, elevation and NDVI were significantly correlated with EC value (P < 0.05). From that, Equation 4.5 was generated to map soil salinity change. The regression model has significant estimation (Prob > F = 0.000) and good fit in the area (R^2 = 0.73 and RMSE = 0.680). Furthermore, the t-test was applied, the slope was found significantly different from zero (F = 0.0018). Also, the correlation analysis showed a strong relationship between measured EC and predicted EC values, with the coefficient of correlation (r^2) being 0.65 (Figure 4.7). Hence, the prediction of salt-affected areas can be done using the regression model of EC (Equation 4.5) of the study area.

Table 4.4: Soil salinity predictors in Djilor

Explanatory Variables	Coef.	Std. Err.	95% Conf. Interval	
Intercept	9.980	0.633***	8.735	11.225
Distance to river (m)	-0.001	0.000***	-0.001	0.000
Elevation (m)	-0.209	0.040***	-0.287	-0.131
NDVI	-6.582	0.023***	-14.499	1.335
TWI	0.000	0.000	0.000	0.000

Note: n = 304, R^2 = 0.73, Prob > F = 0.000, ***= statistical significance at the 0.05 level

$$EC = 9.98 - 0.0005\, d - 0.20\, e - 6.58\, NDVI + 0.00007\, TWI \tag{4.5}$$

Where *d* represents the distance to river (m), *e* denotes the elevation in the area (m), *NDVI* is the Normalized Difference Vegetation Index and *TWI* is the Topography Wetness Index of the area.

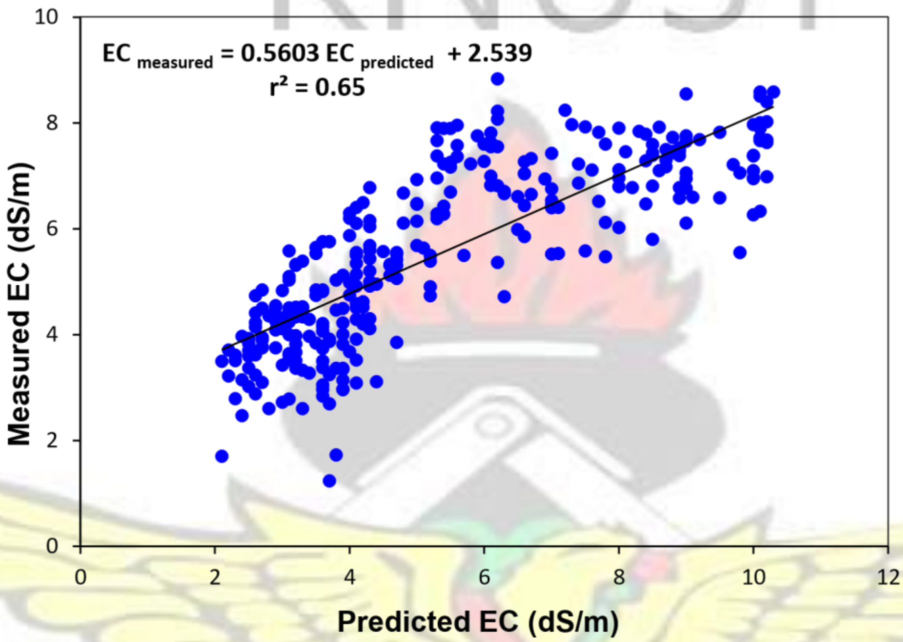


Figure 4.7: Relationship between measured EC and predicted EC values

4.3.2.2. Soil Salinity Change

Figure 4.8 shows the salt content maps for the years 1984 and 2017 with four salinity classes (non-saline, slightly saline, moderately saline and highly saline). Table 4.5 represents the statistics of salt content noticed in the study area from 1984 to 2017. Regarding the year 1984, moderate saline soils registered the highest extent (165.8.km^2) corresponding to 38.9 % of the area. Highly saline areas cover was 32.65 % of the total area while slightly saline and non-saline soils were the lowest in extent 18.5 and 9.93 %, respectively. In 2017, the slightly saline areas were highly represented in the area with 39.69 %, followed by moderately saline (25.6 %). Highly saline and non-saline soils registered respectively 20.85 and 13.88 %.

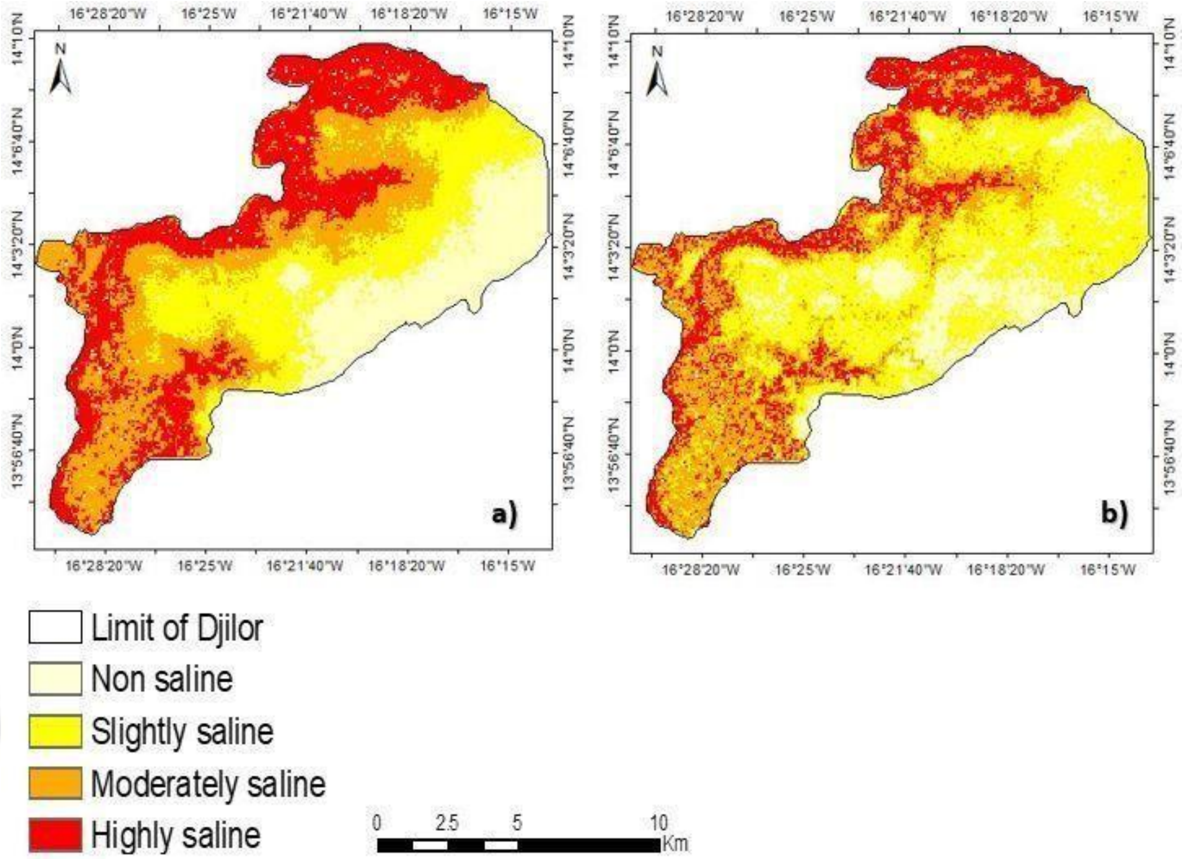


Figure 4.8: Soil salinity extent in Djilor for the years 1984 (a) and 2017 (b)

Table 4.5: Soil salinity level for the years 1984 and 2017

		1984		2017	
Salt content (dS/m)	**Salinity class**	**ha**	**%**	**ha**	**%**
	Highly saline	13906	32.65	8879	20.85
	Moderately saline	16583	38.93	10901	25.60
2 - 4	**Slightly saline**	7879	18.50	16904	39.69
<2	**Non-saline**	4228	9.93	5912	13.88
>8					
4 - 8					

Total	42596	100	42596	100

*Note: Salinity level (dS/m) classification is based on the global standard salinity ranges (*Azabdaftari *et al.,* 2016*)*

The period 1984-2017 is characterised by a slight decrease in salinity level over the area. In fact, slightly saline and non-saline soils have gained respectively 42.14 % and 7.85 % between 1984 and 2017, while highly saline and moderately saline areas lost (-23.47) and (-26.53%), respectively (Figure 4.9).

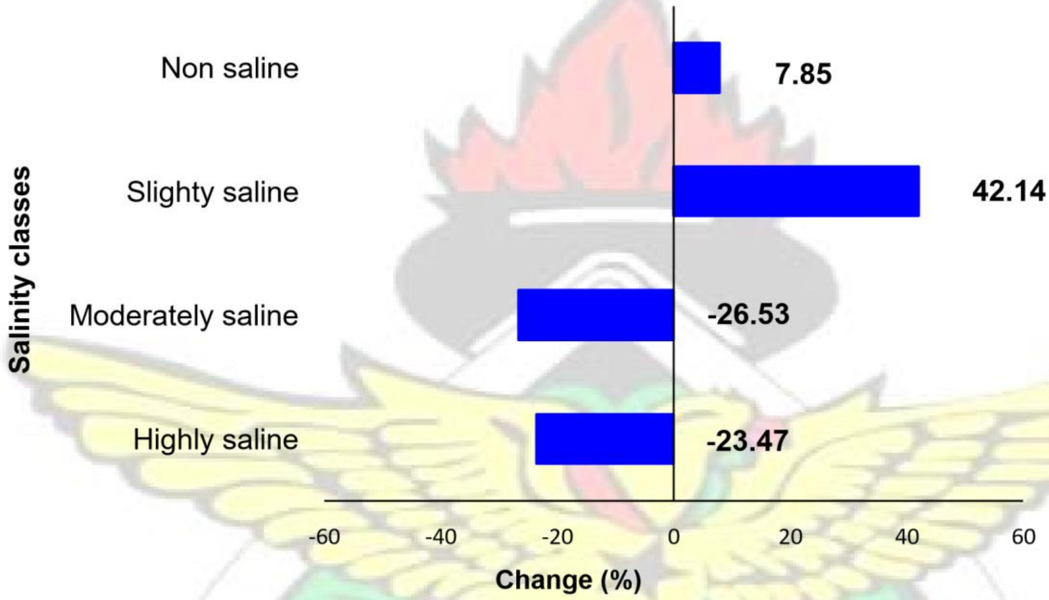


Figure 4.9: Changes in salt affected areas for the period 1984 to 2017

Figure 4.10 shows the percentage of salt affected areas per land use types for the years 1984 and 2017. Sabkha and salt marshes have the largest salt affected areas over time. In 1984, 31 % and 28 % of highly saline category areas were located in sabkha and salt marshes soils, respectively. Croplands registered about 9% of the highly saline category soils whereas savannah had the lower salinity. In 2017, high salinity areas in sabkha and croplands had decreased by 20 % and 2% whereas high salinity area in salt marshes had increased by 44%.

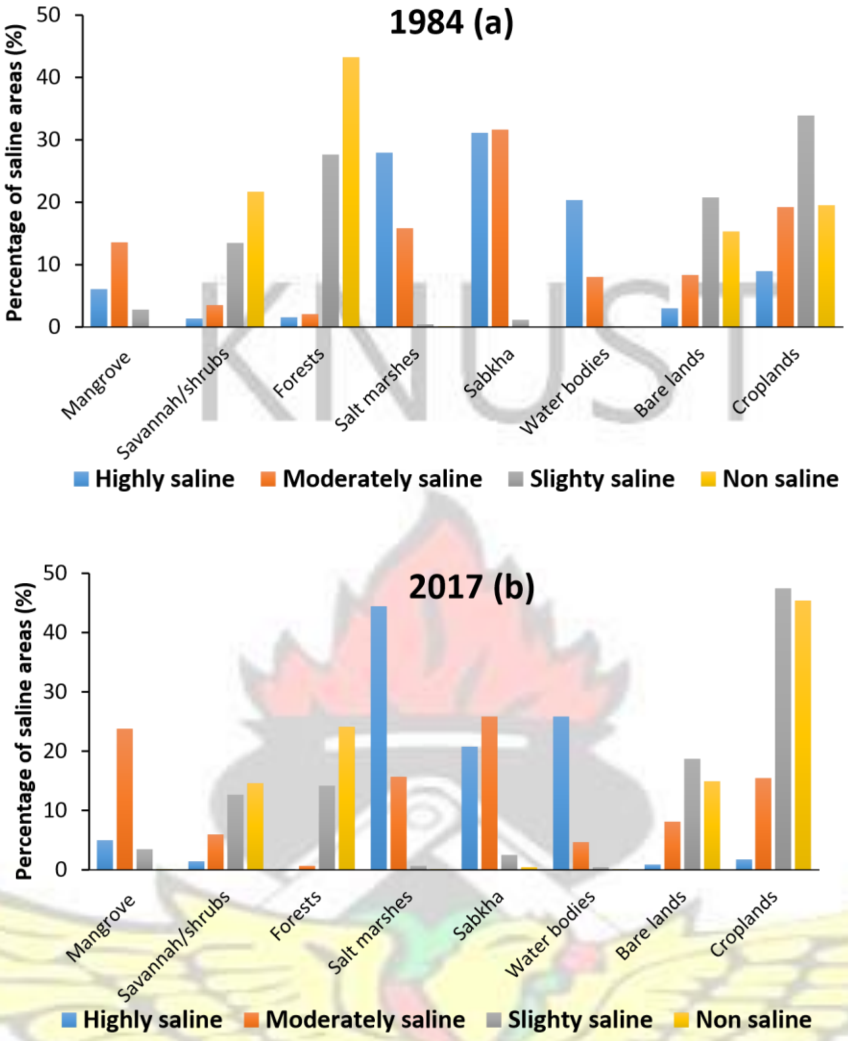


Figure 4.10: Percentage of salt affected areas per land use type for the year a) 1984 and b) 2017

4.3.3. Soil Salinity Dynamics: Sub Model

Among the three estimators chosen for calibration, spatial econometric estimator showed better the effect of elevation on salt content (Figure 4.11). In addition, spatial econometric also showed a strong correlation with the measured EC values (r^2=0.70) (Figure 4.11). Thus, in this study, spatial econometric estimator (Equation 4.6) developed by Dasgupta *et al*. (2015) was used for modelling soil salinity empirically in Djilor. Table 4.6 gives the different descriptive statistics of the EC values of the sampled plots based on three estimators (spatial econometric, OLS and Panel RE).

$$EC = -0.665\, e + 0.334\, s - 0.003\, R + 0.249\, T \qquad (4.6)$$

Where e denotes the elevation in the area (m), s *is the* salinity of the river (ppt),

R is mean rainfall (mm) of the station and T is the maximum temperature (°C).

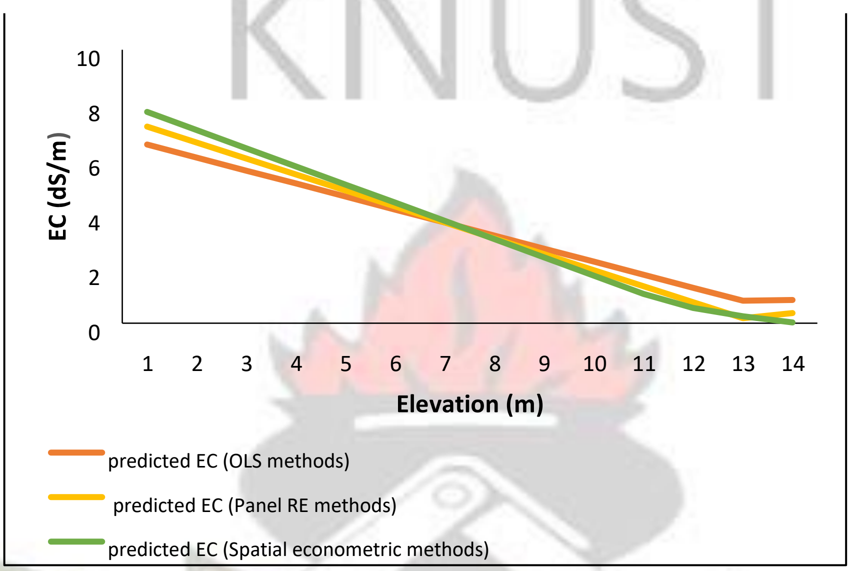


Figure 4.11: Relation between EC and elevation given by three different estimators

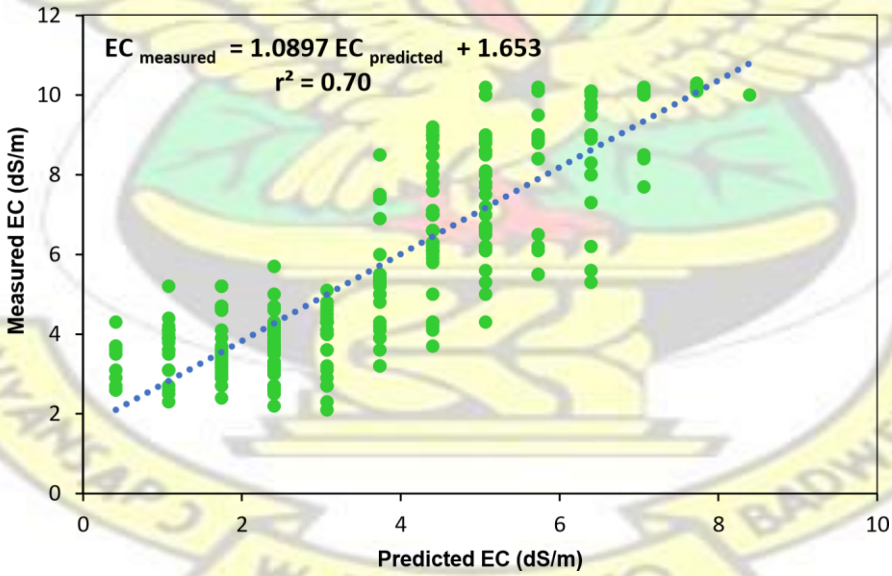


Figure 4.12: Correlation between predicted EC derived from Equation 4.6 (spatial econometric estimator) with measured EC values

	Mean	StdDev	Min.	Max.	Conf. level (95%)

Table 4.6: Descriptive statistics of the EC values of the plot based on the three estimators

Measured EC	5.43	2.42	2.10	10.30	0.27
Spatial econometric	4.35	2.14	3.58	8.54	0.24
OLS	3.35	1.88	1.56	7.01	0.17
Panel RE	3.40	1.53	2.74	7.77	0.21

Note: StdDev = Standard deviation, Min. = Minimum, Max. = Maximum, Conf. Level= confidence interval at 95 % level

Based on Equation 4.7, it was assumed that measured salt content (EC) increases by 0.249 dS/m for each one degree (1 °C) increase in temperature. Thus, the relationship between the salt content (EC) and the temperature can be numerically expressed as follows:

$$EC_t = EC_{t-1} + 0.249\,T \qquad (4.7)$$

Where, EC_t is the salinity content of the plot at time t, which was assumed as a response to the increase of temperature, representing the salinity dynamics;

EC_{t-1} is the EC of the previous year,

T = temperature increase scenarios (° C)

4.4. Discussion

4.4.1. Land use-land cover Mapping and Accuracy

The land use /land cover change analysis showed an increase in agricultural and bare lands to the detriment of forests which are characterised by a high loss. These results are an evidence of the ongoing loss of vegetation (e.g. deforestation) in the area. Similar results were observed in the neighbouring area of Fatick in Senegal (Sambou *et al*. 2016) and in

South-Eastern part of Senegal (Faye *et al., 2016)*. These changes in LULC are mainly due to human activities by continuously expanding farms to sustain food production. Also, salinization is a severe phenomenon that has contributed to LULCC (Allbed *et al.*, 2017). This could be seen in the percentage of salt affected areas per land use type over the period 1984-2017, in which the sabkha and salt marsh areas registered the largest saline areas compared to the forests and croplands. Another important finding of this study was the reduction of salt-affected areas in sabkha and croplands in 2017. This decrease can be explained by the slight improvement in rainfall noticed in the area since the drought period of 1971, which contributed to leach out the salts from the soils. As well, LULC change was more intense in the first period 1984-1994. Historical evidence may explain this finding since that period was characterised by an increasing resource pressure and land degradation due to severe events such as drought.

4.4.2. Soil Salinity Dynamics

As shown in Figure 4.8 and Table 4.5, salinity level registered a strong change between 1984 and 2017 in the region, which is characterised by a relative decrease in soil salinity level. These results concur with the reduction of the extent of salt-affected areas registered in the different land use types in 2017. Such decrease of salinity could be related to the improvement of rainfall recorded in the area as well as the various adaptation and mitigation measures (e.g. anti-salt dams, revegetation and conservation of trees, use of manure and mulching, etc.) implemented by the local communities and some NGOs. Similarly, Sambou *et al*. (2015) showed slight restoration of affected areas by the construction of anti-salt micro-dam and the improvement in rainfall in Casamance (Southern Senegal). In addition, it was also noticed that the year 1984 registered the higher salt-affected areas that may be explained by the deficit in rainfall that occurred during that year in the region. In fact, from 1971 to 1985, the Sahel in general and Senegal, in particular, went through a severe drought period characterised by a drastic reduction in rainfall, and that contributed to the expansion of salt affected areas noticed over the country (Sadio and van Mensvoort, 1993). This finding is in accord with the observation of Kairis *et al.* (2015) who stated that areas with low amounts of rainfall (< 650 mm) are more likely to be affected by salinity.

Moreover, the spatial distribution of salinity in Djilor showed that the highly saline areas are mostly located along the river, generally corresponding to the salt marshes and sabkha areas. Suggesting that the salinity gradient is mostly horizontal and gradually moving from the river to the uplands. These findings support the fact that soil accumulation in this region is generally caused by inundation and deposits of salt from seawater intrusion combined with a high temperature. Also, the results show that vegetation cover is a determining factor of spatial distribution of salinity in the area. In fact, patches of non-saline soils are more pronounced in vegetation areas (forests and savannah), comparing with non-vegetation areas (bare land and sabkha) which registered high content of salt. This finding corroborates a study in Saudi Arabia (Oasis), which reported that vegetation areas exhibited the lower salinity, while high salinity was found in non-vegetation areas (Allbed *et al.*, 2017; 2014b). This may suggest that planting salt tolerant tree species may further reduce salinity, but it needs further investigation.

Among the remote sensing indices, only the NDVI was relevant in the assessment of salinization. These results are similar to those of Emad and Emad, (2017) in northern Egypt and Jabbar and Zhou (2012) in Southern Iraq, who reported that NDVI index gives good results in assessing salt affected areas. However, it was noticed during the stepwise regression that NDVI, coupled with biophysical data such as elevation, distance to the river, and TWI gave high R^2 than combining remote sensing indices alone. This result confirms the strong influence of such biophysical factors in the expansion of salt affected areas in

Djilor and their importance in monitoring soil salinity in coastal regions as shown in Chapter 3.

4.5. Conclusions

The Land use-land cover and salt affected areas patterns, as well as their respective changes that have occurred in the study area from 1984 to 2018, were investigated. The results show that the dynamics in LULCC in Djilor is characterised by an increase in agricultural areas and bare land at the expense of forest cover. The intensity change analysis showed an overall loss of forest cover and gain of croplands over the period 1984-2017. These changes attest to the ongoing deforestation in the area and the continuous expansion of farms by local communities who adapt to soil degradation by expanding agricultural lands to sustain food production. Annual area of land cover change was faster during the period 1984-1994 than during 1994-2007 and 2007-2017. Historical evidence explains this finding since there was increasing resource pressures and land degradation in 1984-1994 due to severe events such as drought.

Furthermore, changes in soil salinity level for the years 1984 and 2017 revealed a slight decrease. Slightly saline and non-saline areas have increased at the expense of highly saline and moderately saline areas. However, despite this decrease in salinity level, soil salinity remains one of the main factors of soil degradation in the study area as salt-affected areas (i.e. highly saline and moderately saline areas) covered around 60 % and 45 % of the total area of Djilor in 1984 and 2017, respectively. Spatial distribution of soil salinity is mostly related to vegetation in the area. In fact, the highly saline soils were mostly located in the non-vegetated areas (sabkha, salt marshes, croplands) while non-saline areas are situated in the vegetated areas (forests and savannah).

The findings give a good understanding of Land use-land cover change and soil salinity dynamic in Djilor. Even though the results on LULCC analysis and soil salinity were based on analysis of medium resolution of satellite images, they were satisfactory and are useful for guiding decision makers, land planners and smallholder farmers to reverse vegetation decline and restore salt-affected areas through the improvement of existing land management as well as integrating new strategies for soil salinity mitigation and reduce its effects on people livelihoods. Furthermore, using high-resolution remote sensing images may improve the work and give better results. Regarding the predicted future climate change (increase in temperature and sea level rise, and decrease in rainfall), further investigations on modelling future soil salinity as well as assessing the impacts of some adaptation and mitigation strategies on soil salinity may be useful for sustainable soil salinity management in the study area.

CHAPTER 5 : HOUSEHOLDS PERCEPTIONS AND DECISIONS IN A SALINE AGRICULTURAL LANDSCAPE

5.1. Introduction

Soil salinity has become a major concern in the world and particularly in sub-Saharan countries, as it severely affects agricultural land and limits crop productivity. According to Jamil *et al*. (2011), there will be more than 50% of salt affected farmland in the world by the year 2050. In Senegal, as in most of West African countries, agriculture constitutes one of the dominant economic activities and source of subsistence of people. However, due to soil salinity expansion and dependency of local communities on land (73% of the population) (ANDS, 2013), agriculture appears as the most affected and vulnerable sector in the country, endangering populations survival and livelihoods. Salinity has reduced soil productivity, and in severe cases, led to the abandonment of agricultural lands in Senegal (Diome and Tine, 2015; Sambou, 2016). Rice production is one of the visible effects of salinization in the country (Camara *et al.*, 2012). Based on the study of Sow *et al.* (2016), the country lost about US$ 22 million per year due to salinity in rice fields. This may be explained by the fact that rice farming is one of the main agricultural activities and represents an important resource for foods and income. However, because of salinity stress, ricefarming has been significantly reduced and most of the valleys abandoned. In Djilor, this decline of agricultural lands has made smallholder farmers the most vulnerable ones to salinity effects and has exposed them to food security and livelihood challenges.

Various actions and approaches have been undertaken to reverse soil salinity effects, and salinity process, drivers and dynamics investigated by many authors in the region (Sadio, 1991; Sambou, 1991; Faye *et al.*, 2005; IDRC, 2012; Diome and Tine, 2015; Sambou *et al.*, 2016; Dieng *et al.*, 2017). However, the assumptions that farmers have good knowledge on soil salinity dynamics and management has been unprivileged. Few of the studies consider farmers' perception and their degree of participating in soil conservation to face negative effects of soil salinity. Moreover, the perception of local populations is very important in assessing salinity dynamics and drivers because farmers have a better understanding of their environment and the difficulties they face. Thus, the integration of households' decisions in soil salinity model becomes relevant in predicting future salinity. Therefore, for a successful plan to overcome soil salinity, investigating local perception and their decisions in utilisation of saline landscape constitute an important step in salinity management. Thus, this chapter attempted specifically to:

1. Assess the households' perception of soil salinity change and indicators;
2. Determine soil salinity effects on farmers' livelihood and their adaptation strategies;
3. Formulate and calibrate household decisions and crop yield sub-models.

5.2. Methodology

5.2.1. Sampling Design and Data Collection

For farm household characteristics, a combination of household survey and focus group discussion was conducted. A total of 304 households were randomly selected representing the owners of sampled plots. The data were collected from December 2017 to March 2018. A questionnaire was designed and administered to the households. The key categories of the questionnaire were: 1) households and farming characteristics, 2) crop yields, 3) farmers' perception of soil salinity indicators and trend, 4) soil salinity effects on their livelihoods and their adaptation strategies and 5) land use choices. Furthermore, five focus group discussions (FGD) were conducted with farmers to obtain general information and perception of soil salinity in the study area. Participants were the same respondents of the survey who were experiencing salinity problem. They were randomly selected. Each group was composed of at least five farmers (i.e. three men and two women). The discussions were done in the *Serere* language (the local language).

5.2.2. Data Analysis

5.2.2.1. Descriptive Statistics

The quantitative data were analysed and summarized in the form of tables and graphs by using appropriate descriptive statistics. Spearman's rank correlation was used to determine if there were statistically significant relationship in the perception of soil salinity dynamics among the different categories of respondents. Data were analysed using the Statistical Package for Social Science software (SPSS).

5.2.2.2. Modelling Households' Decisions

Household making decisions were investigated through two cases: 1) willingness of household to change or not to change land use (*Land use-adoption*); and 2) the willingness of household to change land use into fallow or abandoned areas (*Land use-choice*). They were estimated using the following analysis:

Binary Logistic Regression Analysis

Firstly, a binary logistic regression analysis was used to model the willingness of households to change or not to change land use as a consequence of soil salinity problem. The model was constructed by an iterative maximum likelihood procedure using SPSS 20 package. The model characterizing *Land use-adoption* is specified as:

$$log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (5.1)$$

Where i denotes the *i-th* observation in the sample,

Pi is the predicted probability of adoption, which is coded with 1 (willingness to adopt) or with 0 (not to adopt), $ß0$ is the intercept term, and $ß1$, $ß2$, ..., $ßk$ are the coefficients associated with each explanatory variable x_1, x_2, ...x_k.

Multi-Nomial Logistic Model

Secondly, a multi-nomial logistic model (or M-logit regression) was used to model the willingness of household to change land use into fallow or abandoned areas, which identified the main factors affecting land -use choices of households. The M -logit model is based on the random utility model, and its algebraic manipulation of the equation is as following:

$$P(y_i = k) = \frac{exp(X_i \beta_k)}{1+\sum_{j=1}^{j} exp(X_i \beta_j)} \quad (5.2)$$

Where dependent variable categories $k = 1, 2, \dots J$, to predict the probability (P) of a land use to be chosen (y_i), as the observed outcome for the *i-th* observation on the dependent variable, X_i is a vector of the *i-th* observations of all explanatory variables, and β_j is a vector of all the regression coefficients in the *j-th* regression.

The coefficient parameters were estimated by the maximum likelihood method based on the plot-based dataset of household agent using the SPSS package version 20.

Table 5.1 shows the different variables used for the M -logit model, where land -use choice by a farming household (*P_choice)* is the dependent variable. They are two categories of choice: 1) Fallow land, and 2) abandoned areas. The independent variables include various variables that may affect households' decisions. There are grouped into two variable types: 1) Household and farm characteristics, and 2) biophysical characteristics.

5.1: Explanatory variables influencing household decisions

Variables	Description	Sources	Direct linked module
Dependent variable: Land-use choice by households			
P_choice	1 for fallow land, 2 for abandoned areas, and 3 for the other land-use choice	Field survey and observation	Patch Landscape
Household and farm characteristics			
h_age	Age	Field survey	Households Population
h_gender	Gender	Field survey	Households Population
h_size	Household size	Field survey	Households Population
h_dependents	Dependent ration	Field survey	Households Population
h_labour	Labour	Field survey	Patch Landscape
P_crop	Crop type	Field survey	Households Population
P_yield	Crop yield	Field survey	Households Population
Biophysical characteristics			
P_river	Distance to river	GIS-based calculation	Patch Landscape
P_soiltype	Soil type	Shapefile from INP (2012)	Patch Landscape
P_salinity	Soil salinity	Laboratory analysis	Patch Landscape
P_pH	Plot pH	Laboratory analysis	Patch Landscape
P_elev	Plot elevation (m)	DEM	Patch Landscape
P_slope	Plot slope (degree)	DEM	Patch Landscape

5.2.2.3. Modelling Crop Yield Dynamics

The production function of Cobb-Douglas formula was applied to generate the crop yield sub model. Cobb-Douglas approach used labour and capital as predictors for yield (Tan,

Table

2008). This function is widely used to represent the relationship of output to inputs and is formally expressed as follows:

$$P(L, K) = bL^{\alpha} K^{\beta} \qquad (5.3)$$

Where, P is total production (monetary value of all goods produced in a year);

L is labour input (total number of man-days employed in a year); K is capital input (e.g. agrochemical, seedlings, etc.); b is total factor productivity; α and β are output elasticities of labour and capital, respectively; they are constant values as determined by the available technology.

The output elasticity measures the responsiveness of output to a change in levels of either labour or capital used in production, all other things being equal (Tan, 2008). For instance, if $a = 0.15$, a 1% increase in labour would lead to an increase in o utput of approximately 0.15 %.

Table 5.2 presents the different explanatory variables of the production functions for rice, maize, millet and groundnut. These variables were used to perform the production yield equations of each crop as follows:

P_rice =f (P_area, P_salinity, P_labour) (5.4)

P_maize =f (P_area, P_salinity, P_labour, P_seed, P_sand) (5.5)

P_millet =f (P_area, P_salinity, P_slope, P_sand) (5.6)

P_groundnut =f (P_area, P_salinity, P_seed) (5.7)

5.2: Variables used for the crop yield dynamics sub-model

Variables	Description	Sources	Direct linked module
	dependant variable)		
P_yield	Plot crop yield (kg/ha)	Field Survey (n=304)	Patch Landscape
P_area	Size of the plot (ha)	Field survey	Patch Landscape
P_labour	Number of workers	Field survey	Patch Landscape
P_seed	Amount of seeds	Field survey	Patch Landscape
P_fert	Fertilizer (kg/ha)	Field survey	Patch Landscape
P_salinity	Salinity content	Laboratory analysis	Patch Landscape
P_sand	Sand content (%)	Laboratory analysis	Patch Landscape
P_slope	Slope of the plot (%)	DEM	Patch Landscape

The crop production yield data were collected together with the socio-economic survey between December 2017 and March 2018. A total of 304 respondents provided data on agricultural inputs (e.g., fertilizer, labour needed, seeds etc.).

5.3. Results

5.3.1. Households Characteristics

Table 5.3 presents the descriptive statistics of farm households. The age of the respondents ranged between 20 and 85 years old. The age group of 36-54 years were the most represented (46.3%). Of the total respondents, over half of the respondents (61.3 %) did not go to school, (36.3%) had basic primary education and few of the respondents had reached secondary school (2.5%).

The respondents were mostly represented by men (81%), females constituted only 19 %.

Table

Females are usually engaged in rice farming, about 65 % of the rice plots belonged to females. The female headed households were generally widows or their husbands migrated to other places. The average size of a household was 13 with an average farm plot size of 1.6 ha. Most of the respondents got their plot by inheritance (86.5%). Cultivation of crops constitutes the main socio-economic activity and source of income of the respondents (70.6%), followed by livestock (18.9%). In fact, Crop cultivation compared to other activities is reported to be more vulnerable to soil salinity. 93% of the respondents reported that crop yield has been too much decreasing from time to time due to the decrease in fertility resulting from salt accumulation. Based on farmers' perception, the reduction of crop productivity and loss of cultivable lands constituted the most severe effects of soil salinity, respectively as stated by 28.9 % and 26.9 % of the respondents, followed by the destruction of soil properties (19.4 %).

Based on focus group discussion, participants noted that rice farming is the most affected land use type by salinity in the study area. As their staple foods come directly from the land, farmers recognised that potential increase of salt content will cause excessive agricultural losses and consequently promote severe food insecurity in the area. For them, even though they adopted some strategies, they still needed the government support to have access to agricultural subsidies (e.g., salt-tolerant crop varieties such as *Nerica* also named *New rice for Africa*) and to mitigate soil salinity. Also, farmers in Djilor related salt affected areas expanded as a result of drought (i.e. high temperature and low rainfall) and inundation events occurred respectively, in 1972 and 2012, and that led to the abandonment of many arable lands.

5.3: Descriptive statistics of farm households in Djilor district

Variable	HH	N	Mean	StdDev.	Min.	Max.
Age (years)	Total	304	53.4			86

13.08 25

	Female	46	57.7	12.29	35	85
	Male	258	52.6	13.09	25	86
Household size	Total	304	13	7.16	3	80
	Female	46	13	5.77	5	32
	Male	258	12	7.39	3	80
Group membership	Total	304	0.3	0.46	0	
	Female	46	0.4	0.49	0	
	Male	258	0.3	0.46	0	
Farm plot size (ha)	Total	304	1.6	0.74	0.5	4
	Female	46	1.6	0.72	0.5	4
	Male	258	1.6	0.72	0.5	4
Rice plot (ha)	Total	304	1.9	0.85	0.5	4
	Female	46	1.9	0.83	0.5	3
	Male	258	2	0.92	1	4
Maize plot (ha)	Total	304	1.6	0.66	0.5	3
	Female	46	1.5	0.52	1	2
	Male	258	1.6	0.75	0.5	3
Millet plot (ha)	Total	304	1.7	0.77	0.5	4
	Female	46	1.6	0.67	1	3
	Male	258	1.7	0.77	0.5	4
Groundnut plot (ha)	Total	304	1.6	0.80	0.5	4
	Female	46	1.6	0.78	1	3
	Male	258	1.6	0.81	0.5	4

Note: N= sample size (i.e. number of respondents); group membership=dummy variables (0=yes, 1=no), HH= households.

5.3.2. Soil Salinity Changes and Indicators from Households

Most of the respondents (94%) were aware of soil salinity phenomenon over the study area. Figure 5.1 shows the perceived change of soil salinity of the respondents. In fact, soil salinity has been recognized by the communities as a severe problem that has considerably increased

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Table

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over time (82.5% of the respondents). The perception of salinity change varies among the respondents. For instance, the perception of soil salinity change by respondents within age groups is significantly negatively correlated (Spearman's rho r = -0.51, p <0.001). Youngsters perceived salinity as decreasing over time while the elders saw an increase. In fact, 94.6% and 100% of the 36-54 and 56-85 age groups respectively perceived soil salinity dynamic as permanently increasing while 50% of the youth (20-35 years) perceived the change as decreasing.

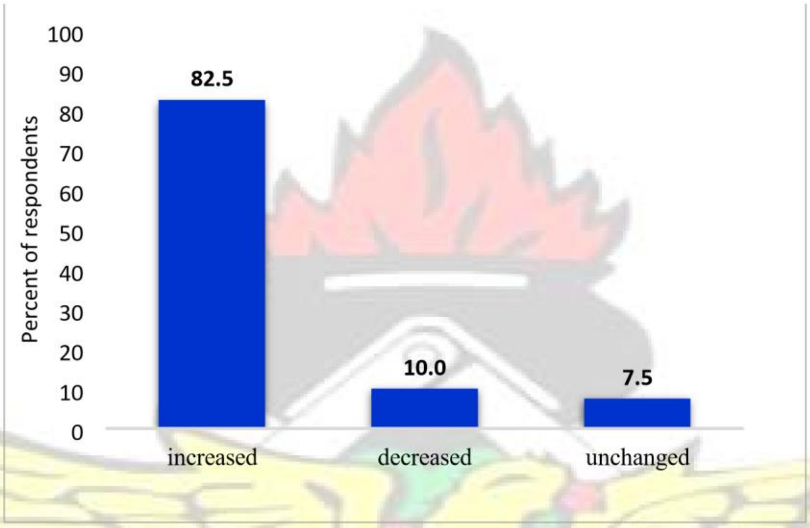

Figure 5.1: Soil salinity change from local farmers

Based on farmers' perception, five (5) main soil salinity indicators were identified in the area: fertility decline, salt crust on the surface, soil crusting (compaction), the presence of salt-tolerant plants and vegetation cover reduction. Accordingly, the soil fertility decline is the most important one (39.1 %), followed by the presence of salt crust on the surface and soil crusting respectively at 28.7 and 12.5 % (Figure 5.2). Some of these salinity indicators are illustrated in Figure 5.3.

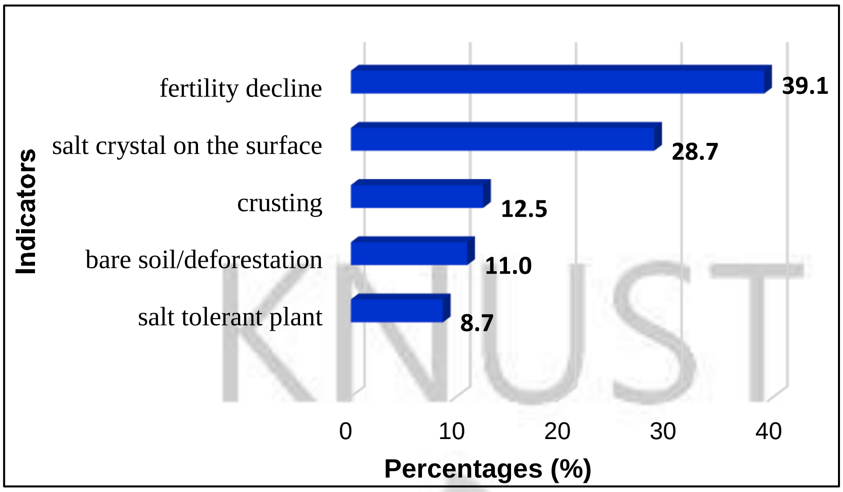

Figure 5.2: Soil salinity indicators from households

Figure 5.3: Visual indicators of soil salinity in Djilor: (a) Salt crust on soil surface; (b) soil cracking due to high temperature; (c) death of nearby trees; (d) *Tamarix senegalensis* (halophyte plant)

5.3.3. Soil Salinity Effects on Farmers' Livelihood and Adaptation Strategies

Ninety-six percent of the respondents are affected by salinization and reported a reduction of their crop yields. Figure 5.4 shows the crop yield in saline and non-saline areas. In nonsaline plots, the highest median crop yield was 800 kg/ha, whereas in saline plots the median of crop yield is almost zero.

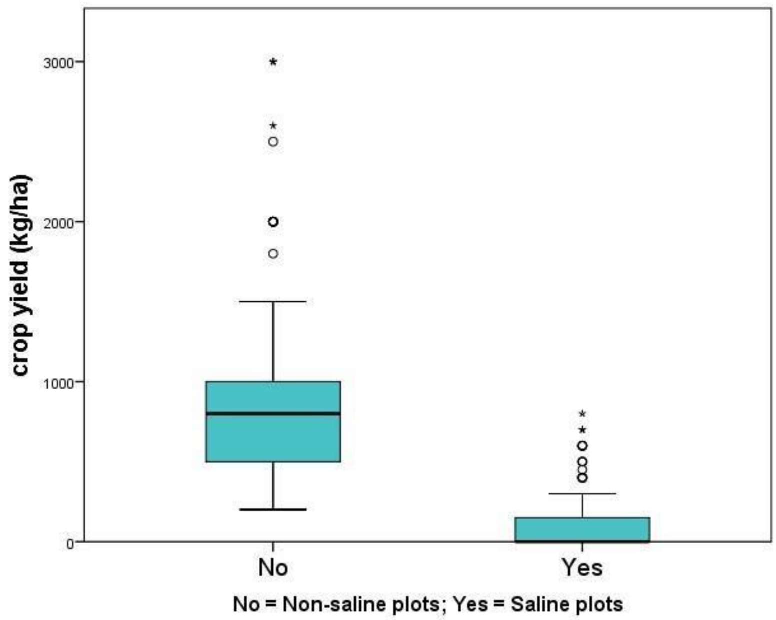

Figure 5.4: Effects of soil salinity on crop yield in Djilor district

Rice is the most affected crop type by soil salinity as described in chapter 3, however, 65% of the rice plots are owned by female farmers, suggesting that they are highly vulnerable to the impact of increasing soil salinity. Furthermore, Figure 5.5 shows that the plots with higher median EC (9 dS/m) belongs to female group in comparison with the men' plots (median EC=7 dS/m).

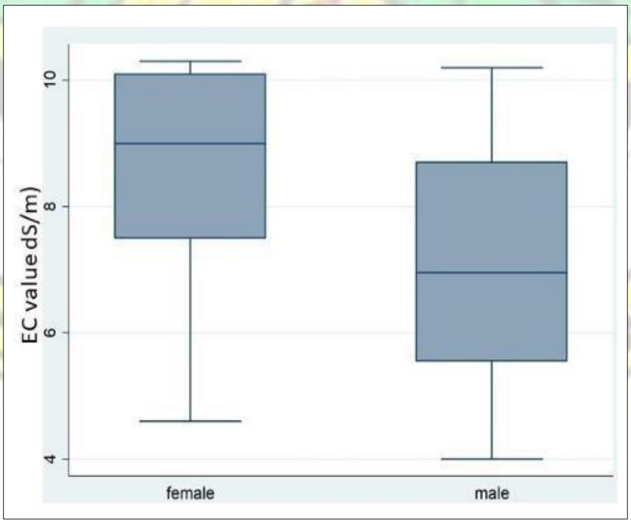

Figure 5.5: Soil salinity and gender in Djilor district The farmers in Djilor have been applying various adaptation strategies to mitigate the negative

effects of soil salinization. A total of seven adaptation strategies were recorded within the study area: chemical fertilizer, organic manure, planting and conservation of trees,

soil bunds, fallowing, tolerant crop varieties and mulching. Figure 5.6 shows the adaptation strategies according to male and female groups. Installation of soil bunds (68.4 %), planting and conservation of trees (65.4 %) and use of organic manure (57.8 %) were the most important strategies for females, while men were more into mulching (96.5 %), fallowing practice (83.3 %) and application of chemical fertilizer (78.6 %).

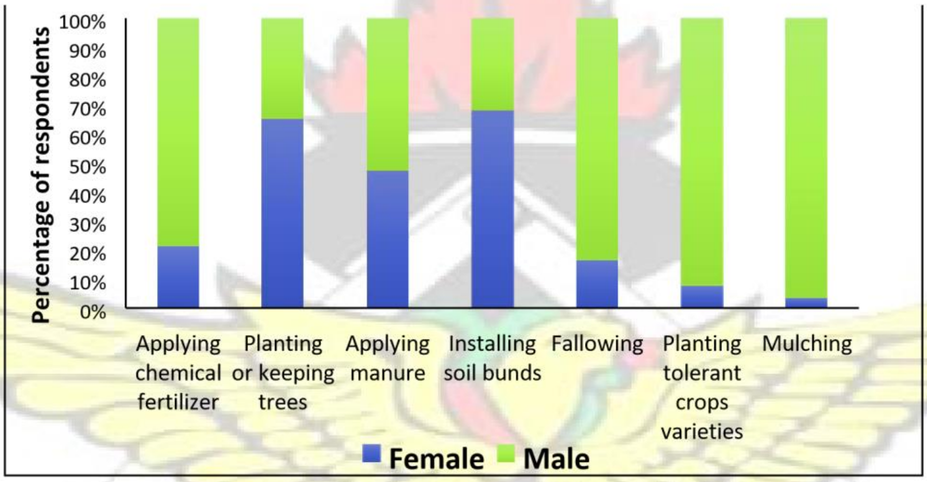

Figure 5.6: Adaptation strategies to soil salinity in Djilor

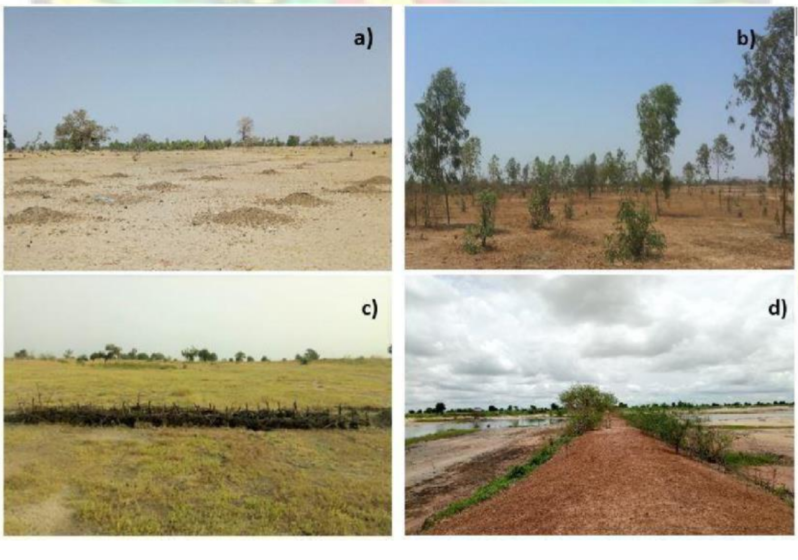

Figure 5.7: Some adaptation strategies in Djilor: a) Application of manure, b) Planting of trees, c) Local dam, d) Anti-salt dam

5.3.4. Households Decisions Sub Model

Households decisions were integrated into the model through two specific sub models: 1) *Land use-adoption* sub-model and *Land use-choice* sub model. The *Land use-adoption* submodel calculated stochastically the probability of the household agents whether to change or not to change based on their preference coefficients (Table 5.4). These preference coefficients were derived from binary logistic regression (Villamor, 2012). Table 5.4 presents the variables that influence the decision of the farmers to change (yes) or not to change (No) their land uses. It shows that 39.5% of the farmers (i.e. 120 farmers) had adopted to change their land use while 60.5% (i.e. 184 farmers) had no intention to change their land use.

Table 5.4: Factors affecting household adoption

Explanatory Variables	Coef.	Std. Err.	95% Conf. Interval	
Crop yield	-0.004	0.001***	0.99	1.00
Lixisols	-0.310	0.622	0.22	2.48
Fluvisols	0.718	0.591	0.64	6.54
Gleysols	3.163	0.915***	3.94	141.89
Number of females	-0.103	0.076	0.78	1.05
Number of males	0.193	0.094***	1.01	1.46
Soil salinity	0.672	0.149***	1.46	2.62

Note: Likelihood ratio test (chi-square statistics): 151.13; *df* = 8; *p* = 0.000; Pseudo R^2= 0.77, **Yes (N=120), No (N=184)**

Likewise, *Land use-choice* sub model corresponding to the probability of farmers to convert their plots to fallow land or abandoned area was estimated using M-logit model. Table 5.5 shows the factors that influence farmers' choice to change their land use to fallow land or abandoned area in response to the level of salinity. Chi-square tests showed that the empirical M-logit model is significant (*p = 0.000*). The model was able to explain 73.3 % relationship between the variables and the land use adoption probability (Nagelkerke's pseudo-R^2 =0.733). The model has also a good overall predictive power of 81.9 %, and predicted willingness with 69.6 % of the sample cases correctly in adopting abandoned area and 68.2 % in fallow land adoption.

Seven variables were used to run the model. Among them, five were found significantly related to the choice of abandoned area ($p < 0.05$): salt content (+), labour (-), distance to river (-), crop yield (-), and crop type (+) (Table 5.5). The positively significant coefficient of salt content with the option of abandoning area indicates its positive influence on farmers' decisions which was as presumed. This suggests that the higher the salinity content, the higher the probability of farmers to abandon their plots. The coefficient of distance to the river was negatively significant, which implies that the nearer the plot is to the river, the higher the probability of adopting abandoned area. As well, the crop yield is also negatively significant to the probability of adopting abandoned area, which means that the lower the crop yield of the plot the higher the probability of farmers to abandon it. The level of the adoption of abandoned area is also linked to the labour and the crop type. Farmers who have low labour force and cultivating rice tend to abandon their lands.

In the same order, farmers also tend to devote their land to fallow land. The probability of them to choose fallow land rather than abandon the area is significantly influenced by some factors (Table 5.5). Variables that significantly influence the decision of households to select fallow land include labour (+), distance to the river (+), crop type (+), crop yield (-), and soil type (+). Plots that required more labour were mostly converted to fallow land. Regarding farm plot distance, the probability of households to choose fallow land increase as the distance of the farm plots from the river increases. Plots of fallow land are those with low yield and are also located in Lixisols.

Table 5.5: M-logit model of land-use choices of households who have change their land use to fallow or abandoned areas (N=112 plots)

			95% CI	
Variables	**Coef.**	**Std. Error**	**Lower Bound**	**Upper Bound**

Fallow land	Intercept	-11.569	3.598***		
	Soil salinity	0.258	0.144	0.976	1.716
	Labour	1.067	0.452***	1.199	7.047
	Distance to river	0.000	0.000***	0.999	1.000
	Gender	0.756	0.731	0.508	8.915
	Crop type	0.698	0.272***	1.180	3.423
	Crop yield	-0.003	0.001***	0.995	0.999
	Soil type	0.916	0.313***	1.353	4.618

Abandoned areas	Intercept	-5.015	4.375***		
	Soil salinity	0.713	0.199***	1.380	3.013
	Labour	-0.182	0.560***	0.278	2.499
	Distance to river	-0.001	0.000***	0.999	1.000
	Gender	-1.332	0.721	0.064	1.084
	Crop type	0.727	0.305***	1.138	3.763
	Crop yield	-0.005	0.002***	0.990	1.000
	Soil type	0.776	0.451	0.897	5.259

*Likelihood ratio test (chi-square statistics): 289.4*** df = 14; p = 0.000*

Pseudo-R^2 *= 0.733 (Nagelkerke); 0.614 (Cox and Snell); 0.525(McFadden)*

Percentage correct predictions: Fallow land: 68.2%

Abandoned areas: 69.6%

Others: 89.6%

Overall percentage: 81.9%

5.3.5. Crop Yield Dynamics Sub-Model

5.3.5.1. Descriptive Statistics

of rice, maize, millet and groundnut are summarized in Table 5.6. The average yield obtained from the field for these three cereals were 116 ± 67 kg ha^{-1} y^{-1} for rice; 195 ± 319 kg ha^{-1} y^{1} for maize, 544 ± 596 kg ha^{-1} y^{-1} for millet and 740 ± 628 kg ha^{-1} y^{-1} for groundnut.

Table 5.6: Description statistics of yield per crop type

Crop types	Number of plots	Mean (kg ha^{-1} y^{-1})	StdDev	CI at 95 %	Minimum	Maximum
Rice	23	116.1	67.20	29.1	0	300
Maize	33	195.5	319.27	113.2	0	1300
Millet	163	544.5	596.88	92.3	0	3000
Groundnut	85	740.0	628.76	135.6	0	3000

5.3.5.2. Crop Yield Sub Model

Table 5.7 shows the results of the regression analyses for the crop yield model of rice, millet, maize and groundnut.

Rice

Labour *(P_labour)* and salt content *(P_salinity)* are the significant explanatory variables in the rice yield. The analysis of the results revealed that an increase in labour would increase the rice yield. On the contrary, salt content is negatively related to rice yield, suggesting that

The descriptive statistics of crop yield used as dependent variable for crop yield sub-model the higher salinity, the lower the rice yield as previously shown in this study.

Maize

Labour *(P_labour) is t*he only explanatory variable found to be significantly affecting maize yield. Indeed, an increase in labour would increase maize yield.

Millet

The explanatory variables that are significantly related to millet yield are plot size **(***P_area),* plot slope *(P_slope),* and the amount of sand in the plot *(P_Sand).*The size and the amount of sand of the farm plot positively affect the yield of millet, suggesting that their increase would also lead to an increase in millet output. Further, the slope of the plot is negatively correlated to millet.

Groundnut

Salt content *(P_salinity),* plot size (*P_area),* and the amount of seed in the plot (*P_seed)* are the significant explanatory variables in groundnut yield. The results indicate that an increase in plot size and in the amount of seed would increase the groundnut yield. Also, an increase in salt content will cause a decrease in groundnut yield.

Table 5.7: Crop yield dynamics sub-model per crop type

Crop yield sub	Coefficients model Standard Error	P-value	Confidence Interval at 95% level

Rice (R^2 = 0.59; *p* = 0.000)				
Intercept	-258.0	180.7	0.170	
P_area	25.8	12.9	0.060	0.353
P_salinity	-0.22	7.4	**0.007**	0.649
P_labour	69.3	22.9	**0.007**	0.203
Maize (R^2 = 0.57; *p* = 0.000)				
Intercept	-2412.3	1255.8	0.065	
P_area	-142.9	95.2	0.145	0.217
P_salinity	0.0	0.4	0.961	76.838
P_labour	240.0	101.1	**0.025**	0.176
P_seed	3.6	1.9	0.068	11.381
P_Sand	14.0	9.8	0.164	2.823
Millet (R^2 = 0.43; *p* = 0.000)				
Intercept	-1979.4	1032.3	0.057	
P_area	140.7	50.5	**0.006**	0.113
P_salinity	-0.6	0.4	0.123	32.808
P_slope	-207.0	100.4	**0.041**	0.056
P_Sand	32.4	9.9	**0.001**	1.243
Groundnut (R^2 = 0.48; *p* = 0.000) 524.0				
Intercept		181.3	0.005	
P_area	235.5	86.0	**0.008**	0.166
P_salinity	-1.3	0.3	**0.000**	41.525
P_seed	4.8	1.8	**0.008**	8.186

Statistical significance at the 0.05 level

5.4. Discussion

5.4.1. Household Perception of Soil Salinity Dynamics

Farmers were aware of the soil salinity problem and they showed a good understanding of salinity effects on their plots and livelihoods in Djilor. However, most of them stated an increase of soil salinity, which is in contrast with the results from remote sensing data showing a decrease in salt content. This misperception on soil salinity change is likely as a result of difficulty for the farmers to observe accurately the extent of salinity as earlier reported by (Kington and Pannell, 2003) in Western Australia. In fact, the level or extent of salinity is difficultly perceived by farmers as it usually required laboratory analysis even though they may exist some visual biophysical indicators of salinity. Moreover, this may also result from the errors in the classification. Despite this contradiction with the remote sensing results, farmers have a good perception of salinity indicators and were able to give various visual indicators possibly linked to salinity problem in the area. Similar findings were reported by Kashenge-Killenga *et al.* (2014) in north-eastern Tanzania. However, the presence and importance of a given indicator may depend on site specific socioenvironmental conditions. Decline in soil fertility was the most cited salinity indicator, indicating good awareness of farmers with regard to the negative impact of salinity on soil fertility and crop yield, as shown by previous studies (Nguyen *et al.*, 2016; Shrivastava and Kumar, 2015).

5.4.2. Impacts of Soil Salinity and Adaptation Strategies

Soil salinity in Djilor has gender aspect. From this study, women appeared to be affected by soil salinity due to their dominance in rice farming, which in turn may affect their household's food security. Similarly, a study in Bangladesh showed that women were more concerned about salinization and suffered more from soil salinity problem than men (Rahman, 2010). Moreover, soil salinity constitutes a real threat to local smallholder farmers' livelihood and food security in the area, as earlier revealed by Sambou (2016) study in Fatick Region. Indeed, staple foods in the area are generally cereal based such as rice, millet, groundnut, maize, and sorghum, as well as root crops, fruits, and vegetables. However, due to soil salinity, majority of the households interviewed in the study area agreed that their crop productions had reduced. These findings corroborate with the study in Bangladesh, which showed a negative impact of soil salinity on household food security (Szabo *et al*., 2016). Furthermore, the results of this study showed a strong and negative relationship of salinity content with crop yield as observed by Nguyen *et al.* (2016) in the coastal region of Vietnam. “This is not surprising because yield largely depends on soil fertility or nutrients, which are severely degraded by salt accumulation in the root zone” (Shrivastava and Kumar, 2015).

In order to reduce the negative impact of soil salinity on livelihoods in the study area, households had adopted various adaptation strategies based on their traditional knowledge in agriculture and sometimes with the assistance of implemented projects such as the International Union for Conservation of Nature (IUCN-Senegal). Among the traditional adaptation strategies employed were the application of manure, planting and conserving trees (e.g., *Eucalyptus alba*, *Faidherbia albida*), establishment of soil bunds, fallowing, planting tolerant crop varieties (e.g. new variety of rice named *Nerica*) and mulching. Among these strategies, Fall (2017) noted the mulching strategies as the most efficient method to reclaim salt affected areas in the Saloum river basin. It is interesting to find that the application of chemical fertilizer is one of the top coping strategies identified. In a study of Dah-gbeto and Villamor (2016) in Benin, it also showed that application of chemical fertilizer is the most preferred adaptation strategy to climate variability (e.g. droughts and floods) in the agricultural lands. However, adaptation strategies are also site or context specific (Haider and Hossain, 2013; Machado and Serralheiro, 2017). Nevertheless, farmers' responses to salinity in Djilor were encouraging as they were all conscious of the phenomenon and most of them had started implementing strategies. However, farmers still need assistance from the government or NGOs to be able to improve their strategies and somehow install other strategies.

5.4.3. Households Decisions regarding Land Use Choice

Decisions of households were explored under two cases: fallow land or abandoned area. These two land-use choices (i.e., fallow or abandoned area) were frequently mentioned during the survey. Faced with the increased salt content, local households usually did not have many options to mitigate salinity process and most of them convert their plots to fallow or abandoned lands. Thus, given this behaviour, these latter two cases were assumed (Villamor, 2012). The household's decisions in Djilor were driven by various factors which explain their willingness to land use choice. In fact, the selection of abandoned area' option by a household was significantly related to the salt content of the plot, the distance to the river, the crop type and the crop yield. Regarding the salt content, plots that have higher salinity were more likely to be abandoned. This relationship indicates the positive influence of salinity on abandoned area choice, which was presumed. This result concurs with the observations of Diome and Tine (2015) in the Groundnut Basin of Senegal, who showed that the higher salt content was found in abandoned areas. Likewise, this finding is also in phase with the results described in Chapter 3 of this study, which showed a higher salinity in bare lands (generally corresponding to abandoned areas). The percentage of households who abandoned their plots was less than those who adopted fallowing practice. Indeed, due to the lack of land in the area, most of the farmers preferred doing from two to four years of fallowing practice instead of abandoning their lands. Fallow lands were generally less saline than abandoned areas, which may explain the non-significant effects of salt content on household's choice. In fact, the probability of a household to select fallow land was importantly affected by the labour, the distance to the river and the crop yield.

The land use decisions of households constituted an important component for this study since the results from the binary regression and the M-logit models are incorporated in the Land Use-Salinity Interaction (LUSI) model (see Chapter 6) for salt content simulation.

In some research in land-use decision making, the household agent was disaggregated into two different groups (heterogeneity) (Villamor, 2012; Chabi, 2016). However, in this study, the conventional way has been used which aggregated the household agent as one group in order to simplify the model.

5.5. Conclusions

This chapter highlighted the households' perceptions of soil salinity dynamics and indicators as well as their adaptation strategies and land use decisions. Majority of respondents were aware of the soil salinity issue and described a continuous trend of salt-affected areas as increasing. Fertility decline, salt crust on the surface, soil crusting (compaction), the presence of salt-tolerant plants and vegetation cover reduction were perceived by farmers as the most important indicators of soil salinity in the area, which were in accord with the findings of previous studies. This reveals the good knowledge of local communities on salinity processes which reduce cultivable lands availability and constrain crop production on their farmlands. Indeed, the immediate negative effect of salinity was the low crop yields particularly on rice production that were mainly cultivated by female farmers. As a result, their production decreased from time to time as well as their level of subsistence due to the negative effects of soil salinity, farmers in the study area were using a wide variety of adaptation strategies such as using chemical fertilizer, manure, planting and conservation of trees, and soil bunds.

In fact, most of the factors affecting land use choice was related to plot characteristics (salt content, distance to river, yield, labour, crop type and soil type). These significant variables influencing the household's decisions making have not been much considered in soil salinity assessment with an agent-based model. For that, the coefficients generated for household agent were incorporated in LUSI model for land use choice in the subsequent chapter.

CHAPTER 6 : SIMULATION OF SOIL SALINITY DYNAMICS FOR ASSESSING THE IMPACTS OF TEMPERATURE IN A COASTAL LANDSCAPE

6.1. Introduction

Soil salinity is a very complex phenomenon resulting generally from geopedological context, climate change as well as human interventions at all scale (Schofield, 2003; Zhang and Zhao, 2010). As sea level rises, global warming and precipitations changes caused by climate change are projected to be pervasive in the coming decades; the risks associated with salinity issue will also inc rease for many islands and coastal regions (IPCC, 2018). In Senegal, the predicted climate change (Figure 6.1) will increase the expansion of salt affected areas mainly due to the direct effect of increased temperature and insufficient rainfall on salt movement and accumulation in soil. Moreover, salinity process also depends on a range of biophysical and socio   -economic drivers which interact and induce the continuous change in soil salinity in time and space.

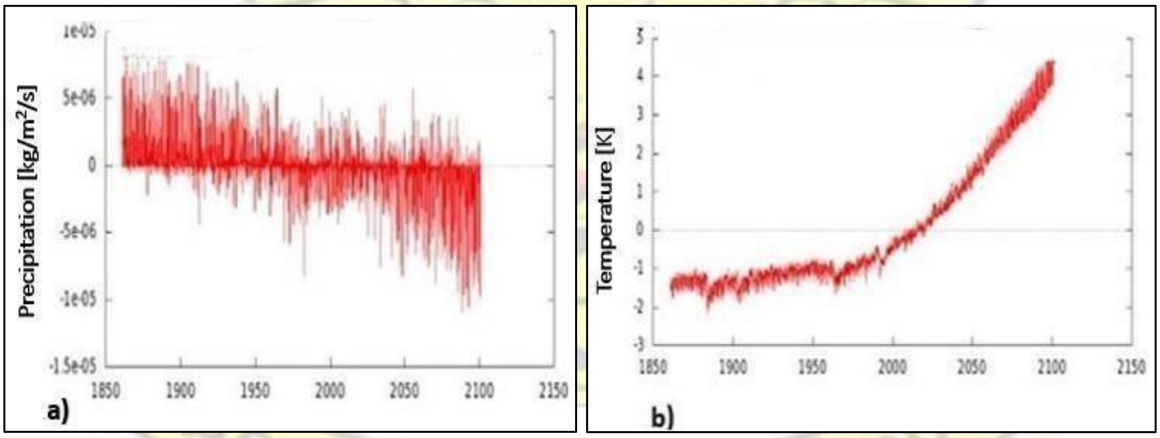

Figure 6.1: Projections of mean rainfall (a) and mean temperature (b) in Senegal for RCP8.5 scenarios (NASA)

To consider such interactive system around soil salinity process, an agent-based model (ABM) allows the combination of landscape and human system interaction in a saline landscape (see Chapter 2 for ABM description).

In Senegal, the application of ABM to understand the issue of soil salinity is novel. In addition, there is lack of data provided from modelling soil salinity change and its future impacts on yield and farmers livelihoods. Thus, the results of this study will contribute toward closing these gaps as well as helping decision makers at the national level. Therefore, the proposed study aimed to develop an agent-based model, namely, Land Use-Salinity Interaction (LUSI) model by combining simplified bio-physical processes affecting soil salinity and farmer decisions to mitigate the negative impacts of salinity in coastal agricultural landscape. Further, this model presents a stylised landscape in which the agricultural land use change is influenced by soil salinity due to increased temperature.

Thus, the following specific objectives were addressed in this chapter:

1. To Apply LUSI model as an integrated model and MAS model that simulates soil salinity dynamics,
2. To explore and compare the dynamics of soil salinity under two temperature scenarios

6.2. Methodology

6.2.1. Description of the Model based on Standard Procedure

ODD (Overview, Design concept, and Details) protocol is a standard structure used to document and describe all Agent-Based Models (ABMs) (Grimm *et al.*, 2006). It aims at making model descriptions more understandable and complete as well as giving consistency in describing such models. However, to adapt ODD protocol in socio-ecological research, it has been updated as ODD + D (ODD + Decision) by which ABMs include human decisionmaking (Grimm *et al.*, 2010; Müller *et al.*, 2013). Human - environmental actions and decisions is a system that represents key elements of standard ABMs as well as LULCC models in such a structured and comprehensive way (Parker *et al.*, 2002). Thus, this study followed the ODD + D protocol to simulate the soil salinity based on temperature and household decisions called Land Use-Salinity Interaction (LUSI) model as an ABM model used in this study. LUSI model is applied in the context of West Africa and particularly in Senegal context and focuses on agricultural saline landscape of coastal region in Senegal.

6.2.2. Overview

6.2.2.1. Purpose

The purpose of the LUSI model is to explore the potential impacts of increased temperature and farmers decisions on soil salinity dynamics in a coastal agricultural landscape. Expecting that, at the end of the simulations, this exploration helps to capture the implications of temperature in future soil salinity extent. In addition, the LUSI model also allows assessing the potential impacts of soil salinity changes on crop yield and on the livelihood of households. A conceptual framework of the model is presented in Figure 6.2. Indeed, four modules serve as the main features of LUSI model: the biophysical system, human system, increased temperature factor and the decision-making procedure. For the representation of salinity change responses to temperature, LUSI contains an internal submodel of salinity dynamics. As well, household agents are equipped with a decisionmaking mechanism as an internal sub-model. The increased temperature is assumed as the main factor affecting the dynamics of soil salinity in the study area. In this way, two scenarios of temperature were defined and tested to determine the temporal and spatial change of soil salinity.

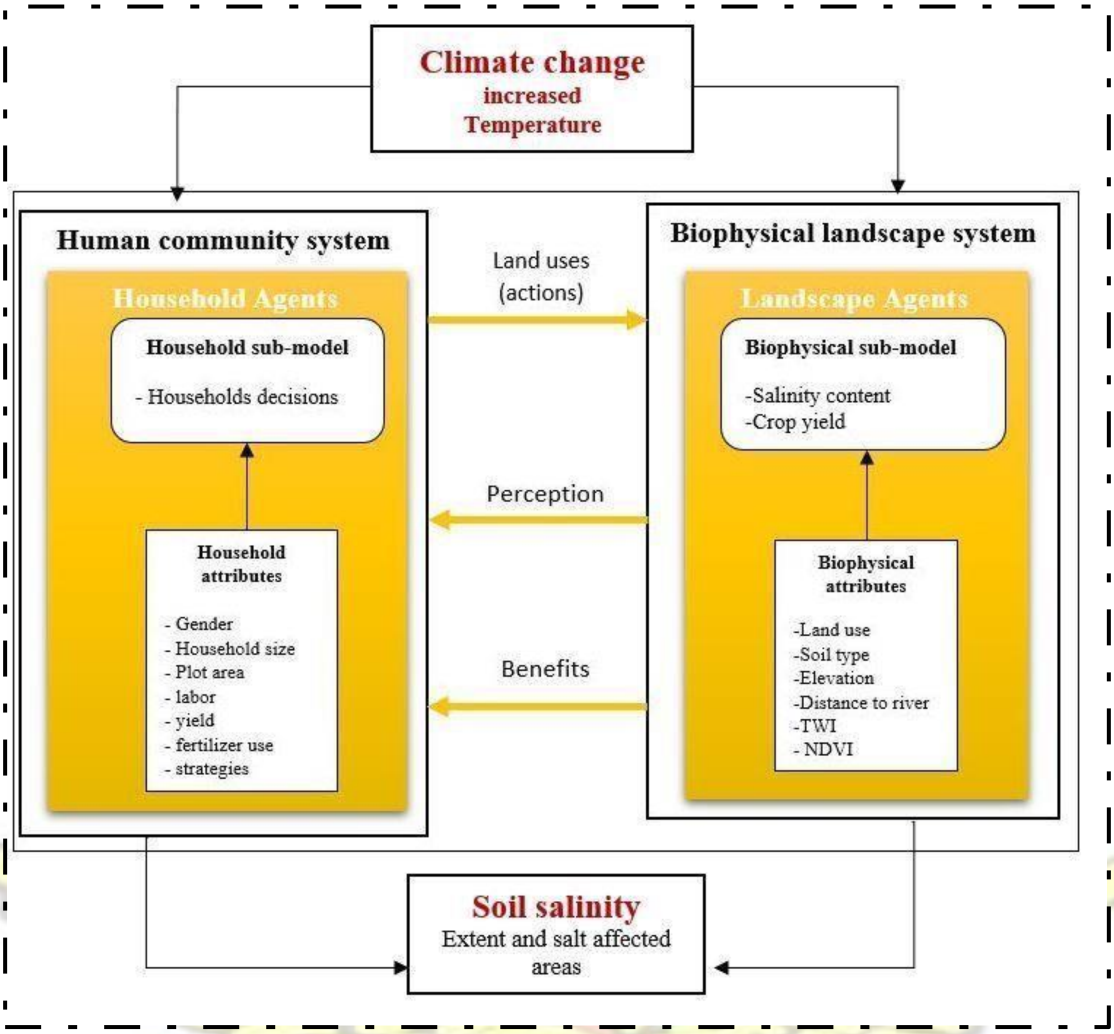

Figure 6.2: Conceptual framework of LUSI model

6.2.2.2. Agents, Variables and Scales

The LUSI model has two types of agents: 1) human agents, and 2) landscape agents. They are both represented by various state variables as given below.

Human agents are representations of individual farming households. The variables of these agents include social identity (household Id), gender, age, group membership, and human resources (e.g. household size, labour and dependency ratio), and natural resources (e.g. land holdings and land structures, adaptation strategies, yield).

Landscape agents are represented by land pixels or patches with variables corresponding to GIS-raster layers of biophysical spatial variables (e.g. land cover, elevation, NDVI and wetness index, salt content, distance to the river).

6.2.2.3. Spatial and Temporal Units

One-time step represents one year. One grid cell or pixel represents 30 m x 30 m (900 m^2), as this resolution corresponded with the land-use map of 2017 classified from Landsat TM/ETM data.

6.2.2.4. Overview Process and Scheduling

Figure 6.3 presents the main steps of the LUSI model which include salinity dynamics, agronomic crop yield dynamics and farmers' land use choice routines integrated into the simulation programme. These are three important sub-models of this study incorporated in the LUSI model. The time loop also called annual production cycle is composed of sequential steps, which are agent-based and integrated with patch-based processes. In most cases, all household agents and landscape agents are called and perform the task in parallel (i.e. synchronising actions).

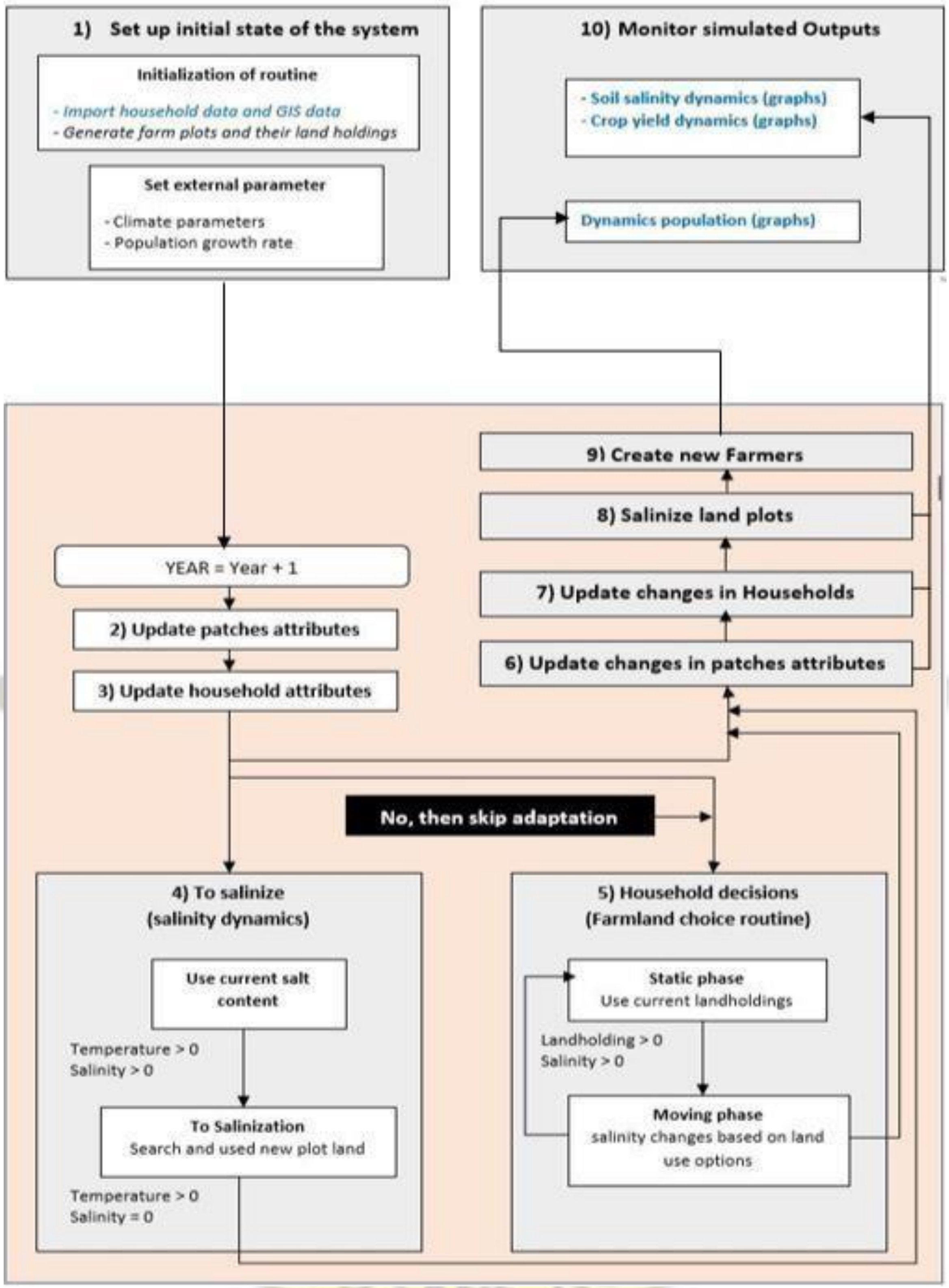

Figure 6.3: Time loop procedure in 10 Steps of Multi -Agent Simulation process of LUSI model (Modified from Le et al., 2008)

6.2.2.5. Design Concepts

Interaction among agents causes emergent landscape/community phenomena that lead to landscape and population dynamics (Le, 2005). Similarly, the LUSI model is designed to explore the soil salinity dynamics relating to interaction between the biophysical and human systems in a coastal region. So far, few MAS models were built on empirical data (Berger and Schreinemachers, 2006) and integrate biophysical and socio-economic model components (Parker *et al.*, 2002). The design of this model refers to various variables and entities that can influence the salt content and the processes within agents. Changes in salt content occur on an annual basis as effects of the simulation process such as an increase in temperature. As for household agents, they are equipped with a decision-making mechanism as a sub-model, which decides to change their land uses into fallow land or abandoned area depending on the amount of salt accumulated in the plot. This means that the conversion of new patches to fallow lands or abandoned areas is constrained by salt content of the household plot. So, to observe the internal dynamics of soil salinity as well as its impacts on agricultural land use, the expected outputs of the model needed are, salinity change areas (e.g., average salt content, salt-affected area extent), salt content per land use/ land cover (LULC) type and socio-economic dynamic (e.g. yield dynamics of each crop type in a context of salinity).

6.2.3. Details

6.2.3.1. Initialisation

In the initial state of LUSI model simulation (at $t = 0$ of the simulation run), the model followed the same sequential steps of the LB-LUDAS (Villamor, 2012).

Step 1: The household and plot sampled data are imported. The initial landscape of the model is imported as GIS-raster files of landscape variables that are either from empirical data (conversion of plots GPS point base to raster, calculation of distance to river) or from secondary data (DEM, Landsat imagery etc.) produced separately by spatial analyses (elevation, wetness index, NDVI, etc.). At this level, the variables of both households and landscape are deterministically set.

Step 2: This step consists of creating the land parcels of newly generated households using the bounded-random rules.

6.2.3.2. Inputs Data

Data and parameters were parameterised and calibrated in text format . Among those data, GIS-raster (land use, NDVI, plot distance to river, plot elevation etc.), households' data (age, labour, household size, plot owner, yield etc.) and other specific parameters. Also, the model used an annual population growth rate of 2.9 % according to the 2013 statistics in Djilor district. Table 6.1 summarizes the input data and parameters used for each sub-model.

6.2.3.3. Sub Models

The framework of LUDAS model is generally composed of more than 10 key sub -models and calculation routines which are integrated. LUSI model adapted the basic procedures of LUDAS However, due to the specific objectives of this research, *Land use-adoption* and *Land use-choice* procedures were added in the decision programme routine i n Farmland choice particularly (Table 6.2).

Table 6.1: Inputs data and parameters used in LUSI model

Sub-model	Parameters	Sources
Generate Salt content (dS/m)	EC values and biophysical attributes (e.g. Elevation, distance to river, wetness index, etc.); vegetation index (NDVI)	Laboratory analysis, and GIS application
Salinity dynamics	EC values, temperature data	(Dasgupta *et al*., 2015)
Crop yield dynamics	Crop yield (kg/ha) Size of the plot (ha) Labour Amount of seeds (kg/ha) Fertilizer (kg/ha) Salt content (%) Sand content (%) Slope (%)	Field survey
Households decisions	Characteristics of plot owner (e.g. age, gender, household size, yield, etc.); biophysical attributes (e.g. Elevation, distance to river, wetness, etc.);	Field survey and GIS application

Table 6.2: Main sub-models/ procedures of LUSI coded in Netlogo (5.3) (Modified from Le *et al*., 2010)

Sub-model/Calculation	Functions	Entities involved
Initialisation	Import GIS data and sampled household data, generate remaining population, create household pixels, generate household coefficients, and calculate initial salt content	Household agent Pixel
Land use-adoption	Calculate the willingness of the household to change the land use	Household agent
Land use-choice	Calculate the willingness of household to change the land use to fallow or abandoned areas	Household agent Pixel
Crop yield Dynamics	Calculate yield production of farmlands in response to production inputs and salt content	Household agent Pixel
Salinity-Dynamics	Calculate salinity content (EC) in response to increased temperature	Pixel
Natural-Transition	Perform natural succession among land use types based on salt content	Pixel
Update-household-state	Update the changes in household profiles annually	Household agent
Create-new-household	Create a young new household controlled by an empirical function of population growth	Household agent
Plot-Graphs	Draw different graphs of system performance	Household agent Pixel

6.2.4. LUSI as an Integrated Model for Simulating the Impacts of Temperature Scenarios on Soil Salinity Dynamics

The LUSI model was specifically designed for the context of the study area (Djilor district). As described earlier, the model was developed to predict soil salinity extent and impacts based on temperature scenarios and household decision-making.

6.2.4.1. Graphic and User Interface

The user interface of LUSI model is composed of 5 mains components:

1. User's input or importation (part 1, Figure 6.4): a set of spatial attributes such as land use, soil type, elevation, distance to river, wetness index and NDVI as well household attribute (plot and households' data) imported. These attributes can be visualized several times.
2. Global (experimental) parameters (part 2, Figure 6.4): it deals with the global parameters such as salinity change, temperature scenarios, household decisions or adoption, and population growth rate. The user externally adjusts the values of parameters to be tested in the model using sliders.
3. Digital Land use-land cover map navigation window (part 3, Figure 6.4): it presents the land-use cover map in the viewer of Netlogo platform, which enables the user to export the map at any time and visualize changes that occur through time steps.
4. Time-series graphs of performance indicators of both biophysical and human systems (part 4a, b, c, d. Figure 6.4): These graphs include annual average salt content in the area, annual average salt content per land use, the number of saline and non-saline patches, and the annual average crop yield.

5. Monitors along with specific time-series graphs are included for further related calculations of indicators including the number of farm owners, and number of plots for each crop (i.e. rice, maize, millet and groundnut) (part 5, Figure 6.4).

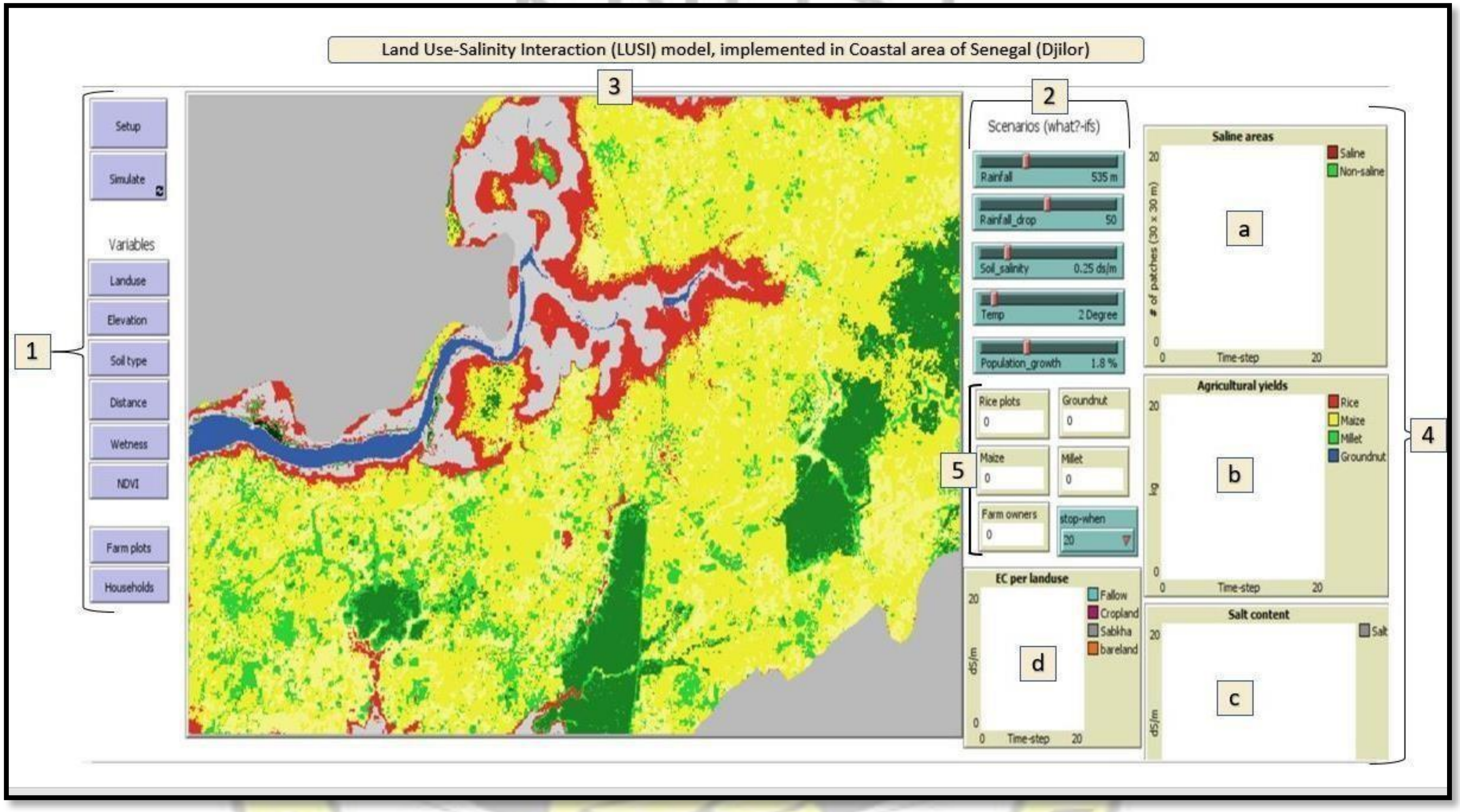

Figure 6.4: LUSI model's graphic-user interface for simulating soil salinity dynamics

6.2.4.2. Description of Decision-Making Mechanism

Two step decisions making sub models were incorporated into LUSI model for simulating farmers' decisions in a saline landscape. This method was based on the study of Villamor (2012), where decision making was developed in LB-LUDAS to capture process based decision making. Therefore, the *Land use-adoption* and *the Land use-choice* sub-models were embedded in LUSI model particularly in *Farmland-choice* representing the household decision-making module. Indeed, the first step of the household decisions consisted of simulating the farmers' willingness to adopt or not adopt land use change, while the second step simulates the choice of farmers to convert their plots either to fallow land or abandoned area. These two-step simulations are different and were therefore independently developed under household decision programme (Figure 6.5). They were designed as follows:

First step: Binary logistic regression analysis was used to develop this first step of the household decision-making. The results of the binary logistic are discussed in Chapter 5. The probability of a household to change or not to change land use (*Land use-adoption*) is integrated in LUSI model through a dummy variable represented by the value 1 (Yes), which reveals when the farmer has decided to convert the land use of its plot, and value 0 (No) otherwise. Indeed, the household decision programme will omit the adaptation process when the value of *Land use-adoption* is 0. Contrarily, when the value of the probability of *Land use-adoption* is equal to 1, the household decision programme will simulate the *Land use-choice* routine (the probability of a household to choose an adaptation option).

Second step: this decision-making sub model was designed and included in the model using a multi-nomial logistic analysis (i.e. M-logit regression). Two main adaptation choices were considered in the M-logit regression namely, *Land use-choice*: 1) fallow land, and 2) abandoned area (see chapter 5 for more details). When a farmer chooses to convert his/her plot to one of these land uses (i.e. fallow or abandoned area), thus that choice will run in the *Farmland-choice* routine (Figure 6.5). Salinity content is the main factor that determines the household choice.

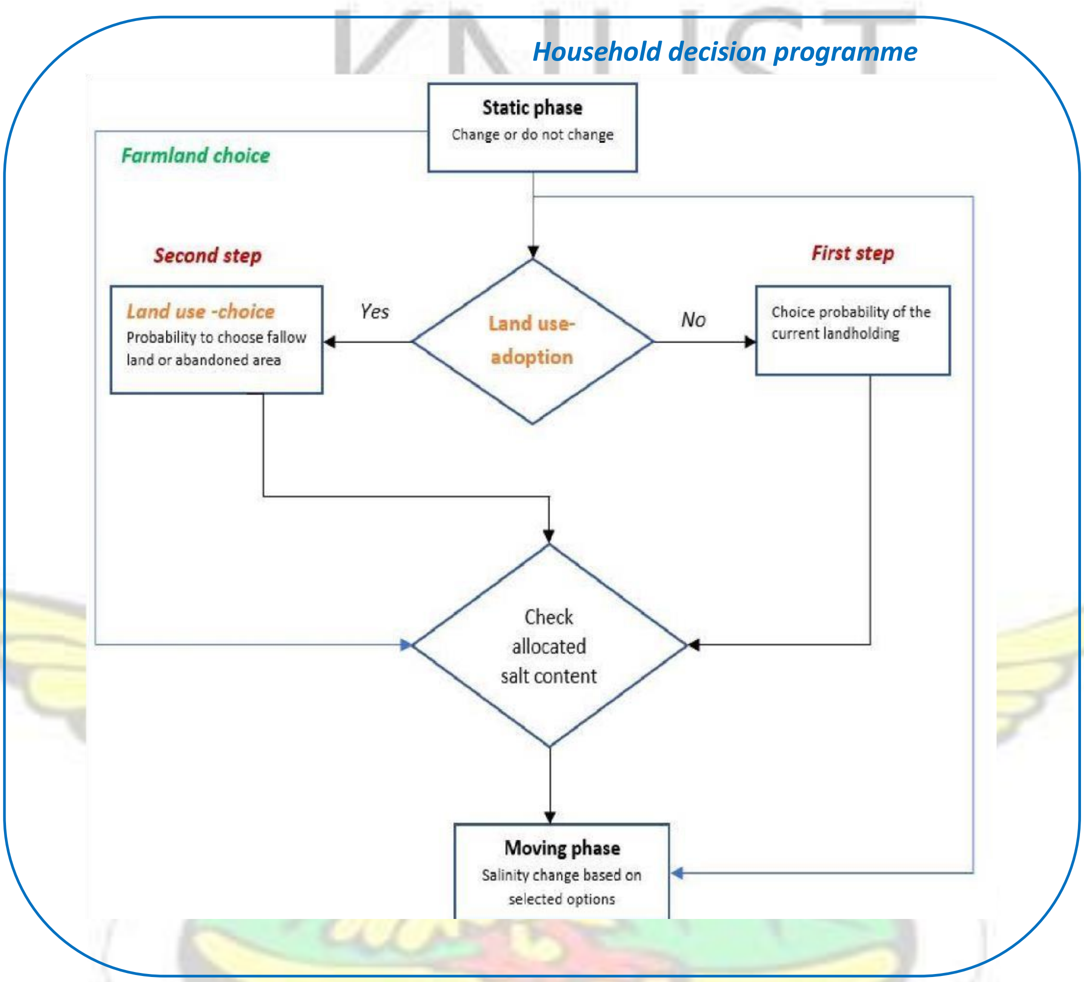

Figure 6.5: *Schematic representation of the two-step decision making routine* integrated in the household decision programme

6.2.5. Scenarios

6.2.5.1. Baseline

The baseline scenario or current trend was based on the following:

- the salt content baseline is the measured EC (dS/m) of the sampled points

- the land cover map of 2017 is initially the land use state
- the initial simulated household is 304 households
- The population rate of 2.9. % per year was assumed
- The initial number of plots is 11 for rice, 34 for maize, 35 for groundnut and 52 for millet

6.2.5.2. Temperature Scenarios

Two scenarios of temperature (i.e. one-degree increase, and two-degree increase in temperature) were tested to determine the impact of future increased temperature on soil salinity. Globally, these scenarios were based on the special report on global warming of 1.5 °C increase in temperature published by the Intergovernmental Panel on Climate Change (IPCC, 2018) which reported that limiting global warming to 1.5 °C compared to 2 °C would reduce challenging impacts on ecosystems, human health and well-being and that a 2 °C temperature increase would induce extreme events such as rising sea levels and diminishing Arctic sea ice, loss of ecosystems, loss of biodiversity, land degradation, among other impacts. Further, projected trends of temperature in Senegal and particularly in Fatick also show a net increase for the next coming decades. Thus, the future impacts of such increased temperature in salt accumulation by 2036 and its associated changes and challenges, was a key focus of the simulation. Then the aim was to compare the two scenarios of temperature in terms of salinity content and crop yield. The scenarios were based on the following:

- The measured EC (dS/m) of the sampled points is used as a base for simulating the next 20 years;
- The assumption is that 1 degree increase in temperature increases the salt content by 0.25 dS/m;
- The actual land cover map of 2017 is used as a base for simulating the next 20 years;

- A population growth rate of 2.9. % per year.

6.2.6. Simulation

A total of five simulation runs were conducted for each scenario. Each run has a simulation period of 20-years (or time steps) and was programmed using Netlogo version 5.3. All scenarios started with initial population of 304 households. The average (with 95% confidence interval) of each performance indicator (both social and ecological) was plotted as time-series graphs to compare scenarios.

6.3. Results

6.3.1. Impact of Temperature on Salt Content

The simulation results of salt content (EC) in the area under three scenarios show a clear increased trend of salinity especially under Temp1 and Temp2 scenarios over the 20-year period as reported in Figures 6.6 and 6.7. However, there was no change in salinity under baseline (BAS) scenario. The average simulated salinity was 6.48 dS/m and 9.77 dS/m for 1 °C increase in temperature (Temp1 scenario) and 2 °C increase in temperature (Temp2 scenario), respectively for the period 2017-2036. Comparing these results to the mean measured EC, Temp1 scenario and Temp2 scenario will contribute to increase the average salt content by 7.7 % and 15.8 % per year over the period 2017-2036, respectively.

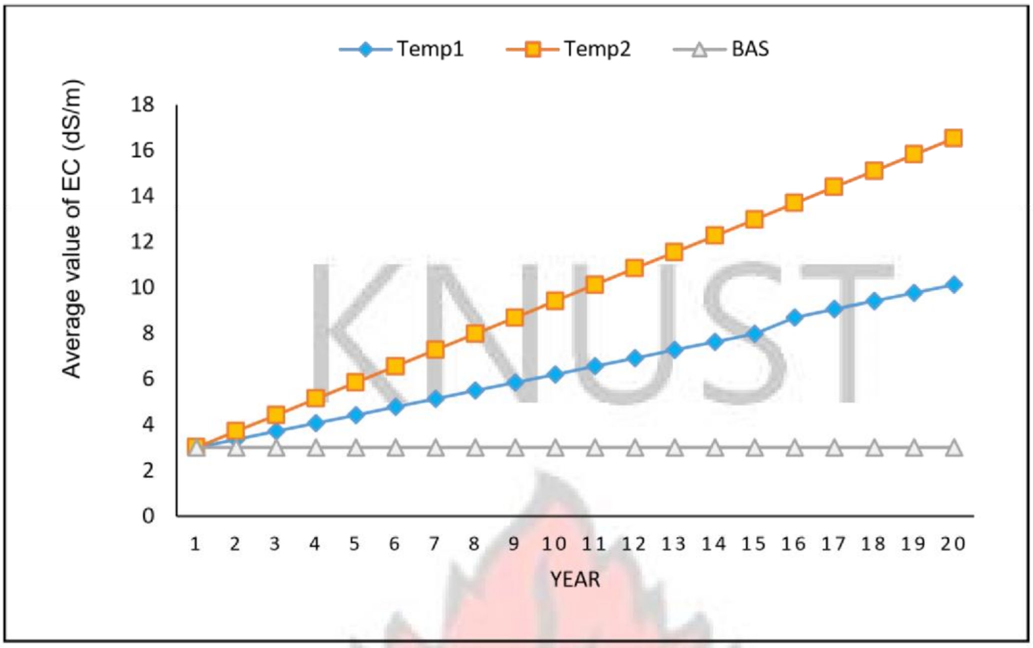

Figure 6.6: Trend of average salt content under three scenarios (BAS, Temp1, Temp2) over a period of 20-years

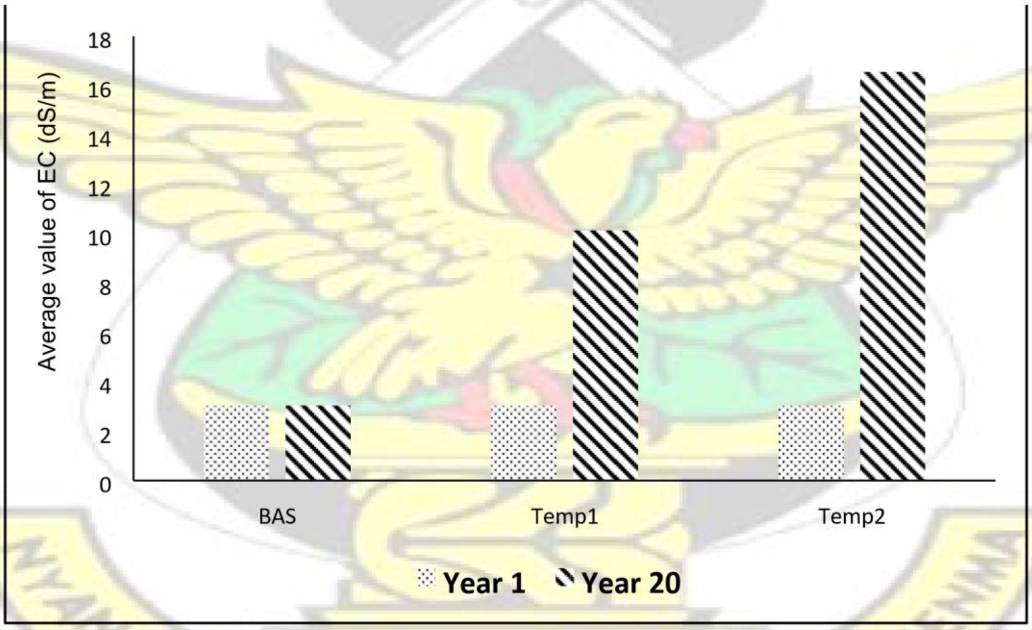

Figure 6.7: Change in salt content between the first and the twentieth year under the three scenarios (BAS, Temp1, Temp2)

6.3.2. Simulated Salt Content under Different Land use-land cover

Figure 6.8 presents the simulated salt content in the different Land use-land cover (LULC) under three scenarios (i.e. Baseline, Temp1 and Temp2) over 20 years. The results show an increasing trend of salinity in croplands, fallow, bare land and sabkha from 2017 to 2036 under Temp1 and Temp2, especially. Under baseline, cropland and fallow registered the lower salt content, compared to bare land and sabkha areas (Figure 6.8a). This result is in line with the pattern of EC under the different land use cover type described in Chapter 3. In fact, for all the scenarios sabkha land use has the highest salt content. It was also noticed that fallow lands could be transformed into salt affected area under Temp1 and Temp2 with a high average EC (Figure 6.8b, c). Moreover, comparing the simulated EC to the measured EC values presented in Chapter 3, average EC for fallow, sabkha and bare land were underestimated by the model by 4.57 dS/m, 5.18 dS/m and 5.38 dS/m, respectively. In contrast, mean EC for croplands was well estimated by the model with a simulated mean salinity content of 5.27 dS/m, not significantly different from the measured EC in croplands (6 dS/m).

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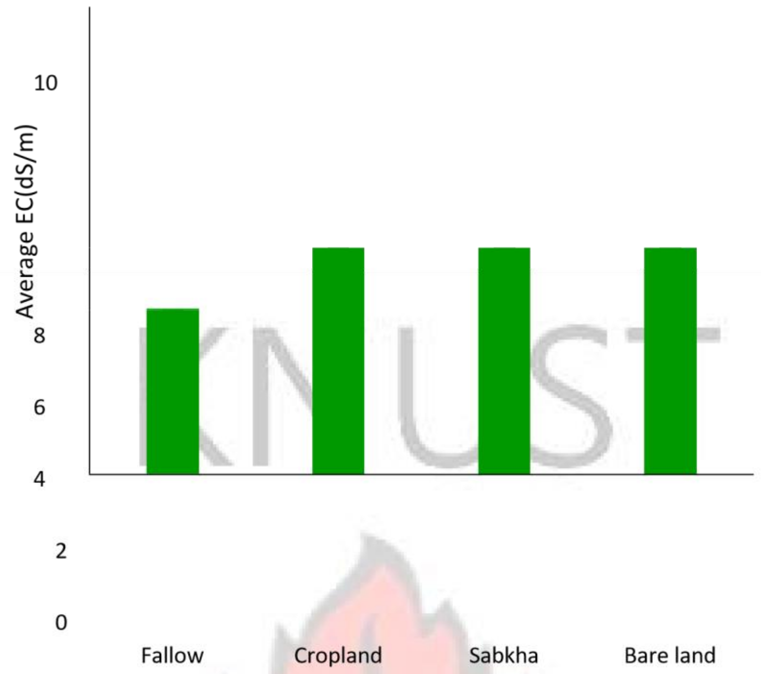
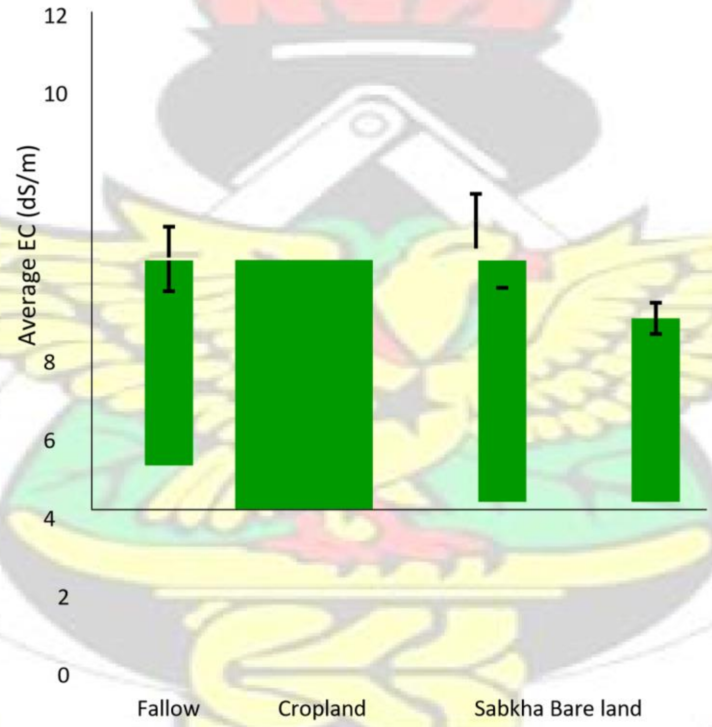
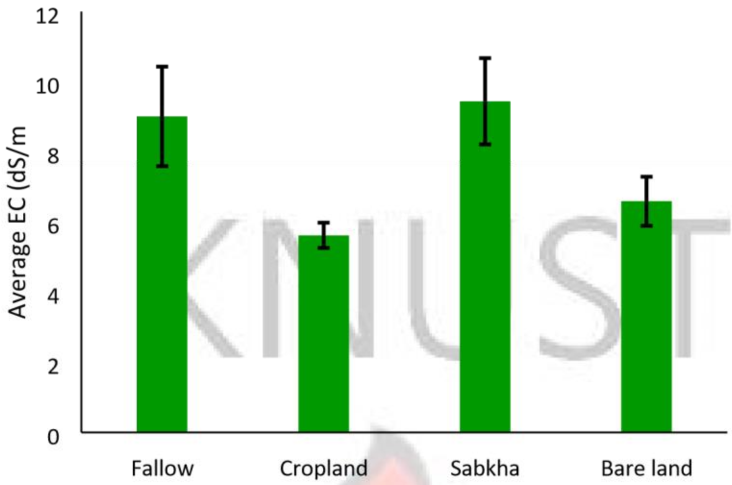

10
Average EC(dS/m)
8
6
4
2
0
Fallow
Cropland
Sabkha
Bare land

a) Baseline


12
10
Average EC (dS/m)
8
6
4
2
0
Fallow
Cropland
Sabkha Bare land

b) Temp1



c) Temp2

Figure 6.8: Simulated salt content in each LULC for three scenarios between 2017 to 2036

6.3.3. Impact of Salt Content on Crop Yield Dynamics

Table 6.3 shows the simulated average crop yields of rice, maize, millet and groundnut under three scenarios (BAS, Temp1, and Temp2). For all scenarios, the results show a general decrease in crop yield over the 20-year period. The four crop types (rice, maize, millet and groundnut) were generally sensitive to the three scenarios with reduction of the yield (Figure 6.9). Rice crop registered the lowest yield over time, compared to maize, millet and groundnut. This reflects the high effect of soil salinity on rice production, which is generally cultivated in lowland. On the other hand, it is also important to notice that even though maize crop is experiencing low yield, its average yield under Temp1 is high compared to baseline and Temp2 (Figure 6.9 b), while for the other crops, their average yield generally show a reduction from baseline, Temp1 to Temp2 scenarios (Figure 6.9 a, c, d).

Table 6.3: Average annual crop yield in three scenarios

Crop types	**Scenarios**		
	BAS	**Temp1**	**Temp2**
Rice (kg ha^{-1} y^{-1})	228 ± 0	187 ± 24	149 ± 45
Maize (kg ha^{-1} y^{-1})	205 ± 19	223 ± 23	200 ± 18
Millet (kg ha^{-1} y^{-1})	836 ± 8	752 ± 58	672 ± 100

Groundnut (kg ha^{-1} y^{-1})	1258 ± 16	1048 ± 126	881 ± 209

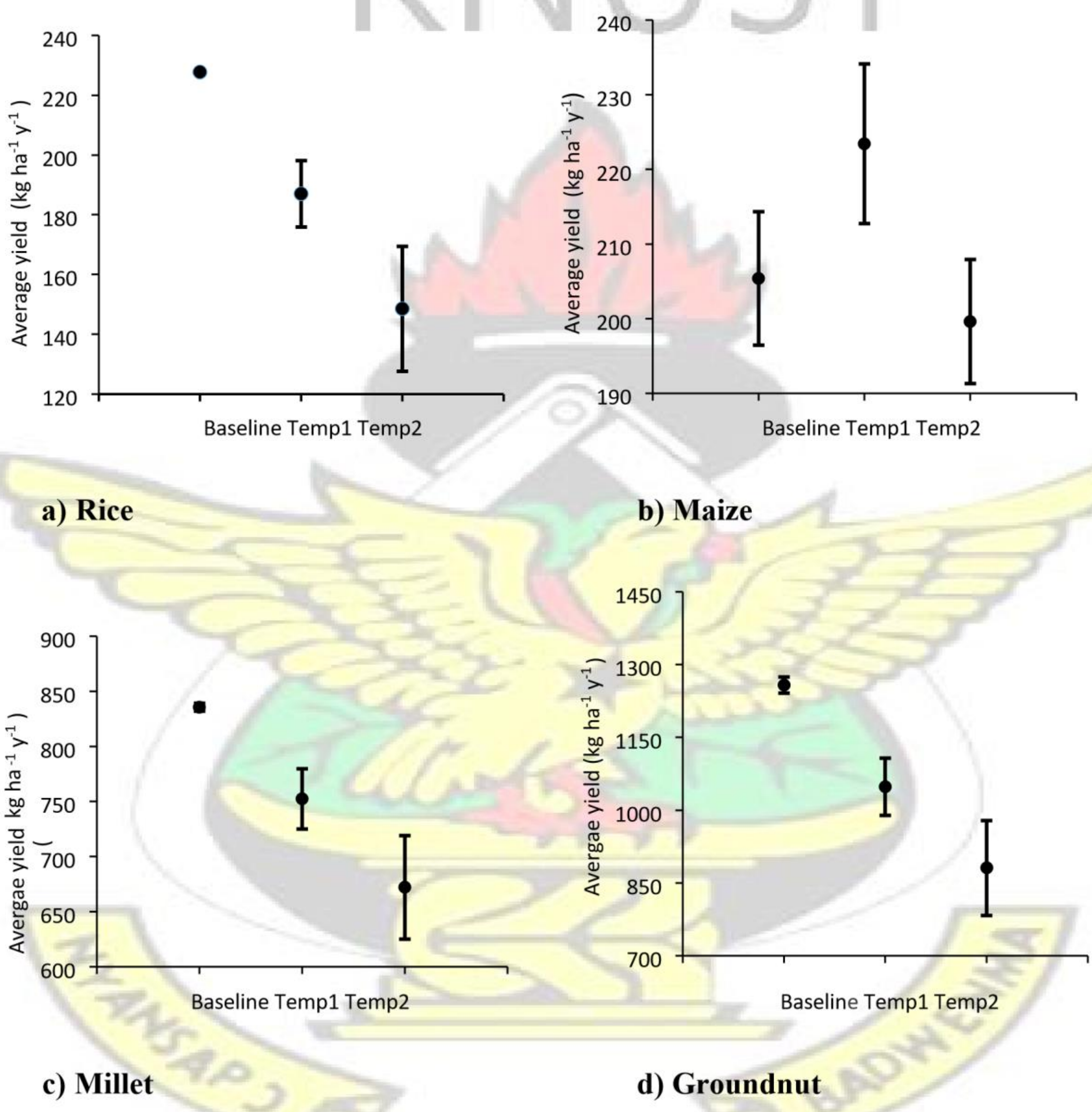


Figure 6.9: Simulated average yield of rice (a), maize (b), millet (c) and groundnut (d) under three scenarios (Baseline, temp1, Temp2). The bars are bounded by the confidence interval (95%) of the means.

Table 6.4 shows the paired comparative analysis of the average yields of each crop between three scenarios. The average yields of rice, millet and groundnut under the baseline scenario is significantly higher than under the Temp1 and Temp2 scenarios. However, the average maize yield under baseline is not significantly different from under Temp2 scenario. In addition, the average yield from rice as well as from maize, millet and groundnut under Temp2 is significantly lower than the Temp1 scenario.

Table 6.4: Comparative analysis of the average yields per major crop under the three scenarios

Comparative scenarios	Contrast (kg ha^{-1} yr^{-1})	St. Error Mean	t test	Significance
Rice				
BAS vs. Temp1	40.7	5.3	7.7	0.000
BAS vs. Temp2	79.2	10.0	7.9	0.000
Temp2 vs. Temp1	-38.5	4.7	-8.2	0.000
Maize				
BAS vs. Temp1	-18.0	5.4	-3.3	0.004
BAS vs. Temp2	5.8	5.1	1.1	0.274
Temp2 vs. Temp1	-23.8	5.3	-4.5	0.000
Millet				
BAS vs. Temp1	83.2	11.6	7.2	0.000
BAS vs. Temp2	163.5	21.0	7.8	0.000
Temp2 vs. Temp1	-80.3	9.7	-8.3	0.000
Groundnut				
BAS vs. Temp1	209.7	25.0	8.4	0.000
BAS vs. Temp2	377.2	43.6	8.6	0.000
Temp2 vs. Temp1	-167.5	19.3	-8.7	0.000

6.4. Discussion

6.4.1. Future Soil Salinity Patterns and Impacts in Coastal Agriculture

With regards to the simulated average EC presented in Figure 6.6, an increase of temperature in the next coming decades would considerably increase the extent of salt-affected area in

Djilor. These results confirm the real implications of climate change on the expansion of salt affected areas in many islands and coastal area regions (IPCC, 2018). Similar results were observed by Szabolcs (1989) who reported that a 1 °C increase in temperature in Europe will exponentially increase the salinity in the next 50 years. As well, Dasgupta *et al.* (2015) indicated that by 2050, soil salinity in coastal Bangladesh will be 39.2 % resulting from adverse effects of climate change (temperature and rainfall change). Similar observations were made by Asseng *et al.* (2010) in Western Australia. In Senegal, few studies have initiated such analysis in modelling of soil salinity in coastal areas. To our knowledge, this study is one of the first applications of ABM in estimating future trend on soil salinity throughout Senegal's coastal region. Thus, these findings fill this gap and give an entry in soil salinity model at the national level.

Furthermore, as a result of the increase in salinity, the simulated results showed a significant decline in average yield for all the major crops (rice, maize, millet and groundnut) in the area. However, salinity has severe implications for rice production as shown in Table 6.3. The study area has already suffered significant losses in crop production that have driven the farmers to be less involved in rice cultivation. That will be increased by potential salinity increase in the coming decades as shown by the simulated results. Indeed, salinization is expected to continue as long as climate change (i.e. sea level rise, temperature and rainfall changes) persists in the country and in coastal regions especially. Such phenomenon will pose significant losses in cultivable lands and food insecurity for local communities who highly depend on agriculture production. Nevertheless, farmers in the area are conscious of soil salinity and its effects on their food needs and livelihoods as they have adapted the land use of their plots to salinity by adopting the fallowing practice, for instance. Like the reality, results showed that most of the farmers adopted fallow land to mitigate salinity (high proportion of farmers involved in fallow) compared to the option of plot abandonment, generally based on salt content and land availability. Indeed, changing land use-based on traditional experience is a typical adaptation of farmers in the area which aims at improving their plots fertility and thereby increasing their crop yield for better living conditions. A similar behaviour of farmers was earlier observed by Pannell*et al.* (2006) in Australia. This result reflects the nature of land use change and ecosystems degradation interaction associated with behavioural human factors as well as environmental system (Hobbs *et al*., 2006).

6.4.2. LUSI model validation

The validation of LUSI model was based on the following steps:

1. Considering expert opinion (Villamor, 2012), especially on the implications of climate change in salinity process in the area, as well as using households survey as verification methods and source of information to better understand decision making regarding land-use adaptation;
2. Simulating the spatial extent of salt affected areas of 2017 under LUSI model (Figure 6.10);
3. Estimating the difference between the simulated extent of soil salinity in 2017 and the classified one of 2017 using Equation 6.1 (Chabi, 2016).

$$Difference = \left(\frac{SS\ 2017 - SSS\ 2017}{SS\ 2017}\right) \times 100 \qquad (6.1)$$

Where *SS* 2017 is the classified soil salinity map of 2017 (see Chapter 4)

SSS 2017 is the simulated soil salinity extent of 2017 under LUSI model.

The results of the household survey as described in Chapter 5 gave a good understanding of farmers' implications and land use decisions in saline agricultural landscape. In fact, farmers reported a higher impact of temperature and rainfall decrease on salt accumulation in Djilor.

It was confirmed by the communities that fallow and bare land recorded the higher salinity in the area and that rice productio n was the most affected crop (see Chapter 5). These households' survey results supported the LUSI model simulations which are in line with farmers' perception of salinity.

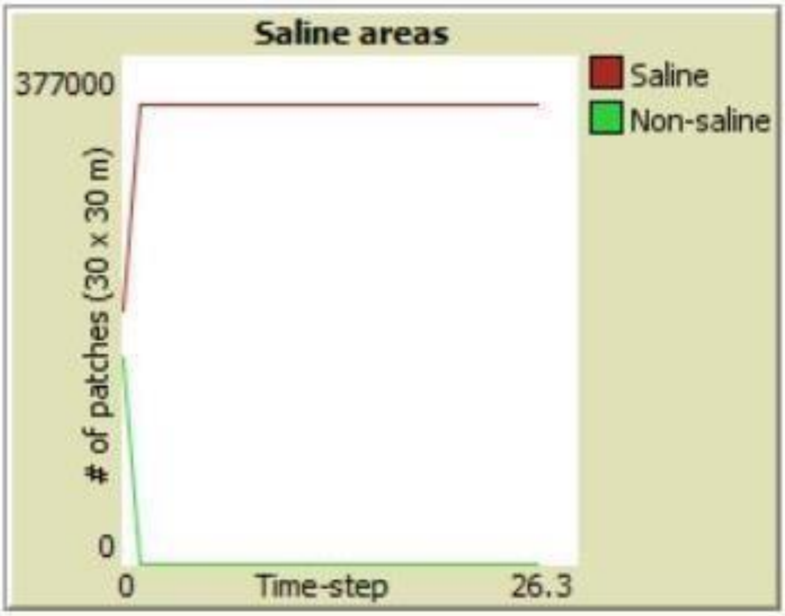


Figure 6.10: Simulated salt affected areas of 2017 under LUSI model

Table 6.5 shows the order of difference with the magnitude of 1.35 % for saline area whereas for non-saline area the difference was estimated to be 6.45 %. The estimated difference between the observed and the simulated salinity is acceptable since it is relatively low. Thus, it confirms that the LUSI model imitates well and simulates satisfactorily the reality and can be used for the prediction of salinity under climate change scenarios.

Table 6.5: Model validation (Simulated salinity versus classified salinity)

Salinity Classes	Area (ha)		
	Simulated salinity 2017	Classified salinity 2017	Difference (%)
Saline area	17038	16583	1.35
Non-saline area	13779	12107	6.45

6.5. Conclusions

In this study, a LUSI model was developed and applied for understanding the soil salinity dynamics of a coastal area as well as comparing the different outputs and exploring the impacts of soil salinity on crop yield. Three scenarios namely BAS (Baseline, current trend), Temp1 (1 °C increase in temperature) and Temp2 (2 °C increase in temperature) were used for simulation. Despite its simplicity, the model was able to reproduce historical dynamics of a saline agricultural landscape and it showed plausible outcomes in exploratory studies. As well, the modelling of salinity using temperature scenarios and farm household decisionmaking gave us expected patterns of salinity that may be seen in single step modelling. Salinity content (EC) simulated from 2017 to 2036 showed an increase as a result of increased temperature. The average EC in the area was estimated to be 6.48 dS/m and 9.77 dS/m for 1 °C increase in temperature (Temp1 scenario) and 2 °C increase in temperature (Temp2 scenario), respectively for the period 2017-2036. In fact, Temp1 scenario and Temp2 scenario will increase the mean EC by 7.7 % and 15.8 % per year over the period 2017-2036, respectively. These results showed how an increase in temperature would impact on the expansion of salt affected areas. Moreover, as the simulation showed, future salinity trend is critical for crop production as salinity increase will considerably reduce the average yield of the main crops in the area namely, rice, millet, maize and groundnut. In fact, there was a significant difference in the average simulated crop yield under BAS, Temp1 and Temp2 for the different crops as presented in Table 6.4.

CHAPTER 7 : CONCLUSIONS AND RECOMMENDATIONS

7.1. Introduction

This study was conducted to give a better understanding of soil salinity dynamics and impacts in an agricultural area as well as to inform policy makers and smallholder farmers about the future extent of soil salinity in Djilor for a better soil management plan. This chapter prese nts a summary of the key findings, the conclusions and recommendations regarding each specific objective.

7.2. Summary of the Findings

<u>Research objective 1: To determine soil salinity pattern and its determinants in a coastal agricultural landscape</u>

The analysis of soil samples revealed that salinity content decreased with an increase in soil depth, indicating high EC value in the topsoil (0-30 cm) (mean EC = 8 dS/ m), compared to the subsoil (i.e. 30-60 cm and 60-100 cm), which registered an average EC value of 5.6 and 5.31 dS/m, respectively. Also, soils in the lower slope were more saline with EC varying between 8 dS/m and 5.1 dS/m, while for upper positions, EC varied between 3.3 and 1.7 dS/m. Salt-affected areas in Djilor are dominated by the presence of sodic soils (ESP > 15%). Soils in low slope showed the highest ESP with 223.5 %, 194.7 %, and 127.3 % in 0-30 cm, 30-60 cm and 60-100 cm, respectively.

Soil salinity pattern in the study area varied significantly under different land uses (grassland, annual crop, bare land and fallow), soil types (Fluvisols, Gleysols and Lixisols) and crop types (rice, maize, millet and groundnut) ($p = 0.000$). Bare land, rice plots and Fluvisols registered higher salt content with mean EC equal to 8.46 dS/m, 9 dS/m and 8 dS/m, respectively.

The analysis of the relationship between measured soil salinity and some environmental factors showed that salt content was significantly associated with elevation, clay content, pH and distance to the river. Clay content, distance to the river and elevation have the highest impact on salinity increase with respectively 39 %, 20 % and 1 8%. Salt content was not correlated with groundwater depth suggesting that the accumulation of salt in coastal agricultural lands was not significantly related to capillarity rise from groundwater contrary to most of the studies in the literature.

Research objective 2: To assess changes in land use and soil salinity over the period 1984 to 2017

The Land use-land cover changes in the area were investigated using time-series Landsat images for the years 1984, 1994, 2007 and 2017. Eight LULC were identified in Djilor: mangrove, forests, savannah shrubs, croplands, bare lands, salt marshes, sabkha and water bodies. Forests, bare lands and croplands constitute the most represented LULC types over time. The intensity analysis revealed a significant increase in croplands between 1984 and 2017, while forest registered the highest loss at the same period. These results show that the dynamic in Land use-land cover in Djilor is characterised by an increase in agricultural areas to the detriment of forests, which attest to the on-going deforestation in the area and the continuous expansion of farms by local communities who, due to soil degradation, need to get more lands to sustain food production. The annual area change during 1984-1994 was faster than the annual area change during 1994-2007 and 2007-2017 periods. In terms of salinity change, in 1984, highly saline and moderately saline areas were the largest in extent being 32.65 % and 38.9 %, respectively. In 2017, slightly saline areas increased to 39.69 %, while highly saline and moderately saline areas decreased to 20.85 % and 25.60 %, respectively. These changes revealed a slight decrease in soil salinity level between 1984 and 2017. Such decrease of salinity can be linked to the improvement of rainfall recorded in the area as well as to the various adaptation and mitigation measures implemented. However, despite this slight decrease, soil salinity remains a serious issue in the study area as saltaffected areas covered about 60 % and 45 % of the total area of Djilor in 1984 and 2017, respectively. Sabkha and salt marshes had the largest salt-affected areas with 31 % and 28 % of highly saline category areas in 1984, respectively.

Research objective 3: To assess household perception of soil salinity and their adaptation strategies

Farmers had a good understanding of soil salinity. Salinity has been recognised by communities as the most severe soil degradation in Djilor (82.5 % of the respondents). Through this study, agriculture and especially rice cultivation constitute the most vulnerable sector to soil salinity. In fact, 93 % of the respondents stated that the decrease in crop yield was the first effect of salt accumulation. Also, because household staple food generally came from the land, land degradation due to salinization has induced agricultural losses and food insecurity in the area.

This study showed that women in Djilor were the most affected by salinity due to their dominance in rice farming. As their subsistence level was reducing from time to time due to the negative effect of soil salinity, farmers in the study area were implementing various adaptation strategies such as using chemical fertilizers, application of manure, planting and conserving trees, (e.g. *Eucalyptus alba*, *Faidherbia albida*), establishment of soil bunds, planting tolerant crop varieties (e.g. new variety of rice named *Nerica*) and mulching to mitigate soil salinity. For that same purpose, farmers may decide to convert or not to convert the land use of their plots to fallow or abandoned lands. Factors such as salt content, crop yield, soil type and distance to the river of the plot are mainly influencing the farmer' decisions. Fertility decline, salt crust on the surface, soil crusting, the presence of salttolerant plants (i.e. *Tamarix senegalensis*) and vegetation cover reduction are the main salinity indicators identified by farmers.

<u>Research objective 4: To develop a Land Use-Salinity Interaction (LUSI) model for exploring potential impacts of temperature scenarios and human decisions on salinity dynamics</u>

The simulation of soil salinity in Djilor revealed the real implication of temperature in affecting salt-affected areas. Temp1 scenario and Temp2 scenario will increase the average salt content by 7.7 % and 15.8 % per year over the period 2017-2036, respectively. As well, salinity will vary under different Land use-land cover with an increase in croplands, fallow, bare land and sabkha from 2017 to 2036 under Temp1 and Temp2. Under baseline, cropland and fallow registered the lower salt content, compared to bare land and sabkha areas, which is in line with the salinity pattern given by the measured EC. In addition, the simulation results showed a general decrease in crop yield over the 20-year period. Rice crop registered the lowest yield over time with 228, 187, 149 kg ha^{-1} y^{-1} in BAS, Temp1 and Temp2, respectively. The four crop types (rice, maize, millet and groundnut) were generally sensitive to the three scenarios with reduction of the average yield. The average yields of rice, millet and groundnut under the baseline scenario was significantly higher than under the Temp1 and Temp2 scenarios (P_value < 0.05). In contrast, the average yield of maize under baseline was not significantly different from the Temp2 scenario. In addition, the simulated salinity under Temp2 affected more the crop yield. In fact, the average yield for all the crops under Temp2 was significantly lower than the Temp1 scenario.

7.3. General Conclusions

The aim of this study was to investigate the patterns and impacts of soil salinity in agricultural land use by developing a Land Use-Salinity interaction (LUSI) model for a coastal area in Senegal. It also explored the impacts of temperature scenarios on salinity dynamics and helped to understand the interaction between social and environmental systems of a saline landscape. Accordingly, four key conclusions can be derived from this study which are related to each specific research objective.

Firstly, regarding the salt content pattern, high EC was recorded in the soil surface (topsoil) and in the lower slope. Salt-affected areas in Djilor are dominated by the presence of sodic soils. Clay content, distance to the river and elevation are the most important factors associated with increasing salinity. From that, it is concluded that soil salinity is mostly caused by inundation and deposits of salt from seawater intrusion in Djilor rather than salt from groundwater.

Secondly, various LULC types have been identified. The land use-land cover change is characterised by an expansion of cropland to the detriment of forest and savannah which registered the higher loss during the periods. Annual area of LULC was faster during 19841994 than in 1994–2007 and 2007-2017. Moreover, the change analysis of soil salinity showed a slight decrease in salinity level over the area. Despite this, soil salinity remains a severe issue in the study area.

Thirdly, farmers have good knowledge of soil salinity problems and suffered from severe salinity constraining production in their farms. Low crop yields, particularly for rice production mainly cultivated by female farmers, was the immediate effect of salinity. Soil salinity has a gender dimension in the area. Farmers in the study area are using a wide variety of adaptation strategies such as using chemical fertilizers, manure, planting and conservation of trees and soil bunds.

Finally, temperature is an important factor that contributes to the salt-affected areas expansion in Djilor. It has been observed that in the coming decades, the contribution of increased temperature to salt content will considerably increase. Consequently, the reduction of crop yield for rice and maize particularly will be alarming for smallholder farmers' survival and livelihood. LUSI model has given convincing results and is, therefore, a good modelling tool capable of explicitly simulating soil salinity from a coastal agricultural landscape.

7.4. Recommendations

7.4.1. Recommendations for further Research

Certain gaps and questions still need to be answered through this study conducted in a coastal agricultural landscape of Djilor.

As sea level rise, temperature and rainfall changes are projected to increase in the future, it is recommended to further investigate the future soil salinity patterns in the region by including other land uses such as the mangrove areas, which play an important role in the salinity process. In addition, the seasonal dynamic of soil salinity in the area need to be investigated to better understand the effects of climate factors on salt accumulation.

This study shows that remote sensing data and techniques can be effectively used for mapping salt affected areas. However, using high-resolution remote sensing images may improve the work and give better results for a better monitoring of salinity dynamics in coastal regions.

Farmers still need assistance from the government or concerned organizations to be able to improve their strategies and somehow introduce other strategies. Thus, further investigations on the impacts of adaptation and mitigation strategies on salt content as well as its gender dimension may be useful for the improvement of existing land management in the study area and give proper land management options to the land planner.

The LUSI model set an entry point to contribute in understanding soil salinity dynamics in the area. However, with regards to the complexity of the salinity process, it is recommended to expand this study by integrating other climate factors such as sea level rise and rainfall for a better understanding and insight of climate change implications on soil salinity. Also, this modelling approach promoted the integration of smallholders' opinion in agroecosystem management and can therefore be repeated in other areas. Furthermore, valuable tools like role-playing games can be developed to validate the model and help stakeholders to understand the model outputs.

7.4.2. Recommendations for Policy

Soil salinity and its effects on land and farmers livelihoods require more attention and efficient management from decision makers. The research findings of this study provide a baseline understanding of soil salinity in Djilor and constitute an important decision-making tool to help decision makers and smallholder farmers to improve soil salinity management and their food security.

From this study, it was noticed that farmers have undertaken actions to reduce soil salinity that need to be improved and reinforced for efficient results. Thus, it is recommended to develop and introduce new adaptation and mitigation technologies from decision makers for a sustainable land management.

As well, the simulation results showed that a future increase of temperature will significantly affect salinity expansion therefore integrating more climate change mitigation options will be a good approach to prevent and reduce future salinity extent in the study area.

So far, farmers have good perception of trends of salinity. However, there are few intentions for livelihood or other activities diversifications. Therefore, the government and concerned organisations should help farmers in reversing the problems and adopt alternative activities so that they can be more resilient to the phenomenon and simultaneously reduce pressure on land resources.

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APPENDICES

Appendix 1: Soil profile description

- **STP3**

Parameters	Layers (cm)		
	0-6	6-15	15-40
Humidity	Very wet	Very wet	water
Colour	brown	Light brown	Dark grey
Spots	Few black spots	Many black stains	Motley yellowish ochre
Organic matter	Little organic	Little organic	No perceptible
Texture	sandy	sandy	sandy
Structure	continuous	continuous	massive
Porosity	Little porous	Little porous	Little porous
Consistance	Friable	Friable	Compact
Biological activity	Some corpse of crab	No perceptible	No perceptible
Inclusion	salt crystal	No perceptible	No perceptible
Roots	No perceptible	No perceptible	No perceptible

Soil profile (STP3)

- **STP5**

Parameters	Layers (cm)			
	0-30	30-60	60-100	100-150
Humidity	dry	dry	dry	wet
Colour	blackish grey	Light brown	Yellowish brown	Reddish brown
Spots	No perceptible	Few whitish ochre spots	Few black spot	No perceptible
Organic matter	organic	organic	Little organic	No perceptible
Texture	clay sandy	clay sandy	clay	clay
Structure	Polyandric	Polyandric fine	Polyandric fine	continuous
Porosity	Porous (some pores)	porous (some pores)	Little porous	Little porous
Consistance	Little compact	Compact (hard)	very compact	friable
Biological activity	Some holes of insects	No perceptible	No perceptible	No perceptible
Inclusion	No perceptible	No perceptible	Few fine ferruginous concretions	Few big ferruginous concretions
Root	Many fine roots	Many fine roots	Few fine roots	Rare fine roots

Soil profile (STP5)

Appendix

2: List of selected villages for soil sampling

N°	Villages	Total Number of Household
1	Goudem	45
2	Mbellane	33
3	Pethie	43
4	Boli serere	30
5	Guague Cherif	92
6	Kamatane	31
7	Djilor	307
8	Sadioga	115
9	Keur Cheikhou	54
10	Yerwago	30
11	Keur Farba	89
12	Keur Mbar	05
13	Keur Oumar	55
14	Bandandar	92
15	Keur Wally	10
16	Lambaye	30
17	Nguekhokh	97
18	Bangalere	51
19	Ndiassane-Saloum	27
20	Ndorong	11

Data source: CADL Djilor, 2015

Appendix

3: Land use-land cover statistic from 1984 to 2017

LUC	1984		1994		2007		2017	
	ha	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Mangrove	2920	6.87	3158	7.43	3337	7.86	3876	9.13
Savannah/shrubs	3908	9.20	3063	7.21	1836	4.32	3539	8.33
Forests	7755	18.26	5895	13.88	4109	9.67	3881	9.14
Salt marshes	4905	11.55	4829	11.37	5532	13.02	5550	13.07
Sabkha	6008	14.14	4959	11.68	4492	10.58	5128	12.07
Water bodies	2591	6.10	2868	6.75	2941	6.92	2740	6.45
Bare lands	5886	13.86	9902	23.31	9268	21.82	5050	11.89
Croplands	8502	20.02	7801	18.37	10959	25.80	12711	29.93
Total	42475	100	42475	100	42474	100	42475	100

Appendix

4 (a): Land use-land cover change matrix between 1984 and 2017

1994

1984

LULC	Mangrove	Savannah/Shrubs	Forests	Salt mashes	Sabkha	Water bodies	Bare lands	Croplands	Total
Mangrove	**2437.83**	1.53	0.54	464.67	28.62	99.36	0.27	0.00	3032.82
Savannah/Shrubs	0.00	**845.1**	1395.72	0.00	4.77	0.00	830.25	695.25	3771.09
Forests	0.00	894.96	**3908.43**	0.00	10.71	0.00	2243.61	770.22	7827.93
Salt mashes	458.01	2.97	4.05	**3322.17**	591.66	437.4	9.00	2.25	4827.51
Sabkha	232.38	46.71	35.19	790.74	**4027.59**	63.36	267.3	556.83	6020.1
Water	57.33	0.99	5.67	206.1	32.4	**2266.47**	4.14	1.53	2574.63
Bare land	1.71	432.9	471.51	5.31	298.53	1.08	**2794.95**	1711.8	5717.79
Cropland	0.00	622.26	73.98	0.63	50.22	0.00	3741.03	**4210.74**	8698.86
Total	3187.26	2847.42	5895.09	4789.62	5044.5	2867.67	9890.55	7948.62	**42470.73**

2007

Appendix

1994

LULC	Mangrove	Savannah/Shrubs	Forests	Salt mashes	Sabkha	Water bodies	Bare lands	Croplands	Total
Mangrove	**2631.78**	0.81	1.62	463.77	17.46	71.82	0	0.00	3187.26
Savannah/Shrubs	1.80	**61.38**	516.69	6.84	52.74	1.62	1089.45	1116.9	2847.42
Forests	1.35	50.4	**2739.78**	9.54	54.99	5.13	968.58	2065.32	5895.09
Salt mashes	592.02	1.8	4.59	**3708**	157.68	323.19	2.16	0.18	4789.62
Sabkha	42.93	47.34	55.8	1015.74	**3616.29**	49.14	164.97	52.29	5044.5
Water	127.35	1.17	2.07	249.3	25.02	**2462.13**	0.18	0.45	2867.67
Bare land	0.27	578.07	553.41	28.53	289.8	6.57	**4036.14**	4397.76	9890.55
Cropland	0.00	781.65	189.18	8.01	333.99	3.33	3059.1	**3573.36**	7948.62
Total	3397.5	1522.62	4063.14	5489.73	4547.97	2922.93	9320.58	11206.26	**42470.73**

4 (b): Land use-land cover change matrix between 1984 and 2017

2017

Appendix

2007

LULC	Mangrove	Savannah/Shrubs	Forests	Salt mashes	Sabkha	Water bodies	Bare lands	Croplands	Total
Mangrove	**3327.39**	54.27	0.00	7.29	4.50	4.05	0.00	0.00	3397.5
Savannah/Shrubs	0.00	**644.85**	4.77	0.36	65.07	0.00	181.71	625.86	1522.62
Forests	0.00	796.32	**2120.76**	5.76	59.13	0.00	215.28	865.89	4063.14
Salt mashes	393.30	61.20	0.00	**4781.88**	209.88	43.29	0.00	0.18	5489.73
Sabkha	0.09	20.52	0.54	529.47	**3876.66**	0.00	9.99	110.70	4547.97
Water	34.74	0.63	0.27	184.59	23.40	**2677.23**	0.36	1.71	2922.93
Bare land	0.00	902.07	721.80	33.57	540.81	0.18	**2589.21**	4532.94	9320.58
Cropland	0.00	982.44	1194.66	0.09	133.02	0.00	1816.74	**7079.31**	11206.26
Total	3755.52	3462.3	4042.8	5543.01	4912.47	2724.75	4813.29	13216.59	**42470.73**

2017

1984

LULC	Mangrove	Savannah/Shrubs	Forests	Salt mashes	Sabkha	Water bodies	Bare lands	Croplands	Total
Mangrove	**2993.67**	26.01	0.00	7.29	4.77	1.08	0.00	0.00	3032.82
Savannah/Shrubs	0.00	**504.99**	1088.37	25.38	45.72	0.00	518.31	1588.32	3771.09
Forests	0.00	1206.27	**2702.43**	9.00	66.87	0.00	1268.64	2574.72	7827.93
Salt mashes	570.60	30.42	0.00	**3842.46**	115.02	269.01	0.00	0.00	4827.51
Sabkha	163.44	127.62	0.54	1541.07	**3885.48**	2.88	41.67	257.40	6020.1
Water	27.81	0.18	0.00	93.96	1.08	**2451.60**	0.00	0.00	2574.63
Bare land	0.00	1055.97	165.78	22.05	544.68	0.18	**1119.15**	2809.98	5717.79

Appendix

Cropland	0.00	510.84	85.68	1.80	248.85	0.00	1865.52	**5986.17**	8698.86
Total	3755.52	3462.3	4042.8	5543.01	4912.47	2724.75	4813.29	13216.59	**42470.73**

Appendix

5: Gains, losses and persistence of Land use-land cover

	Persistence	Gain	Loss
1984-1994			
Mangrove	5.74	1.8	1.4
Savannah/Shrubs	1.99	4.7	6.9
Forests	9.20	4.7	**9.2**
Salt mashes	7.82	3.5	3.5
Sabkha	9.48	2.4	4.7
Water	5.34	1.4	0.7
Bare land	6.58	**16.7**	6.9
		8.8	
Cropland	9.91		**10.6**
1994-2007			
Mangrove	6.20	1.8	1.3
Savannah/Shrubs	0.14	3.4	6.6
Forests	6.45	3.1	7.4
Salt mashes	8.73	4.2	2.5
Sabkha	8.51	2.2	3.4
Water	5.80	1.1	1.0
Bare land	9.50	**12.4**	**13.8**
Cropland	8.41	**18.0**	**10.3**
2007-2017			
Mangrove	7.83	1.0	0.2
Savannah/Shrubs	1.52	**6.6**	2.1
Forests	4.99	4.5	4.6
Salt mashes	11.26	1.8	1.7
Sabkha	9.13	2.4	1.6
Water	6.30	0.1	0.6
Bare land	6.10	5.2	
Cropland	16.67	**14.5**	**15.8**
			9.7
1984-2017			
Mangrove	7.05	1.8	0.1
Savannah/Shrubs	1.19	7.0	**7.7**
Forests	6.36	3.2	**12.1**
Salt mashes	9.05	4.0	2.3
Sabkha	9.15	2.4	5.0
	5.77	0.6	0.3
	2.64	**8.7**	**10.8**
Cropland	14.09	**17.0**	6.4

Water

Bare land

Appendices 6: Illustrations

- **Field work**

- **Survey**