CHEIKH ANTA DIOP UNIVERSITY OF DAKAR (UCAD)

WEST AFRICAN SCIENCE SERVICE CENTRE ON CLIMATE CHANGE AND ADAPTED LAND USE (WASCAL)

SPONSORED BY THE Federal Ministry of Education and Research

DOCTORAL SCHOOL OF LAW, POLITICAL, ECONOMIC AND MANAGEMENT SCIENCES (ED-JPEG)

FACULTY OF ECONOMICS AND MANAGEMENT (FASEG)

WASCAL GRADUATE STUDY PROGRAM IN CLIMATE CHANGE ECONOMICS (GSP-CCE)

Year: 2022

CLIMATE RISK MANAGEMENT IN SENEGAL: CLIMATE CHANGE IMPACT, FARMERS' VULNERABILITY, AND RISK FINANCING MECHANISMS THROUGH INSURANCE FOR RICE FARMERS

PhD Dissertation

Presented and publicly defended on the March 8th, 2023

Submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy: Climate change and Economics

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DEDICATIONS

I dedicate this work to my dear mother who left us

A brave woman who always supported me until her last breath

A source of motivation to whom I would like to share this success...

May Firdaws be your eternal home, Mum!

To my dear father and friend

You both ! this work is only the fruit of your investments in our education, your sacrifices, your prayers and above all your patience.

To

Late Pa Amadou Lamine Ndiaye, May his soul rest in peace!

ACKNOWLEDGMENTS

This thesis is the culmination of three and a half years of research, made possible by the grace of Allah. Alhamdoulilah!!!

I am grateful to the Federal Ministry of Education and Research (BMBF) and the West African Science Center on Climate Change and Land Use (WASCAL) for providing me with the scholarship and financial support for this program.

I am deeply grateful to my thesis director, Professor Babacar SENE, for the time he devoted to supervising this thesis, for the enriching and interesting orientations, allowing me to improve the quality of the work in all rigour. Thanks again Professor for your support.

I thank the entire WASCAL/Dakar GRP coordination team since the beginning of our integration into WASCAL, in particular Prof. Ahmadou Aly MBAYE (Executive Director), Pr. Thione Diop (Deputy Director) and the late Prof. Fatou Gueye Lefevre (Let Heaven be his eternal home). Congratulations to Dr. Barry, Dr. Assane Beye, Dr. Fama Gueye, Dr. Khady Yama Sarr, as well as Bernadette Ndong and Dr. Mbayang Thiam for their good coordination of the program.

I would like to thank all the teaching staff of the Faculty of Economics and Management of Cheikh Anta Diop University in Dakar, in particular all the professors who have been involved in my university course. May Pr. Abdoulaye Diaye see here the expression of my gratitude for having introduced me to research.

To all my family, for their immeasurable, permanent and unwavering support, for their understanding and above all for their patience. I deeply thank my family, especially my big sister Fatou Ndimblane, all my brothers and my little sisters "my little moms", for their eternal and unconditional support, both moral and financial, which without that, I could not achieve this level. To my brothers for their prayers. To my tutors Serigne Mouhamadou Ndimblane and Abdoulaye Ndimblane for guiding and directing me, for your constant advice and encouragement.

I also thank Rokhaya Ndimbélane for his encouragement to move forward.

I would like to thank all those who have contributed to my school career, in particular Mrs. Ndiaye BA who taught me to read and write, to Mr. Mamadou Sylla since high school, and Mr. Hamath Ndiaye and Khalifa Ababacar Sarr for my technical training.

I associate with these thanks my friends with whom I shared the first year at FASEG, in particular Prospère Gueye, Ndiaga Seck, Fatou Sall and Rokhaya Diagne. To my friends Daouda Sarr, Hamidou Ly and Cissé Niang for their encouragement. That my friends and brother of CDAF and unit 20 see here, the expression of gratitute.

I would like to thank my friends and relatives, in particular my cousins Moussa Diané, Moussa Diop and Samba Diop, for their constant encouragement.

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LISTS OF ABBREVIATIONS AND ACRONYMS

AC: Adaptive capacity

AIC: Akaike Information Criterion

AR4: Fourth Evaluation Report

AR5: Fifth Evaluation Report

AR6: Sixth Evaluation Report ()

ARDL: Autoregressive Distributed Lag

CIMA: Inter-African Conference of Insurance Markets

CNAAS: National Agricultural Insurance Company

CO2: Carbon dioxide

CRCA: Regional Insurance Control Commission

CRU-TS: Climatic Research Unit Timeseries

DFID: Department for International Development

DTM: Digital Terrain Model

ECM: Error correction model

ESRM: Endogenous switching regression model

EX: Exposure

FAO: Food and Agriculture Organization

FIML: Full maximum likelihood information

GDP: Gross Domestic Product

GHG: Greenhouse gases

GIS: Geographic Information Systems

HQ: Hannan-Quinan Information Criterion

IBRTP: risk transfer products based on indices

IDW: Inverse Distance Weighting

IPCC: Intergovernmental Panel on Climate Change

LCB: Lower Critical Bound

LDCs: Least developed countries

LVI: Livelihoods vulnerability index

NAP: National Adaptation Plans

NDC: Nationally Determined Contribution

NDVI: Normalized difference vegetation index

OECD: Organization for Economic Co-operation and Development

PI: Potential Impact

SC: Schwarz Information Criterion

SDGs: Sustainable Development Goals

SE: Sensitivity

SLA: Sustainable Livelihoods approach

SPI: Standard Precipitation Index

SSA: Sub-Saharan Africa

UCB: Upper critical bound

UNDP: United Nations Human Development Program

UNFCCC: United Nations Framework Convention on Climate Change

VAR: Autoregressive vector

VEP: vulnerability as expected poverty

VER: Vulnerability as an Uninsured Risk Exposure

VEU: Vulnerability as low expected utility

WMO: World Meteorological Organization

ABSTRACT

Climatic risks, droughts and floods are increasing and appear to be a major threat to the agricultural economies of the Sahelian countries, particularly those of West Africa, given their heavy dependence on rainfed agriculture. To this end, climate change is likely to exacerbate the vulnerability of a large number of farmers already characterized by low means of substances and limited possibilities of choice to adapt to climate risks. Government funding resources being limited, the prioritization of national adaptation policies is therefore an important aspect of effectively meeting the needs of farming communities. This research work examines the impact of climate change on the rice sector in Senegal, the vulnerability of rice farmers and the means of financing climate risks. Autoregressive Distributed Lag Model (ARDL), index Method and Endogenous Switching Regression Model (ESRM) are used to assess the impact of climate change on rice sector GDP, rice farmers' vulnerability and impact of insurance on household income respectively. Using time series data for the period 1961-2020, the estimated results show that in the short term, an increase in precipitation and temperature of 1% increases GDP per capita by 0.54% and by 3. 52% respectively, ceteris paribus. The vulnerability assessment results carried out using an integrated approach combining climatic, socio-economic, socio-demographic and environmental variables show that out of 33 municipalities studied, two (2) are at a very high level of vulnerability of order 0.61 to 0.70, six (6) are in a state of high vulnerability of 0.53 and 0.60 and another six (6) are in a moderate situation (0.46 to 0.52), this which gives an idea of the order of priority of adaptation policies in the different localities considered. Moreover, the results revealed that agricultural insurance is a good financial instrument to deal with climate risks. The policy implications that emerge from this research suggest that communication about insurance and building the capacity of farm households through agricultural extension and advisory services facilitates understanding and encourages farm households to use insurance to climate risk management. The strengthening of human capital through education and training, the development of institutional capital through the development of basic social infrastructure, transport and credit institutions, as well as economic capital through the promotion of agricultural insurance and irrigation development, constitute fundamental policy measures to reduce vulnerability and improve resilience of the farming communities studied.

Keywords: Climate risks, farmer vulnerability, insurance, ARDL, ESRM.

RESUME

Les risques climatiques, sécheresses et inondations se multiplient et apparaissent comme une grande menace aux économies agricoles des pays du Sahel en particulier ceux d'Afrique de l'Ouest aux vues de leur forte dépendance à une agriculture pluviale. A cet effet, le changement climatique risque d'exacerber la vulnérabilité d'un grand nombre d'agriculteurs caractérisés déjà par de faibles moyens de substances et de possibilités de choix limitées pour s'adapter aux risques climatiques. Les moyens de financement des gouvernements étant limités, la priorisation des politiques nationales d'adaptation constitue donc un aspect important pour répondre efficacement aux besoins des communautés agricoles. Ce travail de recherche examine l'impact du changement climatique sur le secteur de la riziculture du Sénégal, la vulnérabilité des riziculteurs et les moyens de financement des risques climatiques. Le modèle autorégressif à retards échelonnés (ARDL), la méthode des indices et le modèle de régression de commutation endogène (ESRM) sont utilisés pour évaluer respectivement l'impact du changement climatique sur le PIB du secteur de rizicole, la vulnérabilité des riziculteurs et l'impact de l'assurance sur le revenu des ménages. En partant des données en série temporelle de la période 1961-2020, les résultats estimés montrent qu'à court terme, une augmentation des précipitations et de la température de 1 % fait augmenter le PIB per capita de 0,54 % et de 3,52 % respectivement, ceteris paribus. Les résultats d'évaluation de la vulnérabilité réalisés suivant une approche intégrée combinant des variables climatiques, socio-économiques, sociodémographiques, et environnementales, montrent que sur 33 municipalités étudiées, deux (2) sont à un niveau de vulnérabilité très élevée d'ordre 0,61 à 0,70, six (6) sont dans un état de vulnérabilité élevée de 0,53 et 0,60 et six autres (6) sont dans une situation modérée (0,46 à 0,52), ce qui donne une idée sur l'ordre de priorité des politiques d'adaptation dans les différentes localités considérées. D'ailleurs, les résultats ont révélé que l'assurance agricole constitue un bon instrument financier pour faire face aux risques climatiques. Les implications de politiques qui ressortent de cette recherche suggèrent que la communication sur l'assurance et le renforcement des capacités des ménages agricoles via les services de vulgarisation et de conseil agricole facilite la compréhension et encourage les ménages agricoles à faire recours à l'assurance pour la gestion des risques climatiques. Le renforcement du capital humain par l'éducation et la formation, le développement du capital institutionnel par le développement des infrastructures sociales de base, de transport et des institutions de crédit, ainsi que le capital économique par la promotion de l'assurance agricole et le développement de l'irrigation, constituent des mesures politiques fondamentales pour réduire la vulnérabilité et améliorer la résilience des communautés d'agriculteurs étudiées.

Mots clés : Risques climatiques, vulnérabilité des agriculteurs, assurance, ARDL, ESRM.

GENERAL INTRODUCTION

1. Introduction

Agriculture is the sector of the economy most directly linked to climate and, thus, likely to be affected by climate change (Mendelsohn et al., 1994; Fisher et al., 2012). In Africa and around the world, agriculture has always been a fundamental source of livelihood because of its ability to provide food to people and its income- and employment-generating nature. Agriculture could play a key role in the socio-economic and sustainable development of least developed countries (LDCs) by reducing food insecurity, poverty and unemployment. However, climate change risks slowing the economic and social benefits generated by the agricultural sector. Driven by a global temperature increase and high variability in precipitation, climate change could significantly affect ecological systems, resulting in much loss and damage with negative consequences for the economy and the well-being of humanity.

In Africa, several key risks have been identified for ecosystems and people, including disruption of ecosystems, loss of food production, reduced economic production and increased poverty, increased disease and loss of life, increased food, water and energy insecurity, loss of natural heritage and infrastructure. The losses and damages are enormous while the capacity to adapt is still low. In the sixth report of the Intergovernmental Panel on Climate Change (IPCC), the impact, vulnerability and adaptation assessment highlights that climate change is causing loss and damage across Africa that exceeds current and projected adaptation limits (Pörtner et al., 2022). Indeed, loss and damage result from climate-related impacts and risks from both sudden events, such as floods and cyclones, and slower-onset processes, such as droughts, sea-level rise, glacier retreat and desertification, and generates both economic effects such as loss of assets and crops and non-economic effects such as loss of assets. biodiversity, heritage and health (UNFCCC Paris Agreement, 2015; Masson-Delmotte et al., 2018; Mechler et al., 2020). All sectors of the African economy are thus threatened, especially the agricultural sector of sub-Saharan African countries (SSA) heavily dependent on rain-fed agriculture.

Across Africa, including West Africa, adverse climatic conditions, combined with weak infrastructure and service development, remain a threat to agricultural livelihoods, particularly for rural households. The low capacity to adapt induces populations into a situation of vulnerability, faced with the decrease in food production, access to food, stocks and income (Evariste et al., 2018; Fuller et al., 2018; Bang et al., 2019 ; Gebre, 2021). To this end, it is urgent to assess the impact of climate change in the agricultural sector in order to put in place effective policies in terms of risk management.

2. Contextual framework and Problem statement

Global temperatures have risen rapidly in recent decades, with 2001-2020 being the hottest period in human history. Each of the last four decades has been successively warmer than all the decades preceding it since 1850 (Masson-Delmotte et al., 2021). This phenomenon observed on a global scale is also detectable in Africa where the temperature continues to rise at an accelerated rate. Changes indicate a temperature increase of 1-3°C since the mid-1970s, with the Sahara and Sahel recording the highest levels across Africa (Cook & Vizy, 2015; Lelieveld et al., 2016; Dosio, 2017; Nikiema et al., 2017; Ranasinghe et al., 2021). However, these changes have consequences for Africa's agricultural sector, which is heavily dependent on rain-fed agriculture. In the IPCC's sixth report, the authors noted that climate change is already negatively impacting agricultural production and slowing productivity growth in Africa (Iizumi et al., 2018; Ray et al., 2019; Sultan et al., 2019; Ortiz-Bobea et al., 2021), with a decrease of 34% since 1961 (Ortiz-Bobea et al., 2021). In addition, impacts are also felt at the micro level, particularly among rural households whose livelihoods depend largely on resources derived from agricultural activities.

Farmers are affected by climate threats to agricultural production, including droughts, rainfall variability, delayed and overall reduction in early growing season, and excess heat (Rankoana, 2016; Elum et al., 2017; Alvar-Beltrán et al., 2020). They consider that yield losses are attributable to these changes they face (Ayanlade & Jegede, 2016). In West Africa, more than half of the farmers surveyed perceive the increase in crop pests and diseases (sources of crop losses) as being due to climate change (Callo-Concha, 2018). Pests and diseases contribute between 10% and 35% of yield losses for wheat, rice, maize, potatoes and soybeans in sub-Saharan Africa (Savary et al., 2019).

Faced with this situation, adaptation to climate change is both a priority and an emergency for farmers. Indeed, implementing adaptation is an inevitable part of the response to climate change (Mendelsohn, 2009; Falco et al., 2014). In developing countries, empirical evidence has shown that households use several means to adapt to climate change. These include crop diversification, changing planting and harvesting dates, adopting water harvesting technologies and irrigation practices, and soil conservation (Deressa et al., 2008; Yesuf et al., 2008; Juana et al., 2013). According to Ellis 2000, livelihood diversification has long been practiced by rural households looking to build portfolios of assets and activities that reduce exposure to climate risk.

However, because most low-income countries are characterized by the low or absence of climate risk transfer services (e.g., agricultural insurance), households' resort to informal risk management choices. Yet, it is well documented in the literature that having a good agricultural insurance system in place can help farmers better adapt to climate change (Dolan et al., 2001; Mcleman & Smit, 2006; Garrido et al., 2011). The use of agricultural insurance also reduces the magnitude of risk exposure and the impact on welfare (Falco et al., 2014).

Although the agricultural insurance market can be advantageous, it sometimes suffers from problems of information asymmetry and high transaction costs that can lead to its failure. This is why new forms of climate risk finance based on index-based risk transfer products (IBRTPs) are emerging. According to Barnett et al. (2008), IBRTPs can address issues that impede financial contracting in low-income rural areas and thus help reduce financial market failures that contribute to persistent poverty. Thus, in light of the factors mentioned above, IBRTPs have been introduced in some African countries to facilitate climate risk management among farmers. IBRTPs are therefore in addition to the conventional form of agricultural insurance that has already been introduced. In Senegal, there are three forms of insurance in the agricultural sector. Indemnity insurance, which provides a payment based on the actual assessed loss incurred by the insured. Income insurance, which protects policyholders against the combined effects of low yields, low prices, or a combination of both, and a decline in net income. This is a product where the sum insured is not tied to the size of the crop but to the revenue or income it generates. Index insurance is a product based on an index and not on a measurable loss. There are two sub-categories here: direct index insurance based on the average yield per area (i.e., average yield or income over the territory); indirect insurance based on the correlation between the losses suffered by farmers and indices of precipitation, temperature or vegetation, calculated from data from meteorological stations or satellite images.

So far, however, there seems to be little evidence to conclude on the impact of adopting an insurance product on farm household welfare. Indeed, despite the breadth of the debate on climate change and its impacts on agriculture, empirical studies are still underdeveloped in parts of sub-Saharan Africa (SSA). In Senegal, for example, there is so far a lack of knowledge about farm households' exposure to climate change, how they are affected by climate shocks and how they manage associated risks. Yet quantifying and understanding the impacts of climate change remains urgent and very crucial as it provides important insights into how much should be spent on mitigation and where, when and how to implement adaptation (Mendelsohn, 2009). In a country like Senegal, where more than half of households depend on agriculture for their livelihoods, it is important to understand how climate change is affecting them. As in most sub-Saharan African countries, agricultural production in Senegal is predominantly rain-fed, making it susceptible to the direct effects of climate change such as drought and floods. These unexpected climatic events have already occurred in Senegal and are becoming more and more frequent, especially in rural areas. Farm households are therefore exposed to the risks of climate change and are likely to suffer serious consequences. Indeed, droughts and floods are likely to affect the performance of agricultural households by causing losses in agricultural production and income that can increase the vulnerability of the poorest households. According to (Agossou et al., 2012), the impacts of climate change on agriculture combined with low resilience and high vulnerability of households to shocks can lead to reduced livelihoods and well-being.

3. Research Questions

The main question of this research is: faced with climate risks, which can exacerbate farmers' vulnerability, what is the point of adopting agricultural insurance as an adaptation strategy? Addressing this research question will generate scientific knowledge in response to some of the requirements of international climate finance mechanisms that recommend that vulnerability to climate change be clearly demonstrated and that adaptation responses address the challenges posed by climate change impacts. To this end, in the process of dealing with this main question, three sub-questions have been taken into account, in particular:

a) What is the economic impact of climate change on the rice sector in Senegal?
b) What is the level of vulnerability of agricultural households, especially rice farmers in Senegal and how this vulnerability is distributed throughout the territory.
c) What is the role of agricultural insurance in managing climate risks in the agricultural sector?

4. Research objectives

The objective of this research is to examine the role of agricultural insurance in managing the climate risks faced by farm households. The first step is (i) to measure the economic impact of climate change on rice production, then (ii) to study the vulnerability of households to climatic shocks (drought and floods), and finally (iii) to assess the impact of agricultural insurance on household welfare, especially agricultural income.

5. Research justification

The originality of this research is that it is developed in a context where countries are in need of producing scientific knowledge, solid to justify their exposure to climate change so that the adaptation options that will be proposed can meet the requirements of international financing mechanisms. For example, in the preparation of National Adaptation Plans (NAPs), the guidelines of the Least Developed Countries (LDCs) Group of Experts suggest that the process should be based on sound scientific knowledge (LDCs-2012). This research is therefore important and timely, as it produces scientific results on the impact of climate change, vulnerability and adaptation strategies of the agricultural sector. It starts from a macroeconomic approach to climate change to a microeconomic analysis to better understand the consequences of climate change on the agricultural sector, particularly in the field of rice production. By combining socio-economic and biophysical variables, this research conducts economic and spatial analysis to better model household vulnerability to drought, the consequences of the phenomenon on production and adaptation options. This type of approach that starts from an analysis from a higher level of the system to a lower level is known as the "top-down" approach. The results of this research will give a much more global vision of the problem of climate change in countries located in sub-Saharan Africa and Senegal in particular. It can serve as a guide for policy makers in the implementation and financing of their National Adaptation Plan (NAP) for the agricultural sector. Indeed, this research is likely to have a considerable impact on the implementation of the NAP and therefore the Nationally Determined Contribution (NDC) because it sheds light on one of the target adaptation options of the Government of Senegal, in particular the promotion of agricultural insurance. The NDCs being near-universal, medium-term, country-driven climate plans formulated in the context of limited self-differentiation (Pauw & Klein, 2021), this research will better guide Senegalese policy makers in the implementation of agricultural adaptation options by providing them with relevant policy implications to improve the resilience of rural households. Indeed, the results that will come from this research will allow them to know the levers on which they must rely to promote agricultural insurance in rural areas. The results will provide a global overview of the structure of the insurance system, the insurance market failures to be corrected, the opportunities and challenges to be addressed in order to encourage households to subscribe and make themselves much more resilient to climate change.

6. Outline of the thesis

This research is structured around three chapters. The first chapter focuses on macroeconomic analysis of the economic impact of climate change on rice cultivation; the second chapter examines the vulnerability of farm households to climate change, while the third chapter assesses agricultural insurance policy as an instrument for managing climate risks among households.

CHAPTER I: ECONOMIC IMPACT OF CLIMATE CHANGE ON THE RICE SECTOR IN SENEGAL

1. Introduction

Risk on a global scale is at the core of the issue (Stern, 2008). Indeed, climate risks are becoming increasingly recurrent and pose a threat to all countries of the world and all sectors of the economy, especially sub-Saharan Africa (SSA) and its agricultural sector. Agriculture in SSA countries (SSA) is highly dependent on rainfall, which is becoming increasingly rare. Global temperatures are constantly rising, which could also affect agricultural productivity. Average annual and seasonal temperatures observed since the mid-1970s have risen from 1°C to 3°C, with the Sahara and Sahel recording the largest increases (Cook & Vizy, 2015; Lelieveld et al., 2016; Dosio, 2017; Nikiema et al., 2017; Masson-Delmotte et al., 2021). Meteorological, agricultural and hydrological drought has become increasingly frequent in the region since the 1950s (Wehner et al., 2021). These observed changes in temperature and precipitation patterns appear to be a brake on the development of agriculture in SSA countries. According to a large number of researchers (Iizumi et al., 2018; Ray et al., 2019;Ortiz-Bobea et al., 2021), climate change is already negatively impacting agricultural production and slowing productivity growth in Africa.[1] Indeed, Africa's total agricultural productivity growth has declined by 34% since 1961 due to climate change, a more drastic reduction than in any other region (Ortiz-Bobea et al., 2021). Projections for West Africa reveal an unfavourable situation for agriculture. Characterized by a gradient of decreased rainfall on the one hand (Dosio et al., 2021),[2] and on the other hand, an increased intensity of heavy rainfall events, combined with the increase in drought occurrences (Giorgi et al., 2019), West Africa is at risk of significant loss and damage in its agricultural sector. As future climate projections have indicated that climate change could negatively affect the growth of agricultural production, especially that of cereals, it is therefore important to study the situation in Senegal to see the response of crops to climate change. Given the importance of rice in terms of its contribution to cereal production in Senegal (45%) and especially the large number of agricultural households and consumers who depend on it for their livelihoods, any positive (or negative) impact would affect agricultural GDP and household well-being in a positive (or negative) way. To this end, the question that arises is: what is the impact of climate change on the per capita gross domestic product from rice cultivation?

[1] High confidence level

[2] Medium confidence level

2. Research objectives and hypotheses

2.1. General objective

The main objective of this research is to quantify the impact of variation in climatic parameters on the economic performance of Senegal's rice sector.

2.2. Specific objectives

In a much more specific way, it is:

(i) to analyze Senegal's rainfall pattern over the last 30 years to highlight periods of drought in order to see the instantaneous variation in rice GDP during drought event.

(ii) assess the impact of increased temperature and precipitation on the gross domestic product of rice cultivation.

2.3. Research hypotheses

This research is based on the following hypotheses: (i) drought-related climatic events will negatively affect rice production and consequently its gross domestic product; (ii) Rainfall is a good factor in the development of rice production, given its importance in terms of replenishment of aquifers and water reservoirs for irrigation, while the increase in temperatures could be unfavorable if it exceeds the optimal threshold of growth and development of the rice plant.

3. Literature review

The debate on climate change and its impact on agriculture and food security is today among the most controversial in the world and more particularly in Sub-Saharan Africa. A flourishing literature on the impacts of climate change on agriculture has been produced in recent years and the weight of evidence has coincided with some particular conclusions that may serve as a basis for an emerging consensus. However, there are also conflicting conclusions between the authors so far, particularly with regard to the impact of climate change on agricultural production. In the following, we synthesize theoretical knowledge and empirical evidence of the impact of climate change on agriculture.

3.1. Theoretical review

In Africa, the dominant agricultural system is mixed cereals-livestock (Thornton & Herrero, 2015; Nematchoua et al., 2019), with pastoral systems in East Africa, and livestock and cash crop systems also representing a significant part of the food system in Southern Africa (Thornton & Herrero, 2015). However, due to climate change, the agricultural sector, the main source of livelihood in Africa, is particularly vulnerable to climate risks due to its high dependence on rainfall. Climate change is manifested by a change in the state of the climate that can be detected by changes in the mean and/or variability in its properties (precipitation, temperature, etc.) and that persists for a long time (Christensen et al., 2007). This phenomenon due to anthropogenic emissions of greenhouse gases (GHGs) is often manifested by a rise in temperature levels, an increase in precipitation leading to floods, a rainfall deficit or pause, or recurrent periods of drought. All these factors, related to climate change, could have positive or negative impacts on agricultural production and consequently on gross domestic product (GDP). For example, the significant crop losses noted in France in 1976 are explained by the precocity, intensity and generalization of the rainfall deficit and the low proportion of irrigated crops at that time (Morardet et al., 1998). In addition, climate change could be more severe in sub-Saharan African countries due to their heavy reliance on rain-fed agriculture. Future projections present adverse situations that may affect people's well-being. Due to low adaptive capacity, future global warming would have a substantial negative impact on food security in Africa, given that 85% of Africa's poor live in rural areas and depend primarily on agriculture for their livelihoods (Mahmood et al., 2019). Decreased rainfall leads to crop failures in the short term and lower production in the long term (Parry et al., 2009). In addition, higher temperatures promote rapid growth of weeds and pests and consequently reduced crop yields (Parry et al., 2009; Habou et al., 2016). Although crop improvement may sometimes be noted in some parts of the world, climate change will negatively affect agriculture and disrupt global food security (Parry et al., 2009). In Niger, for example, significant crop losses are attributable to numerous droughts, floods, locust invasions and other pest attacks (Habou et al., 2016). As a result, farmers are exposed to problems and the performance of the agricultural sector in the country's economy is threatened. In Benin, studies on the impact of climate change on agriculture have made it possible to understand that insect attacks remain the priority constraints (Loko et al., 2013). Moreover, in the recent economic literature, the authors have tried to quantify the impact of climate change on the agricultural economy by taking into consideration variables of interest such as agricultural production or yield, economic growth. The following section gives a general idea of the results found by the researchers.

3.2. Empirical review

According to Adams (2018), agriculture in Africa is vulnerable to future climate change, as part of 90-95% of Africa's food production is rainfed. To this end, any variation in rainfall and temperature is likely to have a considerable impact on crop production and consequently on gross domestic product (GDP). Several studies already conducted in Africa with a high level of confidence, show that climate change has already led to a decline in agricultural production and a slowdown in productivity growth (Iizumi et al., 2018 ; Sultan et al., 2019; Ortiz-Bobea et al., 2021). In addition, authors also indicate that in Africa, yields of cash crops have already been negatively and positively impacted by climate change (Di Falco et al., 2012; Traore et al., 2013; Ray et al., 2019). The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) reveals that in Africa, any global warming of 1.5°C to 4°C without adaptation would lead to a reduction in maize yield at values ranging from 9% to 41% compared to 2005 yield levels (Pörtner et al., 2022). In sub-Saharan Africa, the reduction in yields due to climate change is 5.8% for maize and 2.3% for wheat over the period 1974-2008 (Ray et al., 2019). Indeed, following a synthesis of 35 studies on nearly 1040 localities, the authors find that, even in the event of adaptation, yield losses could not be avoided for crops such as rice, maize, soybeans and wheat. However, adaptation is more beneficial because it reduces the impact of climate change. In adaptation situations, losses are lower (-10%) than without adaptation (-33%) for 2°C warming, while they vary from -23% to -46% when the climate reaches 4°C, compared to 2005 (Hasegawa et al., 2022). Precipitation projections in West Africa show a gradient of decreasing precipitation in the West and increasing in the East (Dosio et al., 2021; Masson-Delmotte et al., 2021) and if there is no adaptation, any temperature change of 1.5°C to 4°C would result in a decrease in median maize yield of 9% to 41% (Hasegawa et al., 2022).[3] A downward trend was also observed on sorghum cultivation. According to Faye et al. (2018), throughout the Sahelian savannah of West Africa, sorghum yields are expected to decrease on average by 2% to 5% for global warming of 1.5°C to 2°C. [4]Although for most research, the results indicate an inverse relationship between temperature and agricultural production, it should be noted, however, that temperature increase can be favorable in certain geographical areas and due to the growth requirements of certain types of crops. In South Korea, for example, the work of Nasrullah et al. (2021) indicates the existence of a significant positive association in the long term; a 1% increase in average temperature can increase rice production by 1.16%. In Pakistan, Chandio et al. (2018)also found a significant and positive impact of temperature on rice production. Moreover, the link between temperature and GDP growth remains ambiguous. A large number of studies have found an inconclusive relationship between annual temperature and GDP growth (Ali, 2012; Waldinger, 2013; Colacito et al., 2018; Sequeira et al., 2018). Thus, given the authors' findings, there is no

[3] Medium confidence level

unanimous conclusion on the link between temperature and agricultural production, which opens the door to any other researcher wishing to investigate the issue. The same is true for rainfall, while some authors have found a negative association with agricultural production, others have found that it promotes agricultural growth.

The study of the impact of changing climatic parameters on rice productivity in Punjab province in Pakistan indicates that in the long term, increased rainfall can decrease rice production (Mahmood et al., 2012). Similar results are found in South Korea. According to Nasrullah et al. (2021), a 1% increase in rainfall would decrease South Korea's rice production by 0.12% in the short term by 0.13% in the long term. The same is true in China according to research by Chandio et al. (2020) on climate change and agriculture. Indeed, Islam et al. (2021) indicate that higher annual rainfall and higher per capita CO2 emissions are not conducive to Saudi Arabia's economic growth. In addition, climate change and variability can negatively affect real agricultural gross domestic product growth. According to Mammo (2022), in the long term, a 1% increase in the coefficient of variation of annual precipitation will reduce agricultural production by 0.0075%. However, the negative effect of rainfall on economic growth is not supported by many authors (Ali, 2012; Ayinde et al., 2011; Cabral, 2014; Odusola & Abidoye, 2015). For example, the results of Cabral (2014) simulations show that Senegal could experience a decrease in poverty due to a projected upward trend in rainfall while Burkina Faso could face an increase in poverty incidence due to an expected downward trend in rainfall. To this end, it must be understood that the current state of scientific knowledge does not allow to give a common conclusion with regard to the impact of climate change on agricultural and economic indicators.

On the other hand, studies on the relationship between carbon dioxide (CO2) emissions and rice production have shown that there is a positive interaction between the two variables. In South Korea, studies Nasrullah et al. (2021) indicate that a 1% increase in CO2 emissions can increase rice production by up to 0.15%. Wang et al. (2015) also stated that a one percent increase in CO2 emissions would lead to a 20% increase in rice yield. This positive interaction appears to be the result of a chemical reaction known as photosynthesis. In the study of rice yield response to elevated CO2, Chandio et al., 2018 ; Lv et al. (2020) state that high atmospheric CO2 may increase rice production in the future, as high CO2 enhances the rice photosynthesis process (Lv et al., 2020).

All in all, although the literature on the economics of climate change indicates that climate change in Africa will have a negative global impact on crop production and gross domestic product, the study of the situation at the regional scale needs to highlight some disparity between geographical regions and cultures. On the one hand, while some authors have shown that increases in temperature and precipitation lead to decreases in agricultural production and GDP, others reveal a positive association between variables. These contradictory results, obviously coming from different geographical areas and sometimes involving different crops, show that there are still research opportunities to study the response of agricultural and economic indicators to the variation of climatic parameters such as temperature, precipitation and CO2 emissions. To this end, this research works tries to see the impact of climate change on the GDP per capita of rice cultivation in Senegal. For this, a preliminary analysis of the data is made to have beforehand, an overview on the interaction between the variables.

4. Data

The data used in this research are drawn from the Food and Agriculture Organization (FAO) database. These include gross domestic product from rice cultivation, average temperature, rainfall, and carbon dioxide (CO2) emissions over the period 1961-2020; The choice of period is based on data availability. A descriptive analysis of the data provides a general overview of the interaction between variables. Since agricultural production depends largely on climatic factors, any change in temperature or precipitation patterns could lead to a change in gross domestic product. Indeed, unlike other research that has been limited simply to the statistical analysis of climate parameters, this research identifies climate risks through the Standard Precipitation Index (SPI) to better understand the immediate effects of drought and floods on the gross domestic product of rice cultivation (See summary of indices in Table 2 and Graph 4, 5, 6 and 7 for details).

4.1. Descriptive data analysis

The graphs below show the evolution of the variables over time, while the following table gives a detailed description of each of the variables. Graphical analysis of the data shows that GDP/capita has followed an increasing evolution over the years, while CO2/capita has been on a downward trend until the end of the 1990s before then taking an increasing trend since the 2000s. With regard to climatic parameters, temperatures have increased over the years, while seasonal trends have been marked by fluctuations that sometimes upwards and decreases, but have become increasingly low in recent years (see Graph 1).

Graph 1: Evolution of GDP/capita, CO2/capita, temperature and precipitation, 1960-2020.

Source: Author's realization based on FAO data, 2022.

Table 1 provides more details on the statistics of the data used. Thus, annual rainfall has evolved by an average of 716.44 millimeters (mm) and reached a peak of 925 mm and a minimum of 458.71 mm over the period 1960-2020. Over the same period, average temperature is 28.56 °C with a minimum of 27.49 °C and a maximum of 29.56 °C. In addition, the gross domestic product from rice cultivation averages 56,490.02 ($1000), and carbon dioxide (CO2) emissions of 207.01 kilotons (kt) for an average population of 8348.21 (1000 inhabitants), or a GDP per capita of $5.28/capita and CO2 per capita equal to 0.03 kt/person. Indeed, the lowest GDP recorded in Senegal's rice business is 7443.00 ($1000) while the highest value is equal to $273,736 (1000).

Table 1: Descriptive statistics of the data: GDP, CO2, Precipitation and Temperature.

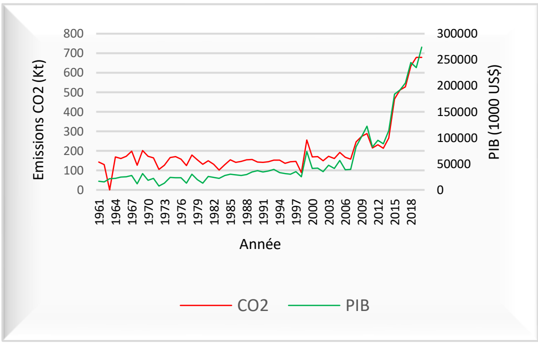
Statistics	GDP (1000 USD)	CO2 (Kilotonne)	Population (1000 inhabitants)	Precipitation (Millimeter)	Average temperature (°C)	CO2/Capita	GDP/Capita
Mean	56490,02	207,01	8348,21	716,44	28,56	0,03	5,28
Maximum	273736,00	677,37	16436,12	925,70	29,56	0,08	15,71
Minimum	7443,00	88,99	3367,08	458,71	27,49	0,01	0,02
Std.Dev	61911,80	134,94	3766,54	116,96	0,50	0,01	2,99
Skewness	2,14	2,46	0,52	0,09	-0,21	1,67	1,62
Kurtosis	6,64	8,11	2,13	2,21	2,40	6,54	6,26
Jarque-Bera	78,74	125,66	4,58	1,63	1,31	59,25	52,89
Probability	0,00	0,00	0,10	0,44	0,52	0,00	0,00
N-Observations	60	60	60	60	60	60	60

Source: Author's calculations based on FAO data, 2022.

4.2. Evolution of gross domestic product of rice and carbone dioxide over time

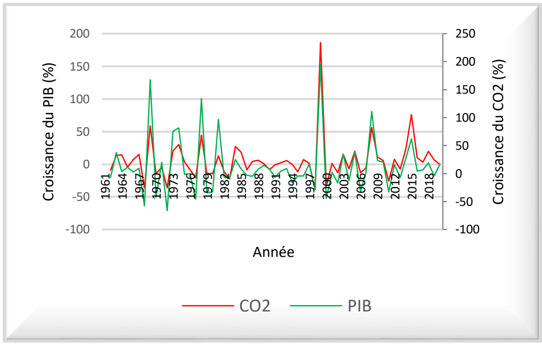
Although the table 1 provides detailed information on the variables, a cross-analysis of the data would provide insight into the interaction between the variables. Greenhouse gas emissions increase with the gross domestic product of rice. As GDP increases, carbon dioxide (CO2) emissions are increasing over time (Graph 3). This situation could be understandable insofar as the increase in GDP requires first the increase of land under crops, sources of CO2 emissions. Indeed, any variation in one of the two variables leads to a variation in the other in the same direction (see Figure 3).

Graph 3: Evolution of CO2 emissions and GDP from rice cultivation, 1961-2020.



Source: Author's calculations based on FAO data, 2022.

Graph 2: Change in carbon dioxide (CO2) and GDP growth, 1961-2020.



Source: Author's calculations based on FAO data, 2022.

The illustrations above show the extent to which agriculture contributes to the increase in greenhouse gas emissions and thus indirectly to climate change. The accumulation of GHGs in the atmosphere intensifies the rise in temperature levels and can lead to changes (upward or downward changes) in globally identifiable global or national or local precipitation patterns. Senegal is a typical example of a country where the phenomenon of climate change can be detected on the basis of statistical analysis of temperature trends and variations in rainfall over a long period of time.

4.3. Analysis of climate risks in Senegal over the period 1990-2020

In accordance with the recommendations of the World Meteorological Organization (WMO) to national meteorological and hydrological services (Svoboda et al., 2012), the Standard Precipitation Index (SPI) is considered in this research as the indicator for measuring drought risk to detect and characterize meteorological droughts. The Standard Precipitation Index (SPI) was developed by McKee et al. (1993). The SPI measures precipitation anomalies (deviation from the mean) for a given locality, based on the comparison between the total precipitation values observed for a given accumulation period (1, 3, 6, 12, 24, 48 months) and the historical average precipitation value recorded during that same period. The magnitude of the lag from the mean is a probabilistic measure of the severity of the humidity or drought observed.

Thus, to determine the Standard Precipitation Index of Senegal over different periods, the following formula is applied:

$$SPI = \frac{P - P_m}{\sigma_p}$$

where

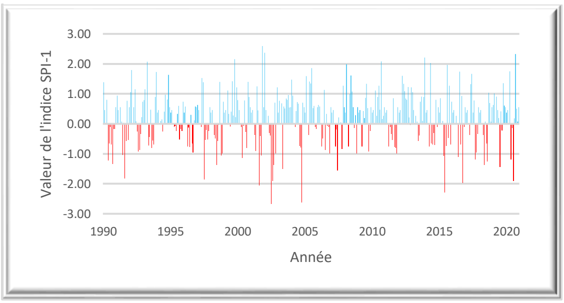
P is total precipitation of a period (in mm),

Pm is the historical average precipitation of the period (mm),

σ_p the historical standard of precipitation of the period (mm).

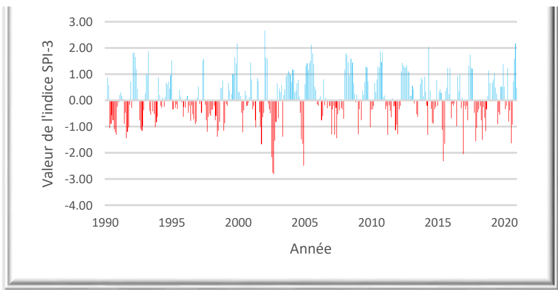
The results of the Standard Precipitation Index (SPI) calculation are presented in Graph 4, 5, 6 and 7. Five (5) indices are determined (SPI-1, SPI-3, SPI-6, SPI-9 and SPI-12) to identify droughts at different levels, short, medium and long term. The indices are classified into seven (7) classes according to World Meteorological Organization (WMO). An index below -1.0 indicates a drought situation while when it is greater than 1 then we speak of humidity. Although the SPI can be calculated according to different periods of precipitation accumulation (range from 1 to 48 months), it should be understood that this index gives a different interpretation of the potential impacts of drought relative to the time horizon considered. The short-term SPI (SPI-1 and SPI-3) can detect short-term soil moisture and crop stress during the growing season, while the medium-term SPI (SPI-6 and SPI-9) provide an indication of inter-seasonal precipitation patterns on an average time scale and help identify abnormal flow situations and reservoir levels. Indeed, long-term SPI (SPI-12) reflects situations of Related droughtes at river flows, reservoir levels and groundwater levels. The following graphs give an overview of the calculated indices.

Graph 5:Standard precipitation index (SPI-1), 1990-2020.



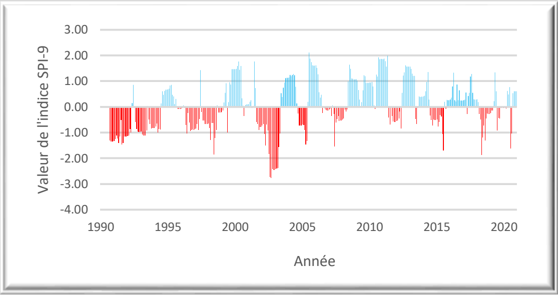
Source: Author's calculations based on FAO data, 2022.

Graph 4: Standard precipitation index (SPI-3), 1990-2020.



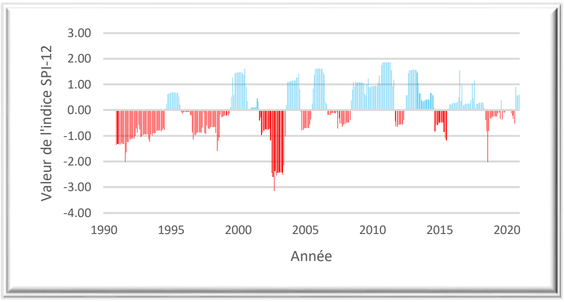
Source: Author's calculations based on FAO data, 2022.

Graph 7: Standard precipitation index (SPI-9), 1990-2020.



Source: Author's calculations based on FAO data, 2022.

Graph 6: Standard precipitation index (SPI-12), 1990-2020.



Source: Author's calculations based on FAO data, 2022.

The SPI calculated from Senegal's rainfall data from 1990 to 2020, shows that the country faces extreme drought 2% of the time, severe drought 2% and moderate drought 5% of the time according to the SPI- 3 and the SPI-6. The frequency of wet periods is between 22% and 30% according to SPI-1 to SPI-12, distributed according to the different classes - moderately wet, very wet, and extremely wet -. Table 2 summarizes events by index. Given that there are periods when Senegal is facing periods of drought, a cross-analysis of the evolution of economic performance in the rice sector would provide insight into the direct effects of climate risks on rice gross domestic product (see next section).

Table 2: Classification of droughts in Senegal according to the Standard Precipitation Index spi-1, spi-3, spi-6, spi-9, spi-12.

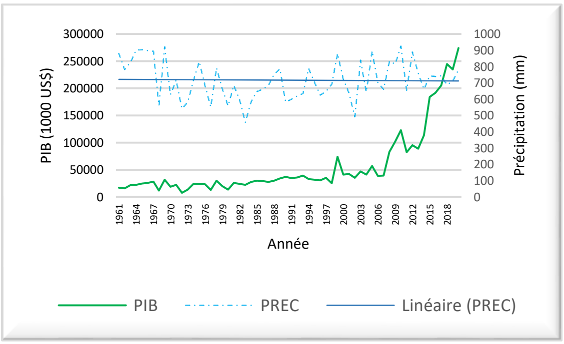
SPI drought classification						
Drought class	**SPI Value**	**Event frequency (%)**				
		SPI-1	**SPI-3**	**SPI-6**	**SPI-9**	**SPI-12**
Extremely humid	SPI ≥ 2.0	2%	1%	1%	0%	0%
Very humid	1.5 ≤ IPS < 2.0	12%	14%	14%	15%	15%
Moderately humid	1.0 ≤ IPS < 1.5	8%	12%	13%	14%	15%
Close to normal	-1.0 ≤ SPI < 1.0	71%	64%	63%	62%	60%
Moderate drought	-1.5 ≤ SPI < -1.0	4%	5%	5%	5%	4%
Severe drought	-2.0 ≤ SPI < -1.5	2%	2%	2%	3%	2%
Extreme drought	SPI < -2.0	1%	2%	2%	2%	3%

Source: Author's calculations based on FAO data, 2022.

4.4. Evolution of gross domestic product of rice and rainfall over time

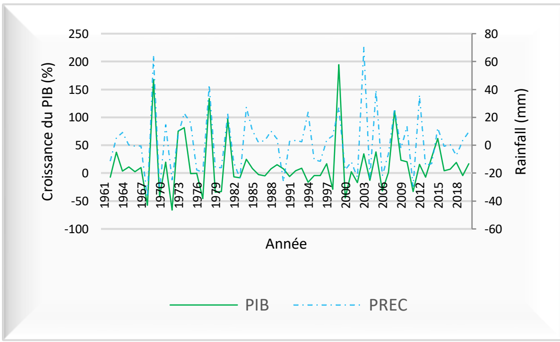
The gross domestic product of rice cultivation in Senegal has experienced an increasing evolution during the period 1961-2020 but it is also marked by periods of decline due to climate change, marked particularly by periods of drought linked to the rainfall deficit (See graphs 8 and 9). In 1968, GDP from rice cultivation fell by 57.6% compared to the previous year; a fall due to a decline in Rainfall below the average for the reference period 1981-2010 (i.e., 549.4 mm versus 682 mm). The 70s and early 80s were marked by several periods of drought in Senegal, with more severe impacts in 1970, 1972 and 1977. Rice GDP fell by 41.95 per cent between 1969-1970, 66.10 per cent between 1971-1972 and 45 per cent between 1976-1977. In addition, increased rainfall appears to have a favourable effect on GDP. A 27.25 per cent increase in precipitation in 1999 was followed by a GDP growth of 194.69 per cent between 1998-1999, while in the period 1999-2000 a decrease in precipitation of 17.72 per cent coincided with a decrease in GDP of 44.42 per cent (See chart 4). On the other hand, the beginning of the 2000s was marked by a decline in rainfall of a value below the average of the reference period. 1981-2010 (e.g., 481.2 mm in 2022 compared to the average of 682.0 mm 1981-2010), which led to periods of extreme drought during the months of July, August, September, October, November and December, corresponding to the calendar of rice cultivation in wintering in Senegal (see annexes to SPI-3, SPI-6, SPI-9 and SPI-12). All forms of drought were experienced in 2002, starting from an agricultural drought linked to the Deficiency of soil moisture in relation to the water demands of plant life some crops, hydrological drought related to the low river flows, and declining Tank levels and groundwater levels. As a result, the gross domestic product of rice cultivation has fallen by -16,71 % compared to 2001 (+2, 32%). Rice GDP also declined by 32.81% in 2011 compared to 20% growth in 2010, partly due to periods of moderate drought in April and November of the year (see SPI-3 in Annex 2). Indeed, to better understand the evolution of rainfall and gross domestic product of rice over time, the graphs 8 and 9 give an illustration the above explanations.

Graph 9: Evolution of precipitation and GDP, 1961-2020.



Source: Author's calculations based on FAO data, 2022.

Graph 8: Change in precipitation and GDP growth and, 1961-2020.

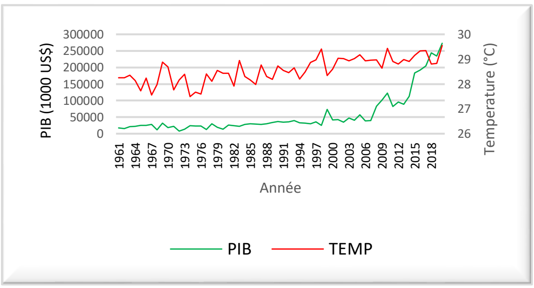


Source: Author's calculations based on FAO data, 2022.

4.5. Evolution of gross domestic product of rice as a function of temperature

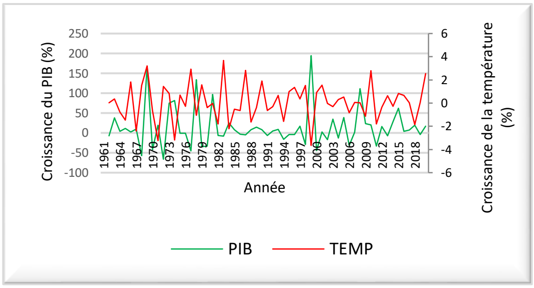
As shown in graph 11, the evolution of temperature in Senegal follows an upward trend over the period 1961-2020, in parallel with the evolution of the GDP of the rice sector. However, when it comes to growth rates as shown in Figure 10, over certain periods, an opposite trend is observed between GDP growth and temperature, thus indicating that the upward/downward variation of GDP does not does not necessarily coincide with an increase/decrease in temperature levels. In other words, there appear periods for which the rate of GDP growth from one year to the next has decreased while the rate of change of temperature is positive in the same period. Concurrently, in some cases, the GDP growth rate has increased while the temperature variation takes a negative sign at the same period.

Graph 11: Evolution of temperature and GDP, 1961-2020.



Source: Author's calculations based on FAO data, 2022.

Graph 10: Temperature Change and GDP Growth, 1961-2020.



Source: Author's calculations based on FAO data, 2022.

5. Methodology

This research uses the Cobb-Douglas production function model (Cobb & Douglas, 1928) to study the impact of climate change on per capita gross domestic product (GDP/capita).[5] To empirically examine its changes, the Autoregressive Distributed Lag (ARDL) is used. The ARDL model is a well-known dynamic model of Pesaran et al. (2001), favoured here over other models because it is much more appropriate for capturing the short- and long-term impact of independent variables on GDP per capita when series are cointegrated or integrated in different orders I(0), I(1) (Frimpong Magnus & Oteng-Abayie, 2006; Nasrullah et al., 2021) but it fails if at least one of the series is integrated into an order greater than one, e.g. I(2). In the latest research published in the economic literature, this same approach has been used by the authors to measure the impact of climate change on either Saudi Arabia's economic growth (Islam et al., 2021), Ethiopia's agricultural GDP growth (Mammo, 2022), or South Korea's rice

[5] This is the gross domestic product of rice per capita: it is calculated by making the ratio between the GDP of rice and the total population of Senegal.

production (Nasrullah et al., 2021), or on the agricultural sector of Bangladesh (Ceesay & Fanneh, 2022). To this end, the ARDL model is used in this research to measure the impact of climate change on the per capita gross domestic product of Senegal's rice sector.

Starting from the Cobb-Douglas production function, gross domestic product per capita (GDP/capita) can be considered as a function of variables such as carbon emissions (CO_2/capita), temperature (TEMP), precipitation (PREC).

$$\mathbf{GDP/capita = f(CO2/capita, TEMP, PREC)} \qquad \mathbf{(1)}$$

By converting all variables in equation (1) to logarithm format, the model is described as follows:

$$\mathbf{lnGDP/capita_t = \alpha_0 + \alpha_1 lnCO2/capita_t + \alpha_1 lnTEMP_t + \alpha_3 lnPREC_t + \varepsilon_t} \qquad \mathbf{(2)}$$

where ln represents the natural logarithm; GDP/capita describes the gross domestic product of rice cultivation in relation to the country's population; CO2/capita represents the amount of carbon dioxide emissions from rice farming in relation to the country's population number; TEMP and PREC represent climatic variables including temperature and precipitation, respectively; α_i represents the coefficient of the associated variable; ε_t being the standard error term.

Starting from equation (2), the ARDL model is written as follows:

$$\mathbf{\Delta lnGDP/capita_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\, \Delta lnCO2/capita_{t-i} + \sum_{i=1}^{p} \alpha_{2i}\, \Delta lnTEMP_{t-i} + \sum_{i=1}^{p} \alpha_{3i}\, \Delta lnPREC_{t-i} + \beta_1 lnCO2/capita_{t-1} + \beta_2 lnTEMP_{t-1} + \beta_3 lnPREC_{t-1} + \epsilon_t} \qquad \mathbf{(3)}$$

where α_0 represents the drift component while Δ denotes the prime difference, ε_t shows the white noise.

The Akaike Information Criterion (AIC) is used to choose the optimal offset number and the bounds test to cointegration or "staggered delay cointegration test" is applied. The choice of offset length should be exercised with caution, as inappropriate offset length can lead to biased results and cannot be accepted for policy analysis (Chandio et al., 2019). This terminal cointegration test is applied against the background of a model that serves as a basis, it is the cointegrated ARDL specification that takes the form of an error-correcting model.

$$\Delta \textbf{lnGDP/capita}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\, \Delta \textbf{lnCO2/capita}_{t-i} + \sum_{i=1}^{p} \alpha_{2i}\, \Delta \textbf{lnTEMP}_{t-i} + \sum_{i=1}^{p} \alpha_{3i}\, \Delta \textbf{lnPREC}_{t-i} + \emptyset \textbf{ECM}_{t-1} + \epsilon_t \quad \textbf{(4)}$$

where $\emptyset$ is the coefficient of the ECM-corrected model for short-term dynamics. The ECM shows the speed of long-term equilibrium adjustment after a short-term shock. The statistically significant and negative sign of the coefficient $\emptyset$ implies that any long-term imbalance between the dependent variables and a number of independent variables will converge towards the long-run equilibrium association. ECM_{t-1}

However, it should be understood that the choice between the ARDL model and the error-corrected model will depend on the results of the boundary cointegration test proposed by (Pesaran et al., 2001). The test includes the Fisher test of the joint significance of the coefficient of the delayed variables to verify that there is a long-term relationship between the variables. The null hypothesis of no long-term association between the variables (H 0: $\beta_1 = \beta_2 = \beta_3 = 0$) is tested and the final decision of possible acceptance or rejection of H_0 depends on three conditions.

The first is if the value of F-test is greater than the upper critical bound (UCB) (F-test>UCB), then H_0 is rejected, and the study variables are cointegrated, i.e., there is a long-term equilibrium relationship between the variables. The second condition is that if the F-test value is less than the lower critical bound (LCB) (F-test < LCB), H0 is accepted and the variables in this study are not cointegrated. The third condition is when the value of F-test is between the upper critical bound and the lower critical bound (LCB⩽ F-test ⩽ UCB), then the decision is inconclusive.

6. Short-term ARDL model estimation results

6.1. Analysis of series stationarity

The ARDL approach to cointegration requires that the variables considered be either zero-order, integrated in order one (i.e., I (0) or I (1)), or co-integrated. The Enhanced Dickey Fuller unit root test (ADF) applied to determine the stationarity level of variables indicates that variables such as lnTEMP and lnPREC are stationary at level with different significance levels of 1% and 5% respectively, while in the first difference all variables are stationary, in particular lnGDP/capita and lnCO2/capita. These results show that all the variables considered are either I (0) e.g., lnTEMP and lnPREC or I (1) as lnGDP/capita and lnCO2/capita, and there is no variable that is integrated into order two (see Table 3). The ARDL model is therefore applicable.

Table 3: Dickey Fuller Stationarity Test Augmented (ADF).

Variables	ADF test (level) Constant and trend	Comment	ADF test (in first difference) Constant and trend	Comment
lnGDP/capita	-2,13	Non-stationary	-7,73***	Stationary I(1)
lnCO2/capita	-1,02	Non-stationary	-7,63***	StationaryI(1)
lnTEMP	-5,94***	Stationary I(0)		
lnPREC	-3,91**	StationaryI(0)		

Note: -2.13 -1.02 -5.94 -3.91 are the critical values at level, -7.73 -7.63 -9.17 -8.18 are the critical values in first difference; ** and *** indicate a significance levelof 5% and 1% respectively. GDP/capita, CO2/capita, TEMP and PREC represent per capita rice gross domestic product, per capita CO2 emissions, average temperature and precipitation, respectively. ln being the logarithm.
Source: Author's calculations based on FAO data, 2022.

After verifying the unit root test, the next step is to use the ARDL approach to verify the long-term relationship between series. For this purpose, it is necessary to choose the appropriate offset length before applying the cointegration test to the terminals.

6.2. Criteria for selecting lags

The optimal lag order of the autoregression vector (VAR) model is used for selecting the appropriate offset order. The results observed in Table 4 show the set of lag selection criteria for the use of the ARDL cointegration test. The lag length is determined using the Akaike Information Criterion (AIC). The principle is to choose the number of offsets that minimizes AIC, therefore equal to one (1). This indicates that the model performs best at lag 1 compared to lags 2, 3, 4, and 5. The AIC criterion gives robust results and has excellent performance compared to the Schwarz (SC) information criterion and the Hannan-Quinan (HQ) information criterion.

Table 4: Lag order criteria using VAR (vector autoregression).

Lag	HE	LR	Df	p	FPE	AIC	HQIC	SBIC
0	141.835				7.8e-08	-5.01217	-4.95572	4.86619
1	229.087	174.5	16	0.000	5.9e-09*	**-7.60316***	-7.32088*	6.87322*
2	239.409	20.645	16	0.193	7.3e-09	-7.3967	-6.88861	6.08281
3	245.8	12.782	16	0.689	1.1e-08	-7.04729	-6.31338	5.14945
4	254.637	17.672	16	0.343	1.4e-08	-6.78679	-5.82706	4.30499
5	270.629	31.985*	16	0.010	1.6e-08	-6.78652	-5.60097	3.72077

Note: *Represents the selection criterion for the offset order. LR, FPE, AIC, SC and HQ represent the sequential modified LR test statistic, final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinan information criterion, respectively. The optimal offset number is the one that minimizes these criteria.
Source: Author's calculations based on FAO data, 2022.

6.3. Specifying the ARDL Model Offset

Based on the Akaike Information Criterion (AIC), the ARDL model is specified according to the optimal lag combination described as follows: ARDL (1,0,1,1). Table 5 shows the matrix of lags.

Table 5: Combination of lag of the ARDL model according to the AIC criterion.

	LnGDP/capita	lnTEMP	lnPREC	lnCO2/capita	AIC
R1	1	0	0	0	14,63
R2	1	0	0	1	-37,02
R3	1	0	1	0	2,55
A4	1	0	1	1	-40,44
R5	1	1	0	0	1,51
R6	1	1	0	1	-36,06
R7	1	1	1	0	-7,09
R8	1	1	1	1	-39,30

Note: AIC is Akaike's information criterion. The optimal number of razors is the one that minimizes AIC. GDP/CAPITA, CO2/CAPITA, SPECT and PREC represent per capita rice gross domestic product, per capita CO2 emissions, average temperature and precipitation, respectively. ln being the logarithm.
Source: Author's calculations based on FAO data, 2022.

6.4. Cointegration test

The results of the bound cointegration test of Pesaran et al. (2001) are presented in Table 6. The calculated F-statistic is higher than the critical values of upper bound I(1) at the significance thresholds of 1%, 5% and 10%, suggesting that the null hypothesis of no cointegration cannot be rejected. In other words, the results indicate the absence of a long-term cointegration relationship between the variables GDP per capita, CO2 per capita, temperature and precipitation. The empirical results of Johansen cointegration, presented in Table 7, provide evidence of the robustness that there is no long-term relationship between variables. For this purpose, equation (3) is considered to estimate the short-term ARDL model.

Table 6: Boundary cointegration test of Pesaran et al. (2001).

F-statistics	Level of significance	Lower boundI(0)	Top bound I(1)	Long-term relationship
2,58	10%	2,72	3,77	No co-integration
	5%	3,23	4,35	
	1%	4,29	5,61	

Note: 2.58 is the Fisher statistic; 2.72, 3.23 and 4.29 are the critical values of the lower bound I(0); 3.77, 4.35 and 5.61 are the critical values of upper bound I(1). If Fisher computed > Upper bound: Cointegration exists; if Fisher computed < Lower bound: Cointegration does not exist; if Lower bound < Fisher calculated < Upper bound: no conclusion.

Table 7: Johansen cointegration test.

Maximum rank	parms	eigenvalue	Trace statistic	Critical value
0	20	.	46,02*	47,21
1	27	0,38	18,72	29,68
2	32	0,20	5,79	15,41
3	35	0,06	2,01	3,76
4	36	0,03		

Note: The null hypothesis of no cointegration is rejected if Trace statistic > Critical value.

6.5. Results of the impact of climate change on the rice sector

The bounds cointegration test indicates that there is no long-term cointegration relationship, so the short-term ARDL model is more applicable in this research. The results of the impact of climate change on the GDP per capita of rice cultivation are presented in Table 8. GDP per capita is estimated as a function of climatic parameters such as temperature, precipitation and CO2 emissions according to the ARDL specification (1,0,1,1). In tests that help diagnose the estimated model, there is no autocorrelation of errors, absence of heteroscedasticity, normality of errors, and good specification of the model (See section 6.6). The results show that in the short term, climate variables significantly affect GDP per capita from rice cultivation. Similarly, the GDP of a year ago has a significant and positive effect on the GDP per capita of the current year. The temperature, precipitation and CO2 emissions of the current year have significant and positive effects on the GDP per capita of the same year. For a more detailed explanation of the impact of the variation in climatic parameters on rice cultivation in Senegal, the results described in the following sections.

6.5.1. Impact of temperature variation on GDP per capita on the rice sector

Temperature has a significant and positive effect on the per capita GDP of rice cultivation at the 5% level. Any 1 % increase in temperature will lead to an increase in GDP per capita of rice production of 3.52 %. This result is similar to those of the work of Nasrullah et al. (2021) in South Korea and Chandio et al. (2018) in Pakistan, indicating that there is a significant and positive impact of temperature on rice production. In South Korea, for example, a 1% increase in average temperature can increase rice production by 1.16%. Indeed, the results of this research are plausible especially since the minimum and maximum temperatures of Senegal over the period 1960-2020 (21.35 ° C and 35.83 ° C) are in the optimal temperature range for good germination (between 20 and 35 º C) as well as for seedling emergence and early growth (between 20 to 30 ºC) (Chaudhary et al., 2003). Moreover, a contradictory effect found in future research cannot put the results back since they are derived from current data and not from climate projections, which could present higher temperature levels, beyond the optimal range.

6.5.2. Impact of rainfall variation on per capita GDP on rice sector

The current year's rainfall positively and significantly affects the per capita GDP of rice cultivation, while when it comes to the previous year's rainfall, the effect on GDP per capita is negative and significant. Indeed, any 1% increase in rainfall for the year will support a 0.54% improvement in GDP per capita. However, it should be noted that taking into account the precipitation of the previous year, the GDP per capita of the current year would have decreased by -0.39%. This result could be justified by the fact that the GDP of year t depends largely on the output of year t, which itself depends on the rainfall of the same year. The negative effect on GDP per capita could also be justified by the fact that at time t, the rainfall of the previous year dries up and appears as a drought situation, thus unfavourable to rice production. Moreover, the results of the existence of a positive association between rainfall and GDP per capita are similar to those of (Cabral, 2014), who predicted that Senegal could experience a decrease in poverty due to an expected upward trend in rainfall.

6.5.3. Impact of changes in CO2 emissions on per capita GDP in the rice sector

The current year's CO2 emissions have a positive and significant effect on Senegal's per capita GDP of rice cultivation. In Senegal, the GDP per capita of rice cultivation would have increased by 1.10% if CO2 emissions increased by 1%. On the other hand, any 1% increase in CO2 emissions a year ago would lead to a decrease in GDP per capita of -0.97%. Indeed, the results of the existence of a positive relationship between carbon dioxide (CO2) emissions and rice production are well present in the literature (Wang et al., 2015; Lv et al., 2020; Nasrullah et al., 2021). Indeed, Wang et al. (2015) stated that an increase in CO2 emissions of one percent would lead to a 20% increase in rice yield. In the study of rice yield response to elevated CO2, Lv et al. (2020) state that high atmospheric CO2 may increase rice production in the future, since high CO2 enhances the rice photosynthesis process. In South Korea, the studies indicate that a 1% increase in CO2 emissions can increase rice production by up to 0.15% (Nasrullah et al., 2021). Thus, the results verify the hypotheses of this research.

Table 8: Results of estimates of the impact of climate change on GDP per capita.

Variables	Coefficient	Std.error	T-statistics	Probability
GDP/Capita (-1)	0,77***	0,07	10,62	0,00
lnTEMP	3,52**	1,67	2,1	0,04
lnPREC	0,54***	0,17	3,2	0,00
lnPREC (-1)	-0,39**	0,17	-2,24	0,03
lnCO2/capita	1,10***	0,12	9,14	0,00
lnCO2/capita (-1)	-0,97***	0,13	-7,71	0,00
Cons	-11,92	5,68	-2,10	0,04
R^2	0,9			

Adjusted R^2	0,89
F-statistic	77,47***

Note: *, * and *** indicate significance thresholds of 10%, 5% and 1% respectively.
Source: Author's work using FAO data, 2022.

6.6. Model diagnostic tests

The robustness of the results found is confirmed by the diagnostic tests of the model. Several diagnostic tests are performed including the Durbin-Watson and Breusch-Godfrey autocorrelation test, the White and Arch heteroscedasticity test, the Jarque-Bera normality test and the Ramsey specification test. The Breusch-Godfrey autocorrelation test gives a chi-squared statistic equal to 4.93 with an insignificant probability, indicating that there is no correlation problem in the model. White's and Arch's heteroscedasticity tests present chi-squared statistics of 355.43 and 0.04 respectively with insignificant probabilities, suggesting that there is no heteroscedasticity in the estimated model. The Jarque-Bera normality test has a chi-square statistic of 2.10 that is not significant, suggesting that the data used in the study are normally distributed. The Ramsey test performed to verify the stability of the ARDL model produces an insignificant probability of the chi-square statistic (0.70), the model is considered stable. In addition, the CUSUM test and the CUSUM squared test are used to evaluate the stability of the coefficients shown in Graphs 12 and 13, and the graphical image confirms the result of the ARDL model. Indeed, the test provides a plot of the squares of the cumulative sum of the frequency as a function of time and the pair of critical lines at 5%. The CUSUM and CUSUM square curves are within the critical lines, indicating that the model is stable and the coefficients are suitable for the dependent variable to predict the future.

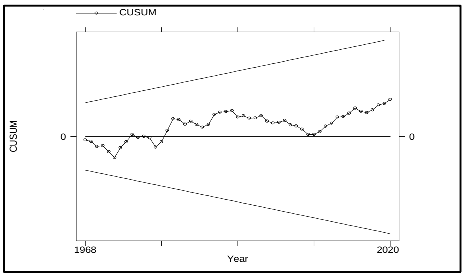
Table 9: Model diagnostic tests.

Test hypothesis	Test	Values (probability)
Autocorrelation	Durbin-WatsonBreusch-Godfrey	2.504,93 (0,10)
Heteroscedasticity	WhiteArch	35,43 (0,13)0,04 (0,84)
Normality	Jarque-Bera	2,10 (0,35)
Specification	Ramsey (Fisher)	0,70 (0,55)

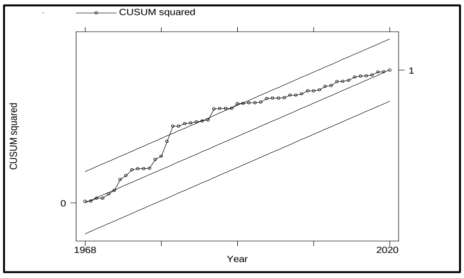
Source: Author's work using FAO data, 2022.

Graph 13: Plot of the cumulative sum of recursive residues.

Graph 12: Plot of the cumulative sum of the squares of the recursive residues.



Source: Author's calculations based on FAO data, 2022.



Source: Author's calculations based on FAO data, 2022.

7. Conclusion

Rice is the main staple food in Senegal, a source of wealth and livelihood for a large number of rural households. That's why it's important to see how climate change might affect its contribution to the economy. To this end, this research examined the short-term effect of changes in climate parameters over the period 1960-2020 using the ARDL approach proposed by Pesaran et al. (2001). The ADF test was applied to verify stationarity before using the ARDL model and the estimated ADF results proved that all variables are stationary at I(0) and I(1). The result of the ARDL binding test revealed the presence of a short-term relationship between the variables and not a long-term relationship. Thus, the short-term estimated elasticity of the ARDL model reveals a significant positive impact of average temperature and precipitation and CO2 per capita. It is concluded that the rise in temperatures during the study period increases the GDP per capita from rice cultivation. The same is true for precipitation, but it seems to have a threshold at which the effect of precipitation on GDP per capita changes sign; this is for example when considering the effect on the previous year. This result is also valid for GDP per capita. In addition, the analysis of the variables revealed that droughts are characterized by a decline in rice GDP, which indicates a dependence of the sector on water. To this end, the development of irrigation could be a good mechanism to deal with the risks of drought.

Although the results of this research indicate a positive effect of temperature and precipitation on the rice sector, future research could be oriented towards the analysis of the impact of its parameters in view of future changes i.e., different climate scenarios.

CHAPTER II: VULNERABILITY OF AGRICULTURAL HOUSEHOLDS TO CLIMATE CHANGE: AN INTEGRATED ASSESSMENT APPROACH ON RICE FARMERS IN SENEGAL

1. Introduction

Africa is one of the most vulnerable continents to climate change and variability because of multiple stresses and its low adaptative capacity (Parry et al., 2007). African agriculture is highly exposed to climate change because of the large number of people active in it and because of its potential to contribute to food security, wealth creation and poverty reduction for a large number of populations. More than half of Senegal's population lives in rural areas and the agricultural sector employs just over 50 % of the total labour force. Agriculture then plays a decisive role in job creation and food, thus in maintaining people's livelihoods. However, agriculture is becoming increasingly threatened by exogenous shocks, different from those it has experienced before. In addition to the constraints long faced such as price shocks, difficult access to inputs, lack of financing among others, are now added other phenomena related to climate change. The most recognized are water scarcity (or drought) and excessive rainfall leading to flooding. Indeed, all these two events can affect the agricultural production process by modifying in particular, the sowing date and the harvest period or even the quantities harvested and the income that could result. Droughts and floods can affect the performance of farm households by causing losses in agricultural production and incomes that can increase the vulnerability of the poorest households. This is why Barnett et al. (2008) and Juana et al. (2013) describe Sub-Saharan African economies as the most vulnerable to climate shocks.

The heavy dependence on rain-fed agriculture in a context of climate change is a major problem in sub-Saharan African countries (SSA). This is the case in Senegal where most of the annual agricultural production takes place over four months (from June to October), with a rainfall regime that varies greatly in time and space. Most crops such as groundnuts, millet, maize, sorghum and rice are grown under rain and are therefore sensitive to temperature variability and rainfall. Thus, difficult access to agricultural inputs (seeds, fertilizers, agricultural equipment), obsolete technologies adopted, the low availability of financing (credit, insurance) and the constraining access to markets for the sale of crops, are posed by climatic risks for agricultural households. The now recurrent climatic shocks, such as drought, late rains or floods remain the major constraints faced by agricultural households in SSA countries. In Senegal, 28% of rice farmers are exposed to climate risks such as rainfall breaks, early cessation of rains, off-season rains, insufficient rainfall or low river flow, and 40% face a drop in production due to reduced rainfall. The known function of agriculture is therefore called into question by climate change and farm households are likely to suffer the very first consequences. Climate change is likely to exacerbate the vulnerability of agricultural households, which are mostly small-scale producers (six out of 10 households) with a total area of less than two hectares. High dependence on rainfall combined with high temperatures and low use of irrigation could reduce households' ability to adapt to climate change. [6]

Despite this, the issue of vulnerability to climate change is not very well documented in the existing literature in sub-Saharan Africa and more particularly in West African countries. The spatial issue is not explicitly developed, so that policymakers can neither distinguish between households most vulnerable to climate change and households with low levels of vulnerability, nor know their geographical location.

However, without knowledge of the vulnerability of the agricultural, tourism, health, etc. sectors and human and ecological systems, the implementation of Nationally Determined Contributions (NDCs) will remain mixed because it will not be guided by reliable information on the degree of vulnerability, its spatial distribution and its evolution over time. To the extent that information on exposure to climate change, the sensitivity of communities and their capacity to adapt is not known, any climate policy related to adaptation is doomed to failure because it does not guarantee effectiveness. To this end, quantifying and understanding the impacts of climate change remains urgent and very crucial because it provides important indications on how much money should be spent on mitigation and where, when and how adaptation should be implemented (Mendelsohn, 2009). Indeed, in an effort to reduce vulnerability to climate change in rural areas, assessing the vulnerability of rice communities in Nghe An was seen as a crucial step to provide policymakers with useful complementary materials to address and mitigate environmental risks (Sujakhu et al., 2019).

In response to this knowledge gap on climate change in West Africa, this research focuses on assessing the vulnerability of farm households to facilitate the implementation of adaptation policies in the agricultural sector in an effective and efficient manner. It uses the spatial and temporal dimension taking into account different parameters such as, physical and biophysical, sociodemographic, technological and institutional, in order to provide geo-localized information on how farm households are affected by climate change, thus facilitating that the targeting of the most vulnerable groups becomes easier for policy makers. This research is particularly interested in rice farmers in the Senegal River Valley and the Anambé Basin, two agro-ecological zones with high rice production potential but different climatic conditions and are now threatened by the drying up of surface water and the decline in rainfall, which could considerably reduce the production of rice, which is a staple food widely consumed in Senegal.

6 This statement is based on survey data used in this research.

The results of this research could be a good guide for adaptation policies for agriculture in general, and more specifically in the area of rice cultivation.

Indeed, this research provides documentation on climate change in West Africa and Senegal and helps to fill this growing need for reliable information and results that decision-makers could rely on to implement climate plans. One of the particularities of this research is that it draws on the brand-new vulnerability assessment method proposed by Zebisch et al. (2021) and the Sustainable Development Goals (SDGs) indicators by providing detailed, geographically explicit information on who and where the most vulnerable agricultural producers are located. It uses geographic information systems to better understand the spatial distribution of vulnerable households in the territory but also to guide climate change adaptation policies towards the most vulnerable localities. The GIS approach is much more realistic than the use of graphs because it allows indicators such as potential impact and adaptability to be cross-referenced and compared with the vulnerability map, which could easily show the compensation effects between components.

2. Research objectives and hypotheses

2.1. General objective

The main objective of this work is to measure the vulnerability of agricultural production sites to climate change.

2.2. Specific objectives

More specifically, this research consists of:

(i) design a composite index resulting from sub-components of vulnerability such as exposure, sensitivity and adaptive capacity of farm households;

(ii) Mapping using geographic information systems (GIS) tools to show the geographic distribution of vulnerability to climate change.

2.3. Research hypotheses

The assumptions underlying this research are as follows:

a. Due to the specificities of localities in terms of meteorological, demographic, socio-economic, institutional and resource endowment, exposure levels and sensitivity and adaptive capacity are different from one locality to another and therefore vulnerability to climate change differs geographically from one area to another.

b. Vulnerability can be reduced by offsetting indicators; In other words, a high potential impact could be offset by a high adaptive capacity to allow the household to find itself in a situation of low or moderate vulnerability.

3. Literature review

3.1. Theoretical review

Sub-Saharan African countries heavily dependent on agriculture are threatened by the climatic conditions of the 21st century. The rise in global temperature and the high variability of rainfall would have severely affected the living conditions of people, especially agricultural households. According to the Intergovernmental Panel on Climate Change, climate change will affect agricultural production and food security (Parry et al., 2007). Indeed, the multiplicity of climate risks poses a problem for the development of rural populations in Sub-Saharan African countries (SSA). To this end, the issue of vulnerability needs to be studied very carefully to better guide climate change adaptation policies. Vulnerability assessment identifies the social, economic and environmental causes of a disaster (Zarafshani et al., 2016). It can be a focal point for the implementation of appropriate adaptation measures to mitigate the negative consequences of climate change. However, it is good to understand that vulnerability is a complex and multidimensional concept and is addressed in different research communities in different ways. The concept of vulnerability originates from latin *vulnus* and *vulnerare*, which mean injury and injury respectively. Simply put, vulnerability refers to the potential to suffer injury. Starting from the sciences, the concept of vulnerability has its roots in geography and research on natural hazards, but over time it has been extended to several other disciplines such as disaster management, development economics, environmental, health and nutritional sciences and more recently in the field of climate change. However, due to its multidisciplinary nature, it is conceptualized differently between disciplines and the methodologies adopted for its evaluation are also different.

In terms of terminology, the terms vulnerability, sensitivity, resilience, adaptation, adaptive capacity, risk, hazard, flexibility, adaptation baseline, are used interchangeably (Field & Barros, 2014; Kelly & Adger, 2000; McCarthy et al., 2001; Parry et al., 2007) but the relationships between these expressions remain ambiguous. The relationship between these terms is often not very clear, and the same term may not have the same meaning when used in different contexts and by different authors. For example, while environmental researchers focus on the concept of risk, social science and climate change authors often prefer to use the term vulnerability (Allen, 2003). However, although social scientists and climate scientists use the same term "vulnerability," the concept is not interpreted in the same way. In the social sciences, vulnerability refers to socio-economic factors that determine people's ability to cope with stress or change (Allen, 2003), while climatologists often consider vulnerability in terms of the probability of occurrence and impacts of weather and climate events (Klein & Nicholls, 1999). Referring to methodological approaches, while natural scientists study vulnerability descriptively, social scientists use specific explanatory models (Fuessel, 2005) but also statistical applications to calculate, analyze, anticipate risks, and measure their impact.

Moreover, even within the same sphere of research, vulnerability is conceptualized and applied in different ways (Brooks, 2003; Fuessel, 2005). This is the case, for example, in the field of climate change, where the concept of vulnerability has developed rapidly both conceptually and methodologically. According to Adger et al. (2004), it can be assessed from a social, economic, physical or environmental perspective or according to the hazard in question as indicated by . On the other hand, Moss et al. (2001) considers, in addition to the physico-environmental and socio-economic dimensions, parameters related to external aid. The United Nations, for its part, identifies four groups of vulnerability factors, including physical, economic, social and environmental factors. Contrary to the conceptualization of Moss et al., 2001; Adger et al., 2004) and the UN system do not take into account the external dimension; This seems more in line with vulnerability assessment at the local level, for example among farmers.

The analysis of the vulnerability of human and natural systems to climate change and variability, as well as their ability to adapt to changing climate risks, is a relatively new field of research, bringing together experts from a wide range of fields, including climatology, development studies, disaster management, health, social sciences, policy development and economics, among others (Brooks, 2003). To this end, there is a rich literature on the conceptual level, which can thus be classified according to three approaches: socioeconomic, biophysical and integrated.

3.1.1. Socio-economic approach to vulnerability

Based on the socio-economic approach, vulnerability is then defined as a function of the socio-economic and institutional variables of individuals or communities (Adger, 1999; Füssel, 2007). With this in mind, vulnerability analysis is carried out following a diagnosis of the initial state of the system, well before it is affected by an event likely to modify its state still called starting point (Kelly & Adger, 2000). However, this approach has a limitation.

The socio-economic approach to vulnerability simply tells us about the differences between individuals or groups of individuals in terms of their socio-economic and institutional characteristics, but does not take into account environmental factors, which may influence the activities of its individuals. The magnitude of environmental shocks such as drought and floods and the resource endowments of the environment in which individuals live can also justify the particularity of vulnerability between individuals or communities. For this purpose, two social groups may have the same socio-economic characteristics but different environmental attributes and therefore different levels of vulnerability and vice versa (Deressa et al., 2008). For example, for individuals with similar socio-economic characteristics and equal natural resource endowments, vulnerability would have varied depending on the severity of the shock they face. Thus, to take into account the potential influence of environmental variables on the state of individuals, the biophysical approach was developed by the authors.

3.1.2. The biophysical approach to vulnerability

The biophysical approach to vulnerability involves assessing the impact of environmental changes on social and biological systems (Deressa et al., 2008). This is for example when trying to assess the impact of climate change on certain outcome variables such as agricultural yield (Adams, 1989; Kaiser et al., 1993) or on farm income (Mendelsohn et al., 1994; Polsky & Easterling III, 2001; Dinar, 1998). The biophysical approach relates economic and social indicators to climatic variables such as temperature and precipitation, since any variation in these variables can lead to losses or gains in productivity and well-being, which can also be valued monetarily. Indeed, as climate change is a global phenomenon with multivariate consequences, its impacts do not spare any sector of economic and social life. To this end, the biophysical approach to vulnerability is used to measure the impact of climate change on the social well-being of individuals and communities. This is the case, for example, with studies that show how climate change affects human mortality and health terms (Du Toit et al., 2001), the availability of food and water (Martens et al., 1999; Xiao et al., 1997) and ecosystem damage (Forner, 2006).

Unlike the socioeconomic approach, which is a starting point analysis, the biophysical approach is considered an endpoint analysis (Kelly & Adger, 2000c); that is, it measures the extent or extent of the damage caused by climate change. However, while providing an instructive explanation of how to assess the impact of climate change, the biophysical approach also has a number of limitations.

The main limitation of this method of analysis is that it quantifies physical damage without distinguishing between different strata of the population, for example between rich and poor. The biophysical approach ignores the difference that may exist in terms of the ability to mitigate climate shocks affecting two groups of individuals with unequal income levels. In the event of a climate disaster resulting in a loss of 50% of crops, poor farmers will feel the damage much more than rich farm households who, despite their savings or other assets, can mitigate this loss by smoothing their consumption or by reducing certain costs (Deressa et al., 2008). Thus, to bridge the limitations of these two approaches, integrated analysis was considered the most comprehensive.

3.1.3. The integrated approach to vulnerability

The integrated approach combines socio-economic and biophysical indicators to measure vulnerability to climate change. Indeed, if the biophysical approach called risk-hazard analysis indicates sensitivity in IPCC terminology (Füssel & Klein, 2006) and, the socio-economic approach provides information on the level of social development or adaptive capacity (Füssel, 2007), the integrated approach reveals a much broader angle of analysis by combining the three components of vulnerability such as exposure, sensitivity and adaptive capacity. To this end, Füssel (2007) and (Füssel & Klein, 2006) argue that this method of analysis best suits the Intergovernmental Panel on Climate Change definition of vulnerability. The IPCC's Fourth Assessment Report (AR4) defines vulnerability as the degree to which a system is susceptible and unable to cope with the adverse effects of climate change, including climate variability and extreme events. It considers vulnerability to be a function of the nature, magnitude and rate of climate change and variation to which a system is exposed, its sensitivity and adaptive capacity (Parry et al., 2007). Indeed, in addition to these three indicators, an intermediate component "potential impact" has been added in agreement with (Schröter et al., 2005; Metzger & Schröter, 2006). However, this definition has undergone slight changes over time, notably with the publication of the IPCC's Fifth Assessment Report. In this IPCC-AR5 WII report (Field & Barros, 2014), the authors introduced a new concept of "climate risk", which is relatively closer to the disaster risk community (Zebisch et al., 2021).

By way of comparison, while AR4 considers vulnerability as the outcome variable, the IPCC's fifth report uses the term risk, to which vulnerability is a determinant. In AR4, vulnerability is a function of three components – exposure, sensitivity and adaptability, while in AR5, vulnerability is one of the components of risk and a function of sensitivity or fragility to damage and lack of capacity to cope and adapt. Risk is an interaction between hazard, exposure and vulnerability (Field & Barros, 2014) and marks the potential for consequences when something of value is at stake and the outcome is uncertain.

a. Concept of exposure to climate change

The exposure defined in IPCC AR4 indicates the character, magnitude and rate of climate change and variation to which a system undergoes. Exposure typically includes factors such as temperature, precipitation, climate water balance, and extreme events such as heavy rainfall or weather droughts. Moreover, it is clear that both rising temperatures and decreasing rainfall are detrimental to African agriculture, which is already subject to heat and water scarcity (T. Deressa et al., 2008). Thus, the authors point out that regions where temperature is higher and precipitation decreases have been identified as the areas most exposed to climate change.

Although, this exposure parameter is also taken into account in the IPCC AR5, it must be understood that the turn of phrase does not remain the same. Exposure in AR5 is the presence of people, livelihoods, species or ecosystems, environmental functions, services and resources, infrastructure or economic, social or cultural assets in places that are likely to be negatively affected.

Indeed, there is a paradigm shift, the exposure function of the previous report is substituted for the term hazard (or chance) which represents the potential occurrence of a meteorological or climatic physical event or trend, or a physical impact likely to cause damage such as loss of life, injury, adverse health effects, and loss and damage of property, infrastructure, livelihoods, ecosystems and environmental resources.

b. Concept of sensitivity to climate change

Sensitivity determines the degree to which a system or species is negatively or beneficially affected by a given climate exposure. In the IPCC concept, sensitivity can be determined by three groups of factors:

- natural/physical factors of a system such as ecosystem types, land cover, slope, water holding capacity and soil erodibility;
- natural/physical factors related to human land management activities and infrastructure, such as the existence and quality of, terraces, irrigation systems, houses, roads, power grids and;
- societal factors, such as population density or age structure.

c. Concept of potential impact

Potential impact is an intermediate subcomponent that combines the effects of exposure and sensitivity without any additional adaptation activities (Zebisch et al., 2021). For example, the authors estimate that yield loss (potential impact) may be caused by crop exposure to torrential rainfall combined with environmental sensitivity due to steep slopes and sandy soils, resulting in erosion and loss of land. Indeed, the impacts of climate change can be classified into two groups: direct impacts and indirect impacts. Direct impacts include damage caused by an increase in the frequency of coastal flooding due to rising sea levels, drought or excessive rainfall, while an indirect impact is for example the loss of income due to a reduction in agricultural yields due to a change in temperature.

d. Concept of adaptability

Adaptive capacity describes the ability of human, institutional or ecosystem systems to adjust, enabling them to guard against possible damage, mitigate the adverse effects of climate change, and take advantage of opportunities. It is determined by economic and governance factors, and knowledge and use of available ecosystem and technical adaptation options (Adger et al., 2004; Preston et al., 2009). Contrary to the definition in the IPCC Fourth Assessment Report (M. L. Parry et al., 2007), autonomous adaptation of ecosystems is explicitly excluded, which, according to the author, is part of sensitivity. According to Zebisch et al. (2021), the AR4 and AR5 reports present different terminologies, but the general idea is the same; that is, "to understand the underlying root causes of potential negative climate impacts, including factors following climatic, natural, physical and socio-economic factors". However, it must be understood that even if the IPCC AR5 makes slightly different changes in terminology, these changes will upset the basic conceptual approach and affect the assignment of variables between subcomponents. Concepts are often intertwined, leading to considerable confusion regarding conceptualizations of vulnerability to climate change (Füssel, 2010). Fortunately, the authors have developed a reference guide containing a set of instructions on how the IPCC AR5 approach to climate risks can be applied (see for example, Adger et al., 2018; Zebisch et al., 2021).

Although the integrated approach is the measure most in line with the IPCC definition, it has been criticized by some authors. Cutter et al. (2012) highlight one of the concerns of this approach, which is the lack of a common metric to determine the relative importance of each aspect of vulnerability-social and biophysical-or the individual variables that compose it. The weights of socio-economic and biophysical variables are different and often unknown, posing problems for the weighting and combination of components to determine the outcome indicator (T. Deressa et al., 2008). Potential changes in adaptation are ignored, resulting in the integrated approach providing a static state of vulnerability without taking into account opportunities that may increase their adaptive capacity (Campbell, 1999; Eriksen & Kelly, 2007) and consequently reduce their level of vulnerability. However, this review by Campbell (1999) and

Eriksen & Kelly (2007) is now considered by the adaptive capacity sub-component and the dynamic aspect of vulnerability can be illustrated with the use of climate scenarios.

Moreover, despite the limitations of the integrated approach, it is most in line with the conceptualization of vulnerability in the latest IPCC reports and receives a great deal of attention in climate policymaking. The integrated approach currently remains the most used by climate change researchers, because it provides an analytical framework in line with the IPCC definition and gives a much more realistic idea given the variables used such as socio-economic, biophysical and institutional. To this end, there is a flourishing literature on vulnerability assessment methodology.

3.2. Empirical review

Methodologically, two main assessment techniques have been developed to measure vulnerability to climate change: the econometric method and the indicator method. While the econometric method assesses the following variables from three different angles of analysis, including vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU), or vulnerability as uninsured exposure to risk (VER) (Hoddinott & Quisumbing, 2003), the indicator approach combines a set of variables to create a vulnerability index.

3.2.1. The variable method or econometric method

This involves measuring the change in the socio-economic characteristics of households, such as consumption or income, as a result of exposure to exogenous shocks such as drought, floods or other parameters such as temperature increase. The econometric assessment method of vulnerability to climate change is an approach to analyzing poverty induced by climate shock in accordance with the definition of Chaudhuri et al. (2002) indicating that, vulnerability is the propensity to experience a well-being shock, bringing the household below a socially defined minimum level. To this end, three econometric models were identified by Hoddinott & Quisumbing (2003) on the basis of three "poverty-utility-risk" concepts: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU), and vulnerability as uninsured exposure to risk (VER). The three methods have one thing in common in that they construct measures of loss of well-being due to stress or risk, but they differ in that the VEP and the VEU measure the ex-ante probability that a household's consumption, income or utility will eventually fall below a given threshold because of current or past shocks. while VER measures ex-post welfare loss due to shocks (Deressa et al., 2008; Hoddinott & Quisumbing, 2003). Much more extensive documentation on models and their applications has been developed by Hoddinott & Quisumbing (2003) and Hoddinott & Quisumbing (2010).

However, based on the terms of Hoddinott & Quisumbing (2003), which express that the analysis of vulnerability to climate change is a research phase that "allows a hundred flowers to flourish", with many definitions and approaches, but without agreement on a preferred measure (Harttgen & Günther, 2007), this part of the research is particularly interested in the index method, which offers an analytical approach relatively more suited to support for decision-making in climate change adaptation policies.

3.2.2. The indicator method

The index method is a measure of vulnerability based on a set of socio-economic and biophysical variables selected and combined to give a composite indicator. This analysis technique differs from the econometric approach in its methodological design and in its diversity of analytical scales. While the econometric method makes it possible to estimate the probability of being vulnerable to a climate shock, or the determinants of losses caused by its shocks at the level of an individual or a household, the index method constructs a composite indicator according to a variety of scales such as, at the local level (See Adger, 1999; Gbetibouo et al., 2010; Morrow, 1999), national (Brooks et al., 2005; o'Brien et al., 2004), regional (Leichenko & O'brien, 2002) or worldwide (Moss et al., 2001; Brooks et al., 2005).

Although several generic vulnerability metrics have been proposed in economic and agricultural studies to determine the vulnerability of a given place or group of individuals (Schimmelpfennig & Yohe, 1999; Pritchett et al., 2000; Heitzmann et al., 2002), however, they are insufficient and incomplete to fully grasp the three dimensions of vulnerability (Luers et al., 2003). The indicator approach provides much more detailed information on the different factors that make up vulnerability, including household sensitivity, exposure to risk and ability to adapt to climate change. The calculated composite index can be illustrated by a simple graph (see for example, Deressa et al., 2008) or by a map using geographic information systems (GIS) tools showing the spatial distribution of vulnerability (see, for example, o'Brien et al., 2004; Gbetibouo et al., 2010; Sehgal et al., 2017). Vulnerability analysis in map form facilitates communication of the spatial nature and extent of the problem, and provides a visual reading of climate change exposure, household sensitivities and adaptive capacity to the risks to which they are exposed. To this end, the GIS approach is used in this research to better illustrate the spatial distribution of vulnerability to climate change in the rice sector in Senegal.

Thus, to understand the state of play on the issue of vulnerability and the results provided by scientists, this research reviews a set of studies previously developed by researchers on the basis of different methodological approaches.

First, the theoretical literature is based on the unanimous conviction that climate change increases the vulnerability of rural households, especially since it is a constraint on wealth accumulation for these individuals whose livelihoods are intrinsically linked to the agricultural sector (Barnett et al., 2008; Parry et al., 2007). Poor households are the population group most vulnerable to the impact of climate change (Juana et al., 2013), given their low adaptive capacity.

Empirically, although the studies were carried out in different geographical areas and sometimes with different assessment methods depending on the author, the results indicate that climate change negatively affects the living conditions of agricultural households (see for example, Deressa et al., 2008; Tessema & Simane, 2019; Zeleke et al., 2021). Indeed, several factors have been identified as sources of vulnerability to climate change, including climatic and non-climatic factors.

3.2.3. Climate factors of vulnerability

Climate shocks and other factors can negatively or positively affect a community, and the effects of climate shocks can be different due to variation in geographic characteristics and ability to cope with shocks (Pörtner et al., 2022); Intergovernmental Panel on Climate Change (IPCC), 2007; IPCC, 2014). In agriculture, many global scientists indicate that farmers are exposed and highly sensitive to variations in rainfall and temperature, as well as to the direct effects of climate change such as droughts and floods (Adams, 1989;(Arouri et al., 2015);(Aryal et al., 2020); Iizumi et al., 2018 ; Mahmood et al., 2019;(Nguyen & Leisz, 2021);(Ortiz-Bobea et al., 2021);(Salik et al., 2015); Sultan et al., 2019;(Tjoe, 2016). In addition, non-climatic factors can influence the vulnerability of farming communities, either positively or negatively.

3.2.4. Non-climatic factors of vulnerability

The Sustainable livelihoods approach (SLA) introduced by the Department for International Development (DFID), takes a participatory approach and considers the connection of different types of shocks to livelihoods, access to different types of assets to adapt to climatic hazards, intervention programs, and policies to maintain sustainable livelihoods. The concept and framework of the sustainable livelihoods approach adopted by DFID in the late 1990s involves the relationships between five types of assets, including human assets (e.g., health, education and training), physical assets (e.g., roads, water, bridges, equipment, machinery and livestock), social assets (e.g., social network and support), financial assets (e.g. savings, credit, insurance, remittance) and natural assets (e.g. land, water, soil, forests and fisheries (Dfid, 1999). Thus, the presence (or absence) of one of these assets could lead to a reduction (or increase) in the vulnerability of populations. According to (Sonwa et al., 2017) and (Basupi et al., 2019), rural communities with poor transport networks, limited access to markets or information, and fewer alternative livelihoods, are less aware of risks and are poorly supported in the event of extreme weather events. In a study in Benin, Lokonon (2019) finds that, lack of financial capital and access to water to implement irrigation, lack of institutional support through extension services, difficult access to credit , low human capital, are factors that weaken the means of subsistence to climatic shocks, due to the fact that the latter are highly dependent on rain-fed agriculture. Indeed, several scientists have confirmed that, in addition to climatic events, factors such as age, education, gender, property, occupation of the head of household, household size, sources of income, access to credit, remittances, social benefits, land tenure, machinery, transport vehicles, social networks, associations, and weather forecast information have had a significant positive impact on the livelihoods of farming households (Arouri et al., 2015);(Huynh & Stringer, 2018; Lokonon, 2019; Nguyen & Leisz, 2021; Tran et al., 2022). For example, in terms of age, ageing farmers were more vulnerable than younger farmers because they were less likely to engage in alternative livelihoods; aging farmers face health problems and have fewer opportunities to seek additional income (Tran et al., 2022). In China, the work of He et al. (2021) found that social support, irrigation rate, gender, cooperative membership, education level, workforce, endowments, farm size, and financial subsidies significantly influenced the adaptive capacity of farm households to cope with natural hazards (He et al., 2021). Education is therefore one of the key factors in adapting to climate change. Results from Lokonon (2019); Tran et al. (2022) indicate that education has strengthened households' capacities to reduce vulnerability and improve their livelihoods. According to Tran et al. (2022), an additional year of education for farmers would reduce their livelihood vulnerability index (LVI) by -0.21% points. On the other hand, climate change can also negatively affect the educational level of farmers' children (Evariste et al., 2018; Fuller et al., 2018). The gender variable has mixed results in the literature. While some authors have indicated that women have been found to be less vulnerable than men (Nguyen & Leisz, 2021), others have found that women have been found to be more vulnerable than men (Aryal et al., 2020). Others indicate that men have been shown to be vulnerable to climate change, while women have remained intact (Hanaoka et al., 2018). In addition, abundant water sources and access to irrigation, the presence of communication technologies and access to extension services are also important aspects that can improve the resilience of farm households. In the Greater Mekong Subregion, for example, water supply, communication, training and other services have been factors that have strongly influenced farmers' adaptive capacity and reduced the level of vulnerability of farming communities to climate change (Kuntiyawichai et al., 2015; Tran et al., 2022). The development of human, social, physical, financial and natural capital is therefore important to improve the resilience of farm households. On the other hand, the low presence or absence of these assets in a community could further disadvantage the situation of individuals. Non-climatic stressors such as lack of access to production inputs and land, lack of education and limited sources of income, exacerbate food insecurity in many parts of the continent (Evariste et al., 2018; Fuller et al., 2018). In addition, other authors take into account the geographical dimension and argue that geographical and social isolation is another type of social vulnerability, especially for pastoralist communities in eastern and southern Africa (Sonwa et al., 2017; Basupi et al., 2019), hence the importance of using geographic information systems to better see the geographical distribution of vulnerability to climate change according to access to social and institutional infrastructure and services.

However, even though there is a growing literature on vulnerability to climate change, little research is focused on sub-Saharan Africa (SSA) and has not provided concrete solutions to the problem. Existing information on the vulnerability of smallholder farmers to climate change is incomplete and insufficient to guide effective and efficient adaptation actions targeting this important social group. Indeed, the conclusions are often made in a general way and do not address the issue of priority in terms of adaptation. Thus, although a large number of studies have addressed the issue, most of them have been carried out in a limited number of sub-Saharan African countries. With the exception of studies in Ghana (see, Asante & Amuakwa-Mensah, 2014; Dasgupta & Baschieri, 2010; Derbile & File, 2016), little research has been done in West Africa, despite the multiplicity of climate risks. In West Africa, most studies on climate change focus on households' perception of climate risks, which is merely an assessment and provides information on the degree of exposure of households to climate change, their sensitivity to shocks or their capacity to adapt (see, for example, Apata et al., 2009; Fosu-Mensah et al., 2012; Kurukulasuriya & Mendelsohn, 2007; Mertz et al., 2009). Other research has examined the determinants of adaptation action, leaving a knowledge gap on the effectiveness of the options adopted and the benefits that could result, for example in terms of improved well-being. With the exception of some authors, some authors have attempted to assess the impact of adaptation measures on agricultural production (Yesuf et al., 2008; Di Falco et al., 2011) or on farm household incomes (Ojo & Baiyegunhi, 2020). Although their research shows the importance of the use of adaptation measures particularly in terms of increasing yields and incomes, it must be understood that these results are not sufficient to guide adaptation policies because they do not give any idea of the status or level of vulnerability of individuals and where they are. In addition, many of these studies ignore biophysical and ecosystem variables, which are not without effect on the agricultural activity of the household. Variables related to accessibility to infrastructure are often not taken into account by some authors, leaving a gap.

To this end, this research aims to fill this gap by using a set of socio-economic, biophysical, topographical, ecosystem and institutional variables that will be combined to create a composite indicator of vulnerability. This research uses the methodology suggested by Zebisch et al. (2021) and provides a detailed approach to vulnerability with the use of Geographic Information Systems which are analysis and decision support tools, to facilitate visualization of a problem in space. With GIS, results can be mapped overlaid to detect compensation relationships between components such as exposure and sensitivity or potential impact and adaptability. The results of this research could guide policy makers for priority and effective implementation of adaptation policies in the agricultural sector.

4. Vulnerability index construction methodology

The indicator method is used in this research to calculate the vulnerability index of agricultural households. It is a question of constructing a composite indicator from a set of socio-economic, biophysical, ecosystem and institutional parameters. The index is constructed by following eight steps, including repair of vulnerability assessment, development of impact chains, identification and selection of indicators, identification and management of data, standardization of indicators, first weighting and aggregation to determine exposure, sensitivity and adaptability, second weighting and aggregation to give the potential impact and vulnerability index.

4.1. Preparing for the vulnerability assessment

This phase consists of defining the context and scope of intervention of the evaluation, the time scale, the target group and the methodological approach to be adopted. This research work is part of a context where the activities of agricultural households are strongly threatened by climate change, especially with rising temperatures and decreasing rainfall, sometimes leading to long periods of drought. Climate change is becoming a huge problem, especially in rural Senegal, where two out of three households are already food insecure. Given this, it seems relevant to conduct scientific research on the issue of vulnerability in order to produce results that could help policymakers take appropriate adaptation measures in the agricultural sector. As the agricultural sector is characterized by a different set of types of activities and crops, this research targets rice farmers in the Senegal River Valley and the Anambé Basin, which are two different agro-ecological zones, likely to be exposed to climate change and variability due to their dependence on rainfall and surface water whose availability is currently at stake. Indeed, the vulnerability indicator is calculated on the basis of individual household variables such as socio-economic, institutional socio-demographic, which are aggregated at the municipal level and then combined with a set of factors relating to the slopes of the environment, the area of irrigated land, the types of soil, temperature and precipitation data and indicators of accessibility to roads, markets and health facilities.

4.2. The development of the impact chain

An impact chain is an analytical tool to better understand the cause-and-effect relationship between drivers and inhibitors that affect vulnerability (Fritzsche et al., 2014; Zebisch et al., 2021). The approach of the fourth IPCC report is therefore preferred because it describes the impact chain by indicating the link between the different components of vulnerability. Climate change exposure (E) and system sensitivity (S) are grouped together to have potential impact (PI), which in turn combine with adaptive capacity (CA) to determine the end result that constitutes the vulnerability index. The description of the impact chain helps to visualize the interrelationships and feedbacks between the indicators, allows the identification of key impacts and at what level they occur (Zebisch et al., 2021). According to the authors, this impact chain analysis helps to clarify and/or validate the objectives and scope of vulnerability assessment is a useful element for involving stakeholders. Moreover, the visualization of the interrelationships between the components – exposure, sensitivity and adaptability – can be done by cross-mapping all these components on the same map. In this case, compensation effects will be easily detected.

4.3. Identification and selection of indicators

The identification and selection of indicators is based on existing literature on the vulnerability of farm households to climate change, expert opinion, or a combination of both. As vulnerability factors are exposure, sensitivity and adaptive capacity, meteorological, socio-economic, physical and ecological variables are then assigned to these different components.

Exposure indicators largely consist of directly measured or modelled climate parameters such as mean temperature, amount and distribution of precipitation, or evapotranspiration data. Because exposure is related to the degree of climate stress experienced by a particular unit of analysis, it can therefore be represented either by long-term changes in climatic conditions or by changes in climate variability, including the magnitude and frequency of extreme events (o'Brien et al., 2004). The parameters used are mostly daily, monthly or annual; this is for example the case of studies by Wiréhn et al. (2015)which use annual changes in temperature and precipitation, Gbetibouo et al. (2010) which consider the frequency of droughts or floods, the change in temperature and precipitation compared to a base period (1961-2000), Žurovec et al., (2017) which use the changes in average annual temperatures and changes in average annual precipitation between two reference periods (1960-1990 and 1981-2010), and Theodrose (2016) which consider data of daily maximum temperatures from the period 1980-2010.

Components of risk sensitivity are generally biophysical or physical factors such as vegetation cover type and density, soil type, elevation and/or slope gradient, and irrigation capacity or systems used (Fritzsche et al., 2014; Zebisch et al., 2021). However, sensitivity can also be related to factors other than biophysical ones, such as demographic parameters such as the number of children in the household or the number of people of advanced age.

Adaptive capacity, on the other hand, is composed of a set of economic, social and institutional indicators. Variables such as household involvement, organization organizations, access to agricultural advice, access to agricultural insurance, number of adults aged 15 to 65, access to formal education, average distance from the hospital, number of households within two (2) kilometers of a main road, access to electricity, access to credit, access to subsidized equipment, Access to subsidized fertilizers, access to subsidized seeds, farm income, are used. Since two individuals can be distinguished between their level of education, gender, health status, wealth, access to credit or information and technology services (Deressa et al., 2008), their coping capacities may therefore be different.

4.4. Data acquisition and management

The data needed to quantify indicators of exposure, sensitivity and adaptability come in a variety of forms, from different sources and are collected using different methodologies. The data used are quantitative and qualitative and come from various organizations. They can be classified according in four factors such as climatological, ecosystemic, socio-economic and institutional that can be divided according to vulnerability components such as exposure, sensitivity and adaptive capacity.

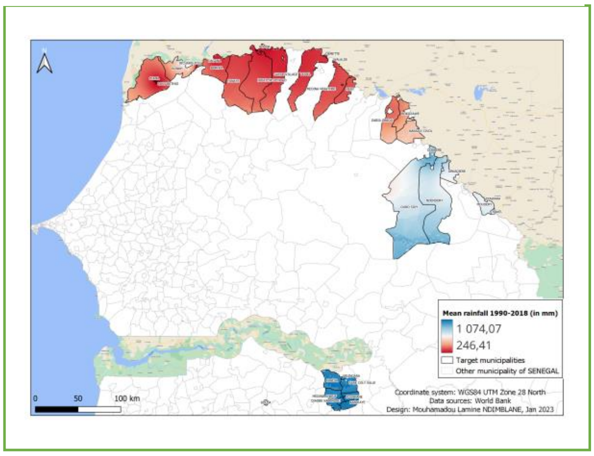
4.4.1. Exposure indicators

4.4.1.1. Climate parameters: rainfall and temperatures

Exposure to climate change is captured by both climate parameters, including temperature and precipitation. The data used in this research come from an updated gridded climate dataset called CRU-TS 4.03 constructed from monthly observations at weather stations across terrestrial regions of the world (Harris et al., 2020). Additional techniques were used using ArcGIS software to sample and then inverse distance weighting (IDW) to obtain the data at the local scale, including in the 33 target municipalities of the study. The time scale considered is from 1990 to 2018, i.e., 29 years. Thus, to see climate change, a comparison is made with the meteorological data observed over the last decade.

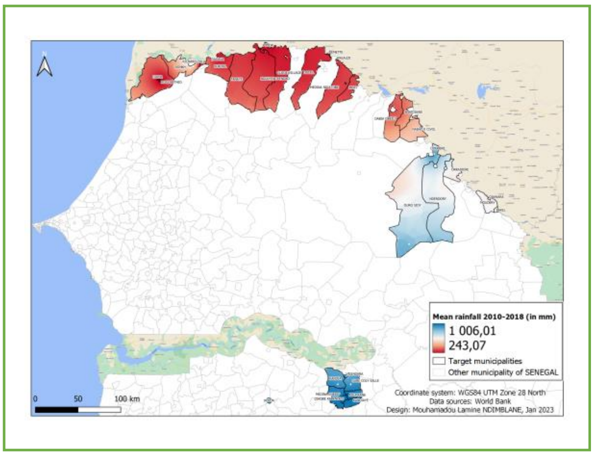
Map 2 shows the average precipitation in millimeters (mm) recorded in the different localities of the study area over the period 1990-2018, while Map 1 provides an overview of the average precipitation observed over the period 2010-2018. The results of the cartographic modelling of precipitation show that rainfall is more intense in southern Senegal with rainfall of up to 800 to more than 1000 mm, than in the north where rainfall is low (about 240 to less than 500 mm), while in the east rainfall varies on average between 500 and just under 800 mm. Compared to the reference period 1990-2018, precipitation decreased in recent years (2010-2018), from 1074.07 mm to 1006.01 mm (a decrease of -6.33%). The decrease in rainfall is much more apparent in the South, in the Anambé basin, particularly in the communes of Vélingara, Kandia, Sare coly salle, and in eastern Senegal in the river valley, more particularly in the communes of Ouro sydi, Ndendory, Odobère, Orkadière, Diawara, Moudéry, and Bakel (see Map 1 and Map 2).

Map 1:Average annual precipitation, 1990 -2018, in millimeters (mm).



Source: Author's work using World Bank data, 2023.

Map 2: Average annual precipitation, 2010-2018, in millimeters (mm).

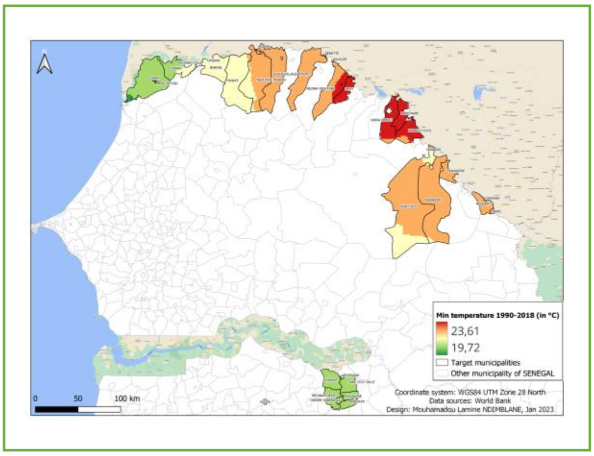


Source: Author's work using World Bank data, 2023.

Maps 3 and 4 give an illustration of the average minimum temperatures of the periods 2010-2018 and 1990-2018 respectively, while maps 5 and 6 provide spatial distribution of the mean maximum temperatures of the periods 2010-2018 and 1990-2018 respectively. The observation is that the highest minimum temperatures (23 °C and more) are recorded in the regions of Dabia obédji, Bokidiawé, Nabadji civol and Mery, while the communes located in the north-east (Diama and Ross bethio) and in the south (Kolda, Medina cherif, Kandiaye, Diaobé Kabendou, Kounkane, Kandia, Saré coly salle and Vélingara) have relatively lower minimum temperature levels (about 20°C). Compared to the reference period 1990-2018, minimum temperatures have increased in recent years (2010-2018), from 23.61°C to 23.68°C, an increase of +0.07°C. The changes are more noticeable in the communes of Dabia obédji, Bokidiawé, Nabadji civol Medina Ndiathbé, Ndiayene Pendao, Ronkh (see map 3 and 4).

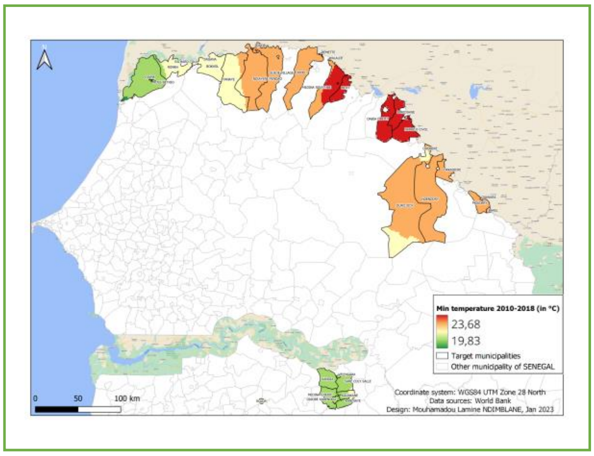
Average maximum temperatures have also increased over time, from 38.17°C in the period 1990-2018 to 28.41°C in the period 2010-2018, an increase of +0.24°C. The changes are observed in all localities but more particularly in the localities located in the East such as Ouro Sydi, Ndendory, Orkadière, Dabia obédji, Bokidiawé, in the North in particular in Dodel and in the South in Vélingara, Kandia, Sare coly salle (see map 5 and 6).

Map 3: Average minimum temperature, 1990-2018, in degrees Celsius (°C).



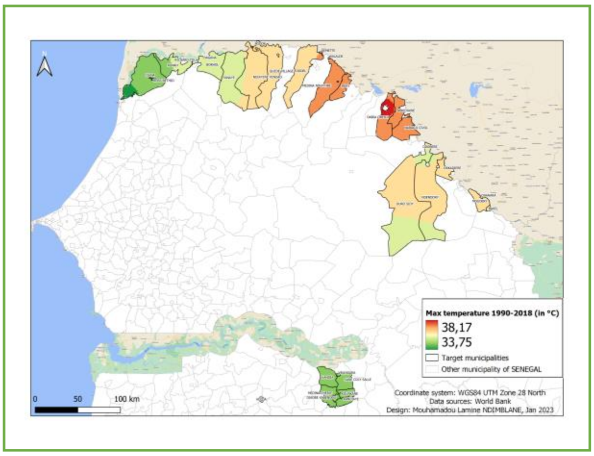
Source: Author's work using World Bank data, 2023.

Map 4: Average minimum temperature, 2010-2018, in degrees Celsius (°C).



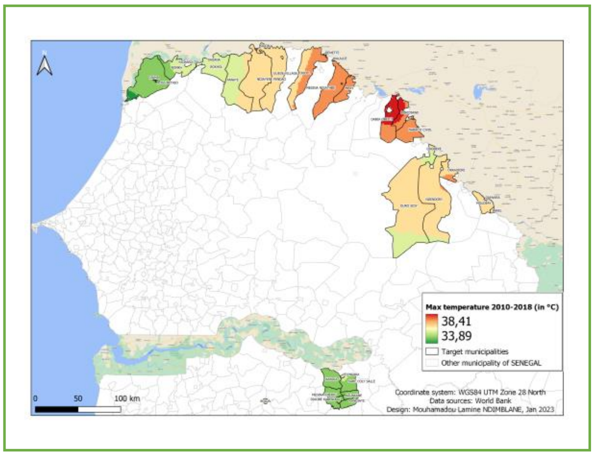
Source: Author's work using World Bank data, 2023.

Map 6: Map 5: Average maximum temperature, 1990-2018, in degrees Celsius (°C).



Source: Author's work using World Bank data, 2023.

Map 5: Average maximum temperature, 2010-2018, in degrees Celsius (°C).



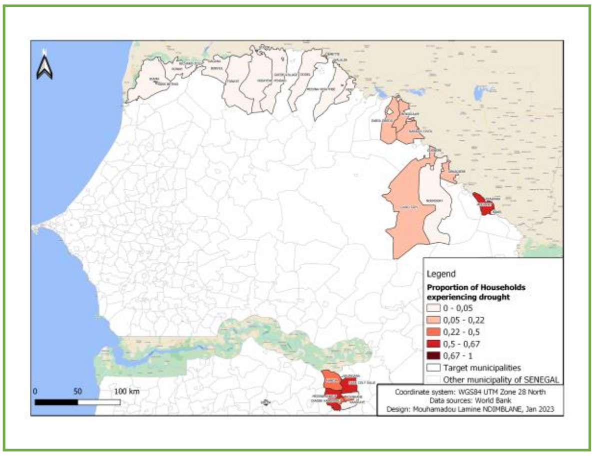
Source: Author's work using World Bank data, 2023.

4.4.1.2. Climate events: droughts and floods

In addition to changes in temperature and precipitation, exposure to climate change incorporates other factors such as climatic events that can occur and appear as a threat to farming communities. Maps 7 and 8 provide an overview of farm household responses to drought and flood issues, respectively. All households surveyed in Kolda reported experiencing a drought in the last five (5) years prior to the survey. Drought is more frequent in the South in the Anambé basin where 50 to 67% of households in the communes of Medina Cherif, and Sare coly Salle have already been affected by drought; and 22 to 50 per cent in the communes of Kandia, Kounkane and Diaobé Kabendou. Also, in the east in the commune of Moudéry, 67% of rice farmers say they have faced drought events (see Map 7). With regard to floods, 38% of households in the municipalities of Ouro sidy salle in the Anambé basin reported flooding, while about 4 to 10% of households in Bokidiawe and in Dabia Obedji in the north-east reported having been affected by flooding (see Map 8).

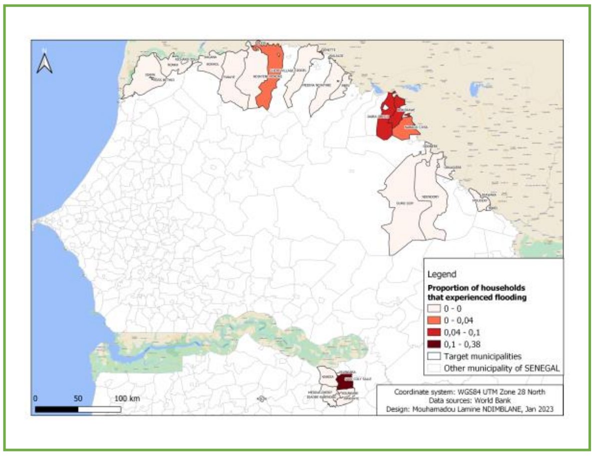
Indeed, the rice farming community of Sare coly salle has been confronted by both drought and flood events in recent years.

Map 7: Proportion of people who experienced drought.



Source: Author's work using World Bank data, 2023.

Map 8: Proportion of people experiencing flooding.



Source: Author's work using World Bank data, 2023.

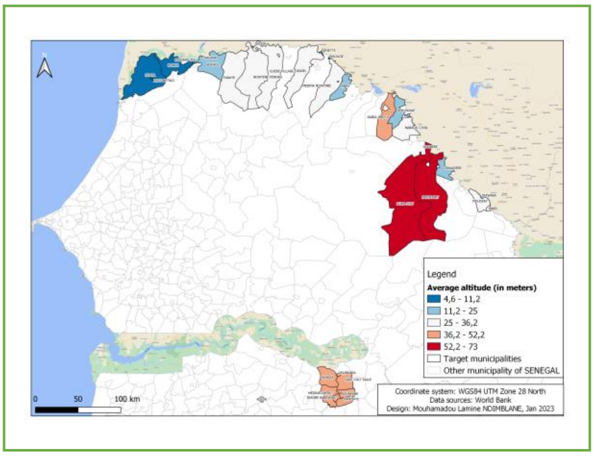
4.4.2. Sensitivity indicators

Sensitivity to climate change depends on several physical and socio-demographic parameters.

4.4.2.1. Physical parameters

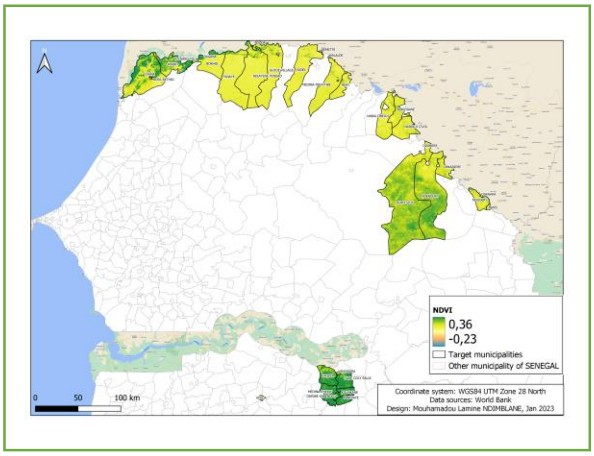
Variables such as slopes or altitude and vegetation quality give an idea of the physical vulnerability of the environment (see maps 9 and 10). The level of elevation obtained from the Digital Terrain Model (DTM) shows that the municipalities of Ouro Sidy and Ndendory are located in areas at high altitudes (52.2 to 73 m on average), therefore less conducive to the development of rice cultivation, which for the most part, develops in low-altitude areas. It is the same for the communes located in the basin of the anambe such as Kandia, Medina cherif, Diobé Kabendou, Kounkane, Kandiaye, Sare coly, Vélingara whose average level of elevation is between 36.2 to 52.1 m. Map 10 of the Normalized Difference Vegetation Index (NDVI) is the result of Landsat8 satellite image modelling using remote sensing from Google Earth Engine. In the study area, NDIV ranged from -0.23 to 0.36. The more developed and healthier the vegetation cover, the higher the NDVI. For this purpose, vegetation is relatively much more favourable in the Anambé basin and in the Senegal River valley, particularly in the north-east (see Map 10).

Map 9: Average altitude in metres (m).



Source: Author's work using World Bank data, 2023.

Map 10: Normalized difference vegetation index (NDVI).

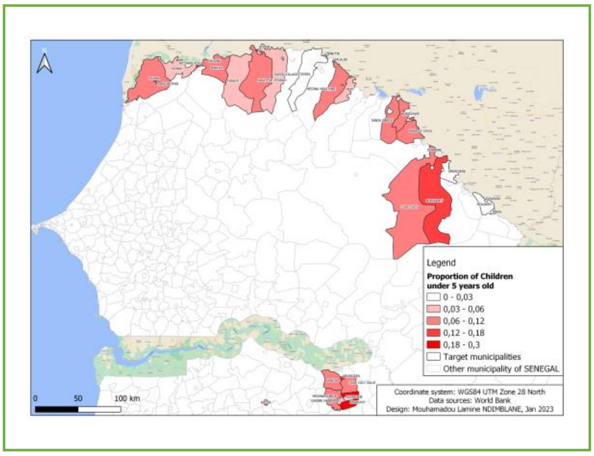


Source: Author's work using World Bank data, 2023.

4.4.2.2. Socio-demographic factors

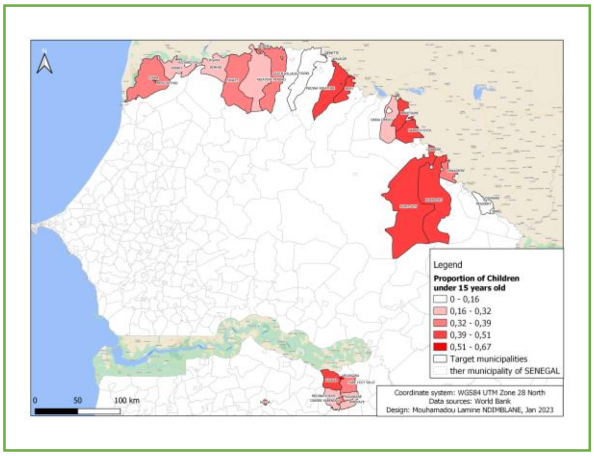
The socio-demographic factors that contribute to the social vulnerability of agricultural households are the number of children under 5 years of age in the family, the number of children under 15 years of age and the number of adults over 65 years of age. The higher the number, the more vulnerable that household is to shocks. Taking as an indicator the proportion of children under 5 years of age, Map 12 shows that the communes of Kandiaye, Vélingara, Kolda, Ndendory and Richard-Toll are relatively more sensitive; Map 11, which provides information on the proportion of people under 15 years of age, reveals that the communes of Kolda, Vélingara, Kandia, Ouro sidy, Ndendory, Nabadji civol, Bokidiawe, Mery and Medina Ndiathbe, Sare coly salle, Diaobe Kabendou , Orkadière , Guede village, Fanaye and Diama are relatively more vulnerable to climate risks. Map 13, which provides information on the proportion of adults over 65 years of age years of age, indicates that the municipalities of Ouro sidy, Orkadière, Dabia obédji, Dodel, Mery, Medina cherif, are relatively more sensitive to climate change than the others.

Map 11: Proportion of children under five (5) years.



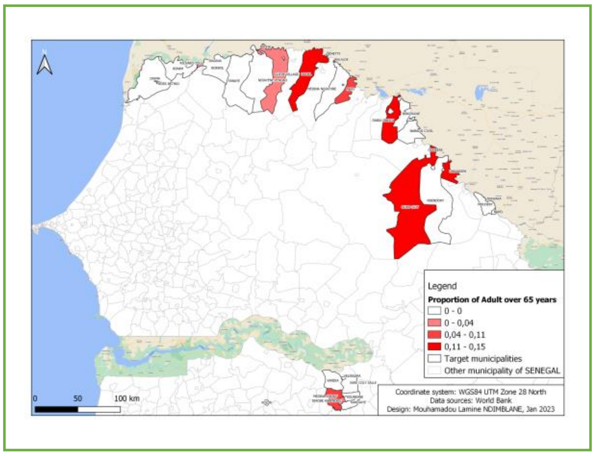
Source: Author's work using World Bank data, 2023.

Map 12: Proportion of children under 15 years.



Source: Author's work using World Bank data, 2023.

Map 13: Proportion of adults over 65 years.



Source: Author's work using World Bank data, 2023.

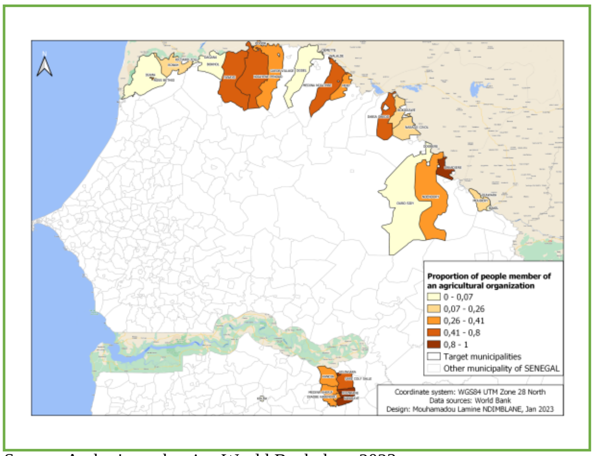
4.4.3. Indicators of adaptive capacity

Adaptive capacity is assessed according to several criteria including social capacity, human resource capacity, institutional capacity and economic capacity.

4.4.3.1. Social capacity factors

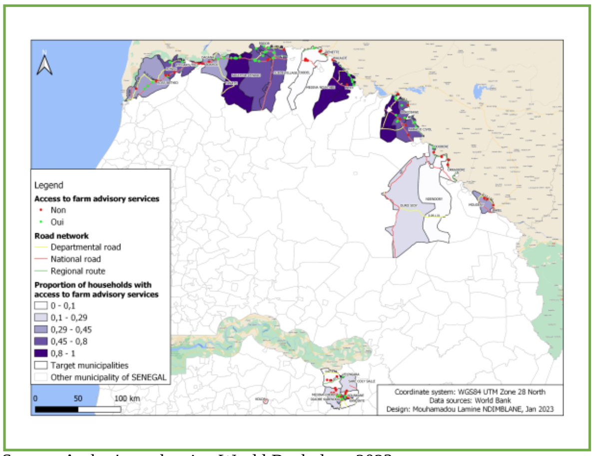
Social potential is characterized by social network and support, defined here as membership in a producer farm organization and access to extension services such as farm counselling. In the communes of Vélingara, Kounkane, Kandiaye and Orkadière, 80 to 100% of respondents are affiliated to an agricultural organization. Similarly, 41 to 79% of the agricultural populations of Fanaye, Ndiayene pendao, Medina Ndiathbe, Dabia Obedji and Sare coly salle declared that they had joined a producer organization. Thus, from an organizational point of view, agricultural households in these localities are relatively better able to cope with climate change than those in municipalities such as Kolda, Ourosidy, Odobère, Bakel, Diawara, Nabadji civol, Bokidiawe, Dodel, etc (see Map 14). In addition, extension services such as agricultural advisory are much more concentrated in areas where people have mobilized in producer organizations (e.g. Fanaye, Ndiayene pendao, Medina ndiathbe, Mery) than in areas with low participation in agricultural organizations (see Map 15). However, some localities appear to be marginalized from farm advisory services despite their organizational mobilization (Kandiaye, Ndendory and Orkadiere), which could be explained by other factors related to accessibility (see for example Map 18: Access to roads).

Map 14: Proportion of people who have joined a farm organization.



Source: Author's work using World Bank data, 2023.

Map 15: Proportion of people with access to farm advice.

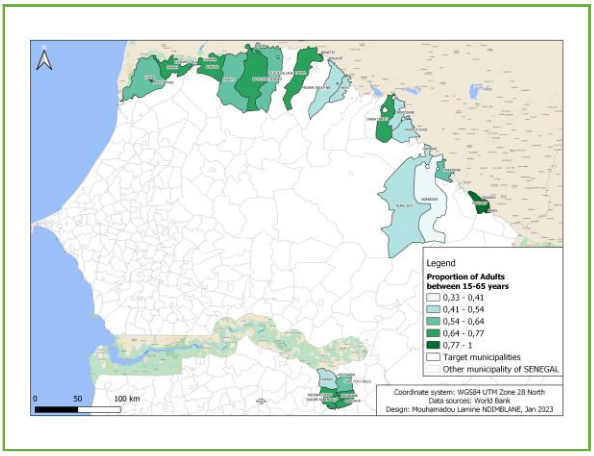


Source: Author's work using World Bank data, 2023.

4.4.3.2. Human capacity factors

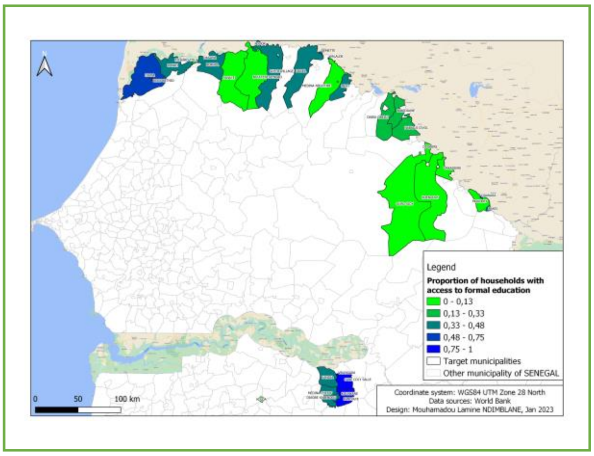
The proportion of adults aged 15-65 in the family and the proportion of households with formal education are two key variables in capturing the human potential of the household and thus the community. Map 16 provides an overview of the proportion of adults aged 15 to 65 in each municipality and Map 17 provides information on the proportion of households with formal education. The human resource potential is relatively higher in the communes of Moudery, Diawara and Bakel (77 to 100%) and relatively lower in Vélingara, Ndendory, Nabadji civol, Bokidiawe, Mery, Medina ndiathbe. With regard to education, a low rate of households had access to formal education in the communes of Ouro sidy, Ndendory, Orkadière, Moudery, Fanaye, Ndiayen pendao, Medina ndiathbe (0 to just under 13 %) and Nabadji civol, Bokidiawe and Dabia Obedji (13 to 33%), unlike other municipalities which have more human capital and therefore better able to deal with possible risks.

Map 16: Proportions of adults aged between 15 to 65.



Source: Author's work using World Bank data, 2023.

Map 17: Proportion of households with formal education.



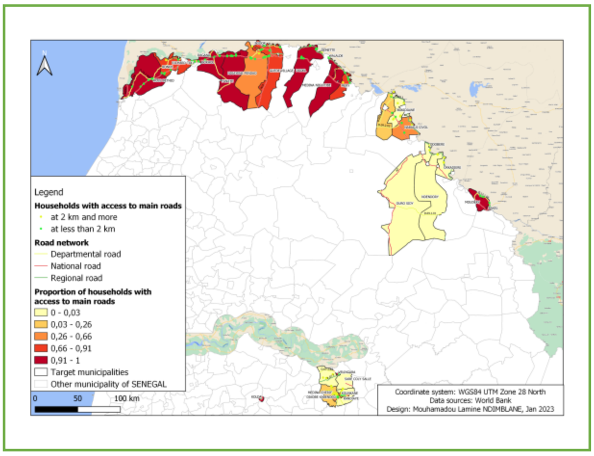
Source: Author's work using World Bank data, 2023.

4.4.3.3. Institutional capacity factors

At the institutional level, several factors can influence the ability of farming communities to cope with climate change, including access to government support in terms of agricultural subsidies, access to roads, access to health infrastructure, access to credit and access to energy including electricity. The road access map (map 18) obtained through the distance matrix provides an overview of the position of households in relation to the main road at a 2 km standard in accordance with indicator 9.1.1 of the Sustainable Development Goals (SDGs). [7] Based on the 2 km standard, the communes in the east of the country, in the river valley such as Ouro sidy, Ndendory, Orkadière, Odobere, Bokidiawe and Dabia obedji and the localities in the south, in the Anambé basin such as Sare coly salle, Kandia, Kandiaye and Medina cherif are all marginalized from road infrastructure. , while in northern localities (e.g. Bokhol, Dagana, Podor, Fanaye, Diama, Rosso), a large proportion of farm households are close to roads, an essential factor for the disposal of agricultural production. Access to health facilities shown in Map 19 reveals that Kandiaye in the south, Ndendory and Orkadiere in the east, Nabadji civol in the northeast and Ronkh in the northwest are poor access to medical care facilities. Rice farmers in these areas travel an average of 2.3 to 5.76 km to access a health post or centre (see Map 19).

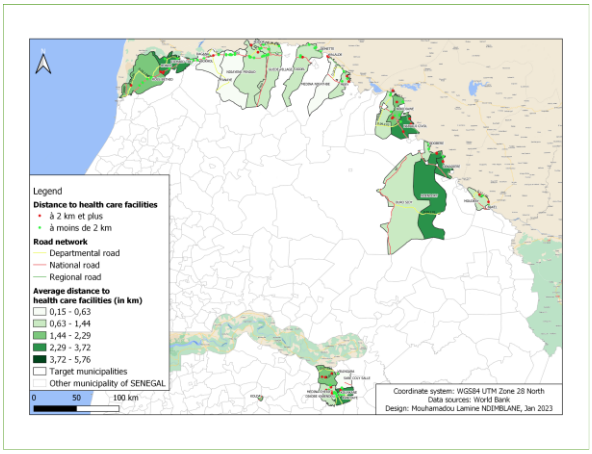
[7] SDG indicator 9.1.1 refers to the Proportion of the rural population living within 2 km of an all-season road.

Map 18: Access to main roads.



Source: Author's work using World Bank data, 2023.

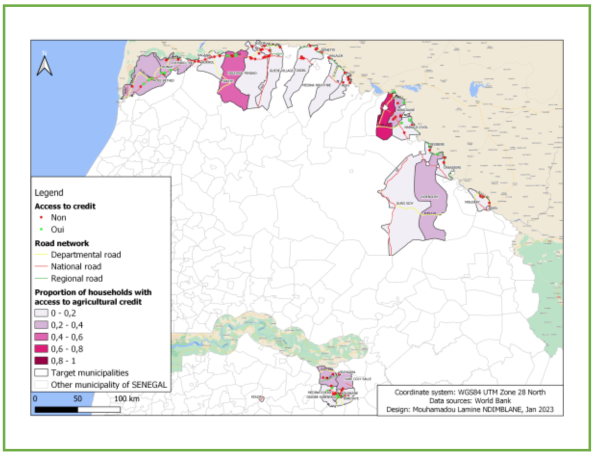
Map 19: Access to health infrastructure.



Source: Author's work using World Bank data, 2023.

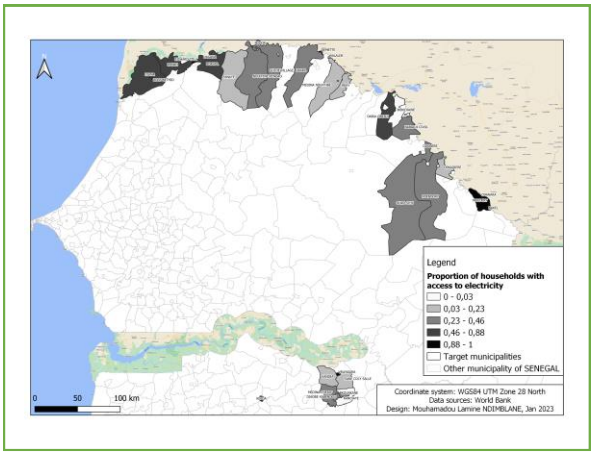
Map 20 shows households' access to agricultural credit, while Map 21 provides information on access to electricity. In the localities of Medina cherif, Kandiaye, Vélingara and Kolda, Ouro sidy, Orkadiere, Nabadji civol, Diawara, Moudery and Bakel, Mery, Medina ndiathbe, Dodel, Guede village, Ndiayen pendao, Bokhol, Richard-toll and Dagana, a small proportion of households reported having had access to agricultural credit (less than 20 per cent). Access to energy, including electricity, remains limited in Kandiaye, Bokidiawe, Kandia, Sare coly salle, Orkadiere, Mery, Medina ndiathbe and Fanaye, where the proportion of households with access to electricity varies between 3 and 23%.

Map 20: Access to agricultural credit.



Source: Author's work using World Bank data, 2023.

Map 21: Access to electricity.



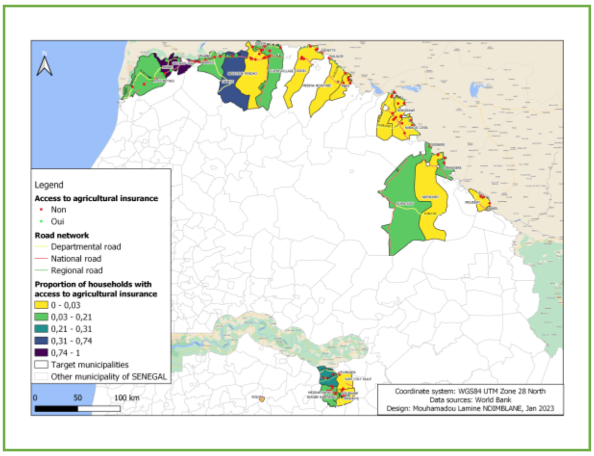
Source: Author's work using World Bank data, 2023.

4.4.3.4. Economic capacity factors

Access to financial services including agricultural insurance, irrigation potential measured by the share of irrigated land in the total area of the municipality and average income, are indicators that determine the economic power of agricultural households within a locality. Map

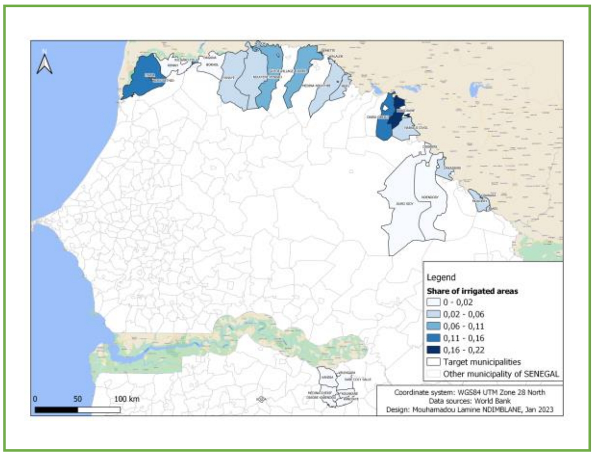
22 shows which households have access to agricultural insurance and those who do not, as well as the proportion of households with insurance in the municipality. The level of access to agricultural insurance is very low (less than 3%) in the Anambé area in the South (Sare coly salle, Kandiaye, Vélingara and Kolda), in the East in the river valley (Moudery and Ndendory), in the North (in Ndiayen Pendao, Dodel, Medina ndiathbe, Mery) and to the north-east in the communes of Bokidiawe, Dabia obedji and Nabadji civol. Indeed, the rate of access to insurance is also low in the localities of Medina Cherif, Diobe Kabendou, Ouro Sidy, Orkadiere, Guede village, Bokhol and Diama where only 3 to 21% of households have subscribed to an insurance product. Access to climate risk management means remains limited and therefore limited in these localities. At the same time, the available water resources are low in the localities of Sare coly salle, Kandiaye, Vélingara and Kolda, Moudery, Ndendory, Ndiayen pendao, Medina ndiathbe, Mery, Nabadji civol, Medina cherif, Diobe kabendou, Ouro sidy, Orkadiere, Bokhol Kandia, Bakel, Ronkh and Ross bethio, where the hydrographic network represents about 2 to less than 26% of the total area of municipalities (see Map 23).

Map 22: Access to agricultural insurance.



Source: Author's work using World Bank data, 2023.

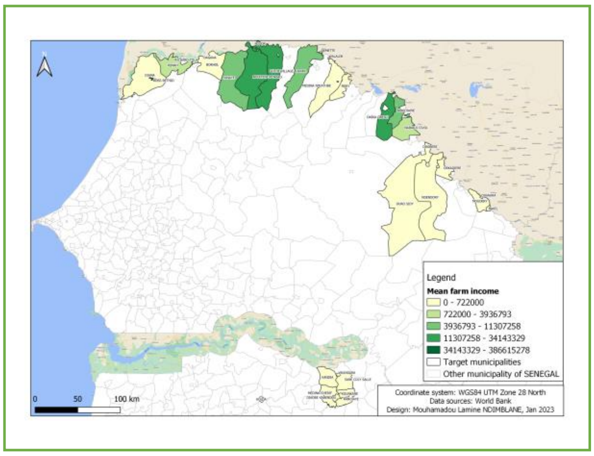
Map 23: Share of irrigated land in total land



Source: Author's work using World Bank data, 2023.

Map 23 shows the spatial distribution of average agricultural incomes by locality. The map shows that insomelocalities such as Sare coly salle, Kandiaye, Kounkane, Medina cherif and Diobe kabendou, Vélingara and Kolda, Ndendory, Orkadiere, Moudery, Bakel, Medina ndiathbe and Mery, income is zero, suggesting that most households are engaged in rice cultivation to meet their food needs and therefore do not sell after harvest. In the communes of Kandia, Ouro sidy, Diawara, Podor, Bokhol and Diama, the average agricultural income for the year is low and less than or equal to 722,000 CFA francs, while the other municipalities earn much higher incomes (for example, Ross bethio, Ndiayen pendao, Guede village, Dabia obédji, Dodel, Bokidiawe, Nabadji civol, etc.), which strengthens their level of economic resilience to climate change.

Map 24: Average average agricultural income.



Source: Author's work using World Bank data, 2023.

4.5. Standardization of indicators

The term standardization refers to the transformation of values of indicators of different scales and units into values without units on a common scale (Organization for Economic Co-operation and Development (OECD), 2008). Standardization is a prerequisite for aggregating individual indicators measured at different scales into a composite indicator. The Min-max normalization method is applied to transform all values on a score rank between 0 and 1.

$$\boldsymbol{X_{ij} = \frac{X_i - MinX_j}{MaxX_j - MinX_j}} \qquad \textbf{(1)}$$

where is the normalized value of indicator (j) relative to municipality (i), X_i is the actual value of indicator relative to municipality (i); and $MinX_j$ and $MinX_j$ are the minimum and maximum values, respectively, of indicator (j) among all municipalities.

If the functional relationship with the vulnerability is negative, that is, if the vulnerability decreases with increasing the value of the indicator (negative correlation), then the following equation is used:

$$\boldsymbol{X_{ij} = \frac{MaxX_j - X_i}{MaxX_j - MinX_j}} \qquad \textbf{(2)}$$

4.6. Weighting and aggregation of individual indicators

Two weighting options are possible to calculate vulnerability using the index method. The first is to assume that all vulnerability indicators are of equal importance and therefore to give them equal weight (Cutter et al., 2012). The second method is to assign different weights given the diversity of indicators used. With regard to this second option, several methodological approaches have been suggested to compensate for differences in the weights of indicators; the most widely used being principal component analysis (Deressa et al., 2008; Gbetibouo et al., 2010; Žurovec et al., 2017), correlation analysis with past disasters (Brooks et al., 2005), and the use of expert judgment (Kaly & Pratt, 2000; Kaly et al., 1999; Ravindranath et al., 2011). However, even if there are many weighting techniques, their relevance is criticized because of their subjective approach. According to Luers et al. (2003), the selection of variables and their relative weight is often done subjectively without a validation test procedure. Indeed, there is no standard method to test the validity and accuracy of these different weighting techniques (Deressa et al., 2008).

For this purpose, this research uses equal weights for the indicators, and proceeds to aggregation by the weighted arithmetic mean. Despite the existence of a wide range of possible aggregation methods, this research focuses on arithmetic mean because it tends to level extreme values and its simplicity gives the advantage to an easy-to-understand interpretation (Zebisch et al., 2021).[8] According to these authors, the other advantage of this method is that it allows complete compensation between components, which means that a high value for adaptive capacity has the potential to largely compensate for a high impact value, hence low vulnerability despite high potential impact. However, they point out that in some cases, this compensation between potential impact and adaptive capacity will not be able to produce, especially if adaptive capacity is defined using generic factors such as income or education level.

Thus, components of vulnerability such as exposure, sensitivity and adaptability are calculated by the following formula:

$$\boldsymbol{CI = \frac{I_1 * w_1 + I_2 * w_2 + \ldots + I_n * w_n}{\sum_1^n (w)}} \qquad \textbf{(3)}$$

Where CI represents a composite indicator -exposure (EX), sensitivity (SE) or adaptive capacity (AC)-; I_i are the individual indicators chosen and; $w_1 = w_2 = w_3 = \ldots = w_n = 1$

4.7. Normalization and aggregation of vulnerability components

The two components of vulnerability are potential impact and adaptive capacity. The sub-index "potential impact (PI)" is an intermediate result resulting from the arithmetic sum of the exposure and sensitivity indicators, whose arithmetic means have been calculated separately from equation (3), while the sub-index adaptive capacity (AC) is determined by the arithmetic mean of the individual indicators which represent adaptability (Equation 3). The final value of

[8] For more details on the different weighting methods, their advantages and weaknesses, see OECD 2008 https://www.oecd.org/sdd/42495745.pdf .

the vulnerability index for each municipality was obtained from the arithmetic sum of these two sub-indices.

Below are the formulas for calculating the potential impact and vulnerability index:

$$\boldsymbol{PI = \frac{EX * w_{EX} + SE * w_{SE}}{w_{EX} + w_{SE}}} \qquad \textbf{(4)}$$

where PI is potential impact, EX exposure, and SE is sensitivity, w is weight; $w_{EX} = w_{SE} = 1$

$$\boldsymbol{V = \frac{PI * w_{PI} + AC * w_{AC}}{w_{PI} + w_{AC}}} \qquad \textbf{(5)}$$

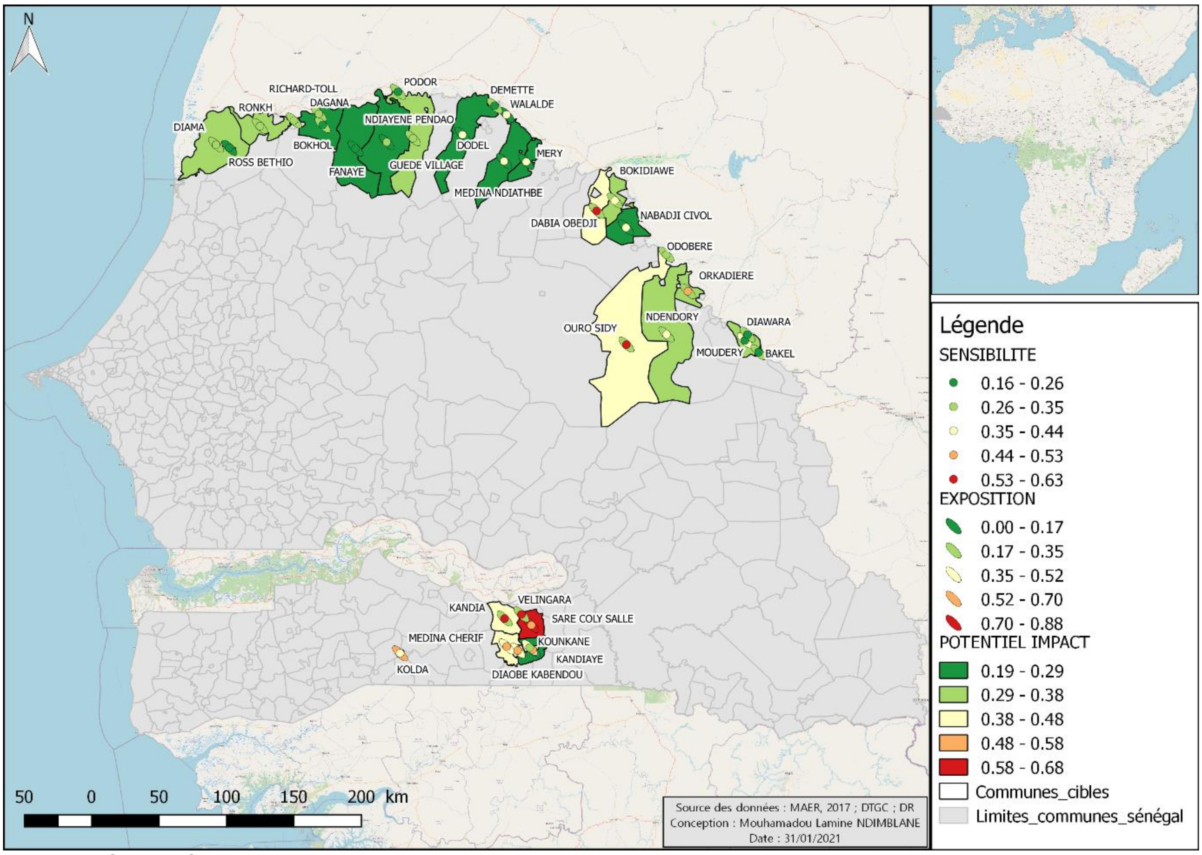
where V is the vulnerability index, PI is the potential impact, and CA is the adaptability; w weight;

with $w_{PI} = w_{AC} = 1$

5. Results of the vulnerability assessment of rice farming communities

The results of this research show the vulnerability profile to climate change of rice production areas in Senegal. A composite index is calculated on the basis of 23 selected indicators and the results are mapped and ranked according to the three vulnerability factors such as exposure, sensitivity and adaptability, according to their degree of importance. Out of a total of 33 municipalities, five (5) have a high level of vulnerability of 0.55 to 0.63 (Ouro Sidy, Dendory, Orkadière, Kandia and Kolda) and one (1) appears very vulnerable with a value of 0.70 (Sare coly salle) (See map 2-6). Six (6) of the 33 municipalities have a moderate degree of vulnerability between 0.48 and 0.55 (Bokidiawe, Diaba obedji, Nabadji civol, Diaobé kabendou, Kandiaye and Medina chérif), 13 are weakly affected with an index between 0.41 and 0.48 (Diama, Ronkh , Richard-toll , Bokhol, Ndiayene pendao, Guédé village, Dodel, Démette, Walalde, Mery, Moudéry, Kounkane and Velingara) and eight (8) have an acceptable profit because they are relatively less affected (Ross béthio, Dagana, Podor, Fanaye, Medina ndiathbé , Odobere, Diawara and Bakel). Map 25 gives an overview of the potential impact of climate change, the degree of exposure and the sensitivity of each municipality. This illustration visualizes the direct compensation effects between factors. A locality characterized by very high exposure level and high sensitivity, suffers a potential impact also high; this is for example the case of Sare colly salle. However, even if the locality is very fragile, the potential impact of climate change can be moderate due to a low level of exposure, as is the case in Dabia Obedji, Ouro sidy, Kandia and Velingara.

Map 25: Exposition to climate change, Sensibility and potential Impact by locality.



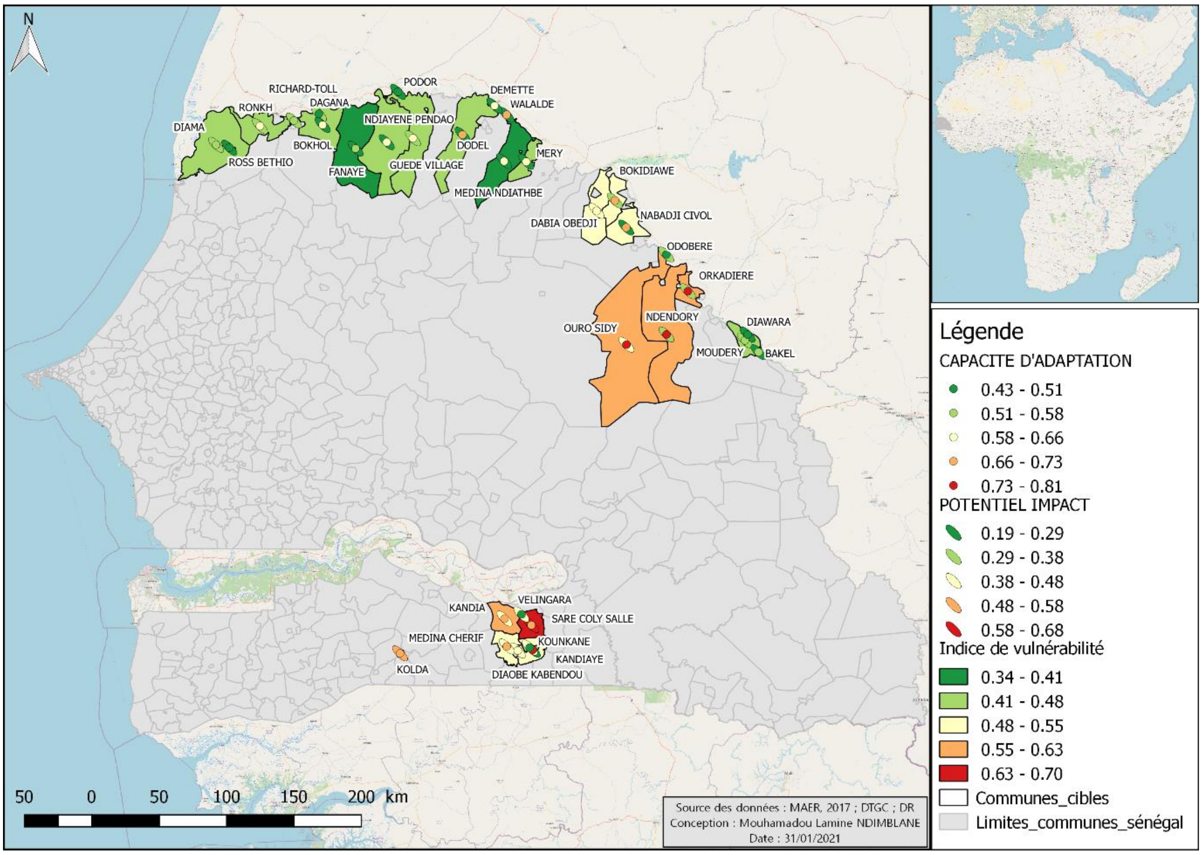
Source: Author's work, 2021.

On the other hand, a municipality with very inadequate human and economic resources and/or a low institutional capacity has a high vulnerability profile despite a low potential impact (see Map2-6). This is for example the case of the communes of Ndendory, Orkadiere and Ouro sidy. However, a very low adaptive capacity associated with a very low potential impact, can lead to a moderate level of vulnerability under the effect of compensation (see the commune of Kounkane in the South). In addition, municipalities such as Ross Bethio, Podor and Diawara give confirmation to the theoretical ideas of Zebisch et al. (2021), indicating a possibility of complete compensation between components; meaning that a high value for adaptive capacity has the potential to largely offset a high impact value, hence low vulnerability.

Moreover, in comparison with other studies carried out in Senegal, the results of this research are plausible and confirm the disparities between the different regions. Vulnerability is higher in the communes of the Kolda region (in southern Senegal), while it is more or less moderate in the east, particularly in Matam, and relatively lower in the Saint Louis region in northern Senegal; the same is true if we take the regional development index or the multidimensional poverty index by region of the United Nations Human Development Program report (UNDP, 2019).[9]

To this end, the municipalities of the regions of Kolda and Matam are priority in terms of agricultural adaptation policies to climate change. Improving the level of support and infrastructure could help strengthen households' adaptive capacity, reduce their fragility, and thus increase their resilience to climate change.

Map 26: Potential impact, adaptive capacity and climate change vulnerability index.



Source: Author's achievement, 2021.

6. Conclusion

In order to prioritize national climate change adaptation policies, it is essential to identify at the local level the areas that are most vulnerable to climate change and that require intervention and support. Given the limited financial and technical capacities of countries, targeting and prioritizing investments in the most vulnerable areas are good strategies to meet the needs of communities. To meet this need of a large audience of policy makers for climate change

[9] Available from https://senegal.un.org/sites/default/files/2021-05/PNUD%20-%20RAPPORT%20RNDH.pdf, January 20, 2023.

resilience policy planning, we used the index method to assess vulnerability and geographic information systems (GIS) to map the spatial distribution of vulnerability at the level of rice farming communities in Senegal. Two major rice-producing areas are considered, namely the Senegal River Valley (in the Saint-Louis and Matam region) and the Anambe Basin (in the Kolda region). Thus, the commune of Sare coly sale is more vulnerable followed by the communes of Ouro sidy, Ndendory, Orkadiere, Kandia, Kolda, and Medina cherif, Diobe kabendou, Kandiaye, Dabia obedji, Nabadji civol and Bokidiawe. These localities are highly exposed to climate change, including changes in temperature, precipitation and events such as floods and droughts. They are also sensitive in view of their altitude, which is less conducive to the development of rice cultivation and, above all, their fragility linked to the relatively dominant age group. Indeed, in these somewhat more remote areas, the adaptive capacity of households remains low; households are far from roads, health infrastructure and have poor access to agricultural credit, extension services and agricultural insurance and are therefore characterized by relatively low-income levels. To this end, the strengthening of social capital through the development of extension services such as agricultural advice; the strengthening of human capital through education and training; the development of institutional capital through the development of basic social infrastructure, transport and credit institutions; as well as economic capital through the promotion of agricultural insurance, are fundamental policy measures to reduce the vulnerability of farm households and thus improve their resilience.

CHAPTER III: INSURANCE AS A MEANS OF MANAGING CLIMATE RISKS FOR FARMERS: IMPACT ON FARM INCOMES

1. Introduction

Several authors are concerned that agricultural losses will be particularly damaging for developing countries (Rosenzweig & Parry, 1994; Mendelsohn & Williams, 2004; Cline, 2007), especially countries like Senegal. Senegal's agricultural production is predominantly rain-fed, which is likely to make it sensitive to the direct effects of climate change such as high temperatures, droughts and floods. These unexpected climatic events are already present in Senegal and they are becoming more and more frequent, especially in rural areas. Rural households are exposed to climatic shocks such as delayed rainfall, low rainfall, reduced river flows or sometimes excessive rainfall that can cause significant damage to agricultural production. Survey data used in this research reveal that in Senegal, one in four rice farmers faces agricultural risks related to climate change such as drought, floods, decreased river flows, off-season rains and insufficient rainfall, resulting in average crop loss rates (drought -47.4%, floods -23.6%, decrease in river flow -23.3%, off-season rainfall -20%, insufficient rainfall -12%).[10] In addition, more than half of rice farmers face attacks from birds and other pests such as insects whose proliferation is often caused by high temperatures. As a result, farm households are at risk of adverse consequences such as reduced livelihoods due to lost production and lower farm incomes, increasing their vulnerability and reducing their social well-being. To this end, climate change is likely to exacerbate the vulnerability of farming households in low-income countries such as Senegal, where more than two-thirds of rural households are poor (69%), and 65% are food insecure (Agence Nationale de la Statistique et de la Démographie (ANSD), 2015). In the face of these many unexpected and recurrent climatic events, which are likely to make farmers more vulnerable to poverty and food insecurity, the adoption of adaptation practices becomes essential to maintain or improve people's living conditions. Adaptation is an inevitable measure in the response to climate change (Mendelsohn, 2009;(Falco et al., 2014) because it consists of adopting practices and structures to moderate potential damage or to benefit from opportunities related to climate change (IPCC, 2001). Indeed, agricultural risk financing seems to be the ideal option to mitigate climate risks and improve the resilience of farm households. Having a good agricultural insurance system in place can help farmers better adapt to climate change (Dolan et al., 2001; Smit & Wandel, 2006).

Created in 2008 following the favorable opinion of the Regional Insurance Control Commission (CRCA) of the Inter-African Conference of Insurance Markets (CIMA) during its

[10] Statistics calculated by the author from household survey data of the Ministry of Agriculture and Rural Equipment (MAER) collected in the framework of the agricultural policy support project.

December 2008 session held in Libreville, the National Insurance Company operates in the form of a public-private partnership and is responsible for providing crop and livestock insurance. The CNAAS provides the farmer with all-risk crop insurance which guarantees compensation payable to the insured of the loss of yield of his crop is linked to disaster risks such as droughts, bush fires or heat waves, floods or excessive rainfall, locust invasions. The crops concerned are cereal crops (rice, maize, millet, sorghum, sesame, etc.), legumes (cowpea), cash crops (peanuts, cotton, etc.), and market garden crops (onions, industrial tomatoes, potato etc). The insured values correspond to crop production costs and are assessed at a maximum of 300,000 CFA francs per hectare for irrigated field crops and a maximum of 800,000 CFA francs per hectare for market gardening. The compensation is fixed according to an agricultural expert and corresponds to the reimbursement of the production costs incurred up to the date of occurrence of the incident. The tariff is calculated according to production costs. The premium to be paid is around 10,000 CFA francs per hectare for irrigated field crops and 18,000 CFA francs per hectare for market gardening.

In its National Climate Change Adaptation Plan (NAP) based on its Nationally Determined Contribution (NDC), the Government of Senegal has chosen agricultural insurance as one of the fundamental adaptation options for the agricultural sector. This appears to be a policy of strengthening the agricultural insurance system that already existed. Moreover, a policy of encouraging agricultural insurance has been adopted since 2008, subsidizing 50% of agricultural insurance premiums for certain types of speculation such as rice, millet and sorghum. Agricultural insurance contracts are exempt from the tax on insurance contracts and the number of insured producers increases from 1,285 farmers in 2009 to 20,000 farmers in 2015, or +93.58% for an insured value ranging from 589 million CFA francs to 10.33 billion CFA francs (+94.29%) over the same period. On the other hand, the amount of compensation paid between 2010 and 2015 increased from 8.7 million CFA francs to 276.8 million CFA francs (100%).[11]

However, while macro-level statistics provide a general overview of the increasing evolution of farmers' costs and participation rates, micro-level analyses reveal a low take-up rate of agricultural households in insurance. Data from this research indicate that among 512 farm households, only one in five households (20%) used agricultural insurance in the 2016/2017 crop year. Senegalese farm households appear to have limited choices, not allowing them to

[11] Briefing note on Agricultural Insurance in Senegal. Retrieved from http://www.papa.gouv.sn/wp-content/uploads/2018/02/PAPA-Note-dinformation-sur-lassurance-agricole-au-S%C3%A9n%C3%A9gal.pdf (last consultation in August 2020).

use effective agricultural risk management options. Agricultural insurance services remain underdeveloped or disproportionately distributed in rural Senegal. The absence of insurance service in the area prevents four out of ten households from subscribing to an insurance product. In addition, while some cite reasons for the high cost of insurance products (20%), others are unaware of its importance (16%) while 23% say that the services offered are not adapted to their needs.

These statistics observed in Senegal on access to financial services in agriculture, confirm the trend noted in other low-income countries. Farm households in low-income countries, such as those in sub-Saharan Africa (SSA), are constrained by access to financial institutions and use a wide range of traditional adaptation measures to mitigate the negative effects of climate shocks. Farmers do this by diversifying crops, changing planting dates, and conserving water and soil (Nhemachena & Hassan, 2007; Deressa et al., 2009; Juana et al., 2013). In the event of a disaster, they can also adopt ex-post measures to mitigate the adverse effects caused by climatic events. They do this by reducing consumer spending, borrowing from neighbours in anticipation of future harvests, dropping their children out of school, and migrating to support themselves (see Carter et al., 2015). In contrast, farmers with limited savings may not take the risk of investing in seeds, fertilizers, irrigation systems or other assets, as the future return on investment remains uncertain due to a potential loss of income due to climate shocks. Poverty thus sets limits on the options they can choose to cope with agricultural risks. According to Barnett et al. (2008), a shortage of financial instruments exacerbates problems related to ineffective ex ante and ex post measures to address climate risks and shocks in developing countries. Unsecured risks then become part of a vicious circle that can keep farmers in poverty and prevent the development of agriculture. Hence the need to implement effective adaptation policies to reduce the adverse effects of climate change and improve the resilience of vulnerable farmers. In terms of adaptation, climate finance plays an important role. In the agricultural sector, agricultural insurance is considered to be the most appropriate means of financing to manage the risks faced by farm households. Insurance companies offer financial protection against losses for a certain premium. Climate insurance can improve adaptive capacity by providing beneficiaries with a climate safety cushion, thereby helping to secure or preserve private investments (Hess & Syroka, 2005).

Although agricultural insurance is recognized by most authors as a good risk management tool (M. Carter et al., 2015; Falco et al., 2014), its importance and benefits, especially in the context of climate change, remain less known in Sub-Saharan Africa. Despite the extent of the debate on climate change and its impact on agriculture, empirical studies on the issue remain underdeveloped in sub-Saharan African countries (SSAs). Feasible solutions for managing climate risks are not well known or remain poorly controlled. Indeed, African researchers have instead focused on analyzing households' perception of climate change and have therefore failed to provide feasible solutions to mitigate climate change risks (see, for example, Kurukulasuriya & Mendelsohn, 2007; Deressa et al., 2009; Apata et al., 2009). Insurance as a climate risk management mechanism remains poorly documented or absent in the African literature on climate change, leaving a knowledge gap as to its importance on the resilience of agricultural households to shocks. This lack of information for policy makers, the private insurance sector and farm households could partly be seen as the explanation for the low involvement of stakeholders in setting up an insurance system, and the low take-up of households where it exists. In Senegal, for example, there is little knowledge about farm households' exposure to climate change, how they are affected by climate shocks, and how they manage the associated risks.

The question is therefore whether agricultural insurance is indeed a good financial means for better climate risk management, by improving the resilience of agricultural households.

Examining the Senegalese agricultural insurance system seems to be important because, on the one hand, it would make it possible to understand the factors that explain the choice of farm households whether or not to adopt insurance as a means of managing agricultural risks and, on the other hand, to better identify the levers on which the government and insurance companies could rely to expand and accumulate more participation rates in areas where services were not previously available. It would also provide a better understanding of the factors hindering the development of financial services in rural areas.

Given the current literature, this research is the first in SSA, assessing the impact of a particular financial mechanism (insurance) in the management of agricultural risks related to climate change. This research aims to fill this knowledge gap on the financing of agricultural risks related to climate change. It complements the existing literature as it highlights the role of agricultural insurance in managing risks related to climate change. It is likely to have a considerable impact on the implementation of the National Adaptation Plan (NAP) because it sheds light on one of the target adaptation policies of the Government of Senegal, in particular the promotion of agricultural insurance. The results of this research will allow policymakers to know the levers they should use to promote agricultural insurance in rural areas. They could also support insurance companies in convincing farm households of the importance of insurance in managing climate risks. Indeed, the results will provide a global overview of the structure of the insurance system, the failures of the insurance market to be corrected, the opportunities and challenges to be addressed in order to encourage households to subscribe to make themselves much more resilient to climate change. This research work will then make it possible to better guide Senegalese political decision-makers in the implementation of one of the key ambitions of the climate plan.

2. Research objectives and hypotheses

2.1. General objective

The main objective of this work is to study agricultural insurance as a model for climate risk management in agriculture. The aim is to assess the role of agricultural insurance in climate risk management by assessing its benefits as an option for adapting to climate change.

2.2. Specific objectives

To do this, we set ourselves the specific objectives of (i) analyzing Senegal's insurance system to understand its functioning, challenges and opportunities; (ii) determine the factors that explain the underwriting of insurance products by farm households; (iii) assess the impact of the adoption of agricultural insurance products on the incomes of agricultural households.

2.3. Research hypotheses

This research is based on the following hypotheses: (i) factors of failures of the agricultural insurance system in Senegal may be an obstacle to the adoption of insurance; (ii) Access to information is a key factor for the adoption of agricultural insurance as an adaptation strategy; (iii) agricultural insurance can play an important role in financing climate risks by improving the income of adoptive farmers; This states that households that have adopted agricultural insurance as a means of managing agricultural risks are likely to have a relatively higher average net income than their counterparts who have not been able to take advantage of insurance.

3. Literature review

Many rural households in low-income countries see climate risks as their main concern. Climatic events such as drought, rainfall breaks and deficits, excessive rainfall and floods, are constraints of paramount importance for wealth accumulation, especially for those who are either engaged in agricultural activities or see their livelihoods linked to the well-being of the agricultural sector (Barnett et al., 2008). In the face of these unexpected and recurrent climate effects, which can increase vulnerability to poverty and food insecurity, the adoption of adaptation practices becomes essential to maintain or improve one's well-being. However, the options for agricultural households to manage climate risks are limited in developing countries. Financial services, including credit institutions and insurance companies, have little or no presence in some rural areas. Formal insurance against changes in crop yields, which is the key determinant of farmers' income, is rarely available (Falco et al., 2014). Moreover, even if insurance services appear, the factors of market failures most often lead to its dysfunction. Information asymmetry and high transaction costs are the most recognized sources of market failure in the economic literature. There is indeed another factor related to climatic conditions, namely covariate risk, which is a major constraint for the development of financial markets in several low-income countries (Besley, 1995). Exposure to covariate risk can lead to enormous damages beyond the insurer's financial capacity to pay compensation to policyholders. Catastrophic space-related losses can exceed an insurer's available reserves, leaving policyholders unprotected (Barnett et al., 2008). Thus, the assumption by governments of a large part of the exposure to catastrophic risks would be a solution to motivate the presence and development of insurance services in low-income countries. Indeed, Binswanger and Rosenzweig, 1986; Miranda and Glauber, 1997 indicate that due to covariate risk exposure, the presence or absence of crop insurance policies in a given country is explained by whether governments are financially or financially responsible for much of the exposure to disasters. In addition, the authors explain the low presence of financial markets in rural areas by the enormous costs of marketing individual insurance policies. Information asymmetry comes in two forms: adverse selection (or hidden information) and moral hazard. If the first is incomplete information concerning the risks to which the insured are exposed, the second consists in the follow-up to the purchase of insurance, to other activities that may be subject to exposure to additional risks not taken into account in the initial negotiations of the insurance contract. Ultimately, these practices lead to erroneous assessments of policyholders' risk (Rothschild & Stiglitz, 1978), leaving the insurer exposed to higher levels of risk than those anticipated when premiums were set because of the administrative costs of calculating and collecting individual premiums and settling claims (Barnett et al., 2008). As a result, insurance services are scarce in areas where people's incomes are quite low, for example in African countries. African farm households then resort to informal risk management measures. In sub-Saharan African countries – land of imperfect and sometimes non-existent financial markets – the literature on the issue of adaptation to climate change shows that, to cope with climate shocks, farmers diversify their crops, change planting and harvesting dates, practice irrigation, or use water harvesting and soil conservation techniques (Nhemachena & Hassan, 2007; Deressa et al., 2009; Acquah, 2011; Juana et al., 2013). However, uninsured risks could keep households in persistent poverty. Financial market failures directly and indirectly contribute to the persistence of chronic poverty (Carter & Barrett, 2006; Barnett et al., 2008; Skees & Barnett, 2006 and informal insurance mechanisms leave consumption vulnerable to idiosyncratic shocks (see, (Townsend, 1994).

Yet, it has been well documented in the literature that agricultural insurance, where it exists, can serve as a means of adaptation to climate change (Dolan et al., 2001). Establishing a good agricultural insurance system can help farmers better adapt to climate change (Mcleman & Smit, 2006; Garrido et al., 2011). To this end, the establishment of a special insurance system seems to be a solution to reduce failures in the insurance market. In sub-Saharan Africa, new forms of climate risk finance are emerging, including index-based risk transfer products (BIRTPs). IBRTPs have been introduced in several SSA countries to facilitate the management of farmers' climate risks. (Barnett et al., 2008) believes that IBRTPs can address issues that impede financial contracting in low-income rural areas and thus help reduce financial market failures. IBRTPs are therefore in addition to the conventional form of agricultural insurance that was previously introduced. However, since the emergence of this new form of insurance, the benefits and scope remain unknown. Little research addresses the issue of climate risk management through insurance, as empirical evidence on the impact of adopting an insurance product on farm household welfare remains inconclusive. If there are theories about the positive effect of insurance, this has only been formulated theoretically and if empirical studies have proven it then these have been carried out in developed countries. One example is the work of Falco et al. (2014) on Italy, indicating that crop insurance, by spreading risk, reduces the magnitude of risk exposure and mitigates the financial consequences of unpredictable crop loss due to extreme events such as drought. However, these results are not likely to be generalized as the contexts are different between developed and developing countries. It requires more scientific research to assess the impact of insurance adoption in low-income countries where farm households are relatively more exposed to climate risks and insurance companies are infrequently. Evidence-based studies could be used to support African policymakers who want to expand the insurance agenda as part of their National Adaptation Program (NAP) in relation to their Nationally Determined Contribution (NDC).

4. Methodology

To cope with agricultural risks, households can decide whether or not to subscribe to an agricultural insurance product. Thus, to study the factors that influence household uptake of agricultural insurance and the impact of this adoption on household resilience to climate change, this research uses an endogenous switching regression (ESR) model. This approach estimates the impact of adaptation strategies on producers' farm income. It takes into account the potential endogeneity of the adaptation strategy, which could lead to biased and inconsistent estimates (Di Falco et al., 2011). From a probit selection model, ESR corrects for potential endogeneity due to self-selection. Farmers' decision to adopt an adaptation strategy in response to the impact of climate change is a latent variable that takes the value 1 if the household subscribes to agricultural insurance and 0 otherwise. The characteristics of farmers are however observed during the investigation period, Y_i^* represents the net benefits derived from adaptation to climate change which are not observed, but which can be expressed in terms of the observed attributes.

$$\boldsymbol{Y_i *= \beta Z_i + \varepsilon_i} \quad \textbf{(1)}$$

Y_i^* = 1 if > 0 and 0 otherwise $Y_i^*$is an unobservable (or latent) variable for the adoption of the adaptation strategy (agricultural insurance purchase); and Y is the observable counterpart (equal to 1 if the farmer has adopted and 0 otherwise).

In the second step, the outcome equations on the impact of insurance adoption on net farm income are estimated by a net farm income function, expressed in equation (2) as:

$$\boldsymbol{Q = f(Y, \beta, Z) + \varepsilon} \quad \textbf{(2)}$$

where Q is the logarithmic form of net farm income of rice farmers; $\boldsymbol{Y}$ Refers to the adoption of an adaptation strategy; $\boldsymbol{\beta}$ is a vector of parameters to be estimated; and Z is a set of explanatory variables used in the model.

Regime 1 (adopters): $\boldsymbol{Q_{1i} = \lambda_1 H_i + v_{1i}}$ **(3a)**

Regime 2 (non- adopters): $\boldsymbol{Q_{2i} = \lambda_2 H_i + v_{2i}}$ **(3b)**

where Q_{1i} and Q_{2i} are the logarithms of farmers' net farm incomes in schemes 1 and 2, respectively; H_i is a vector of regressors which are hypothetically the determinants of net agricultural income; and v_{1i} and v_{2i} are the stochastic error terms. Stochastic error terms are assumed to have a trivariate normal distribution, with a zero mean and a nonsingular covariance matrix. The maximum likelihood complete information (FIML) simultaneously estimates the selection and outcome equations (equations (1), and (3a) and (3b) respectively) to produce consistent standard errors.

The average effect of adopting agricultural insurance as a climate change adaptation strategy can be estimated by the difference between equations (3a) and (3b), namely:

$$ATT = E(Q_{1i} - Q_{2i}|Y_i = 1)$$

In addition, the methodology adopted makes it possible to know the impact of agricultural risk financing on the resilience of rural households. The target audience in this research is mainly farmers who represent more than 53% of the active population in Senegal. Agricultural households are also the most vulnerable segment of the population because their livelihoods result mainly from agricultural activity. The aim is to see to what extent agricultural insurance could be a good way to manage climate risks in order to increase their resilience. The data cover information on rice production, the inputs used to make it possible and the means of financing (see next section). The choice of rice is not arbitrary for two reasons. On the one hand, the production and consumption of rice is an important part of the daily lives of Senegalese. On the other hand, rice production, due to its bilateral dependence on surface water and rainfall, is highly exposed to recurrent climatic risks such as droughts, reduced rainfall and the drying up of surface waters.

5. Data

The data used in this research was collected in 2017 as part of the Agricultural Policy Support Project, implemented by the Ministry of Agriculture and Rural Equipment of Senegal (MAER) in collaboration with the University of Michigan (MSU), the International Food Policy Research Institute (IFPRI) and Africa Lead. A sample of 779 agricultural households located in two different agro-ecological zones, namely the Valley of the Senegal River and Casamane (in the Anambé basin) was interviewed. A great deal of information was collected, including the socio-economic and socio-demographic characteristics of households, prices, quantities of inputs used and production levels, the perception of climate change, climate shocks and their impacts, adaptation strategies, financial services including access to credit and insurance purchase.

Table10 represents the descriptive statistics of the data and gives a comparison between insured and uninsured households. Of the 779 agricultural households surveyed, a sample of 512 rice farmers was selected. In this sample, one in five households was insured (19%) and four in five households (81%) did not subscribe to insurance products. Insured households farm plots of relatively larger area than the uninsured. Taking into account the yields, the figures show a relatively higher production per hectare among the insured. The gender variable suggests that women are less likely to access insurance services. Indeed, statistics seem to show that agricultural insurance is in favour of households that have either received agricultural credit, entered into an agricultural contract with a third party, or joined an agricultural organization or benefited from agricultural advice. Moreover, given the geographical positions of agricultural households, there seems to be a difference in terms of access to insurance services between those located in the eco-geographical zone of the Senegal River Valley and those located in the south of the country, particularly in the Anambé basin. The differences are statistically significant and may be related to factors such as affiliation with an organization, farm support through farm counselling, access to credit and among others. However, more rigorous econometric analyses are needed to determine the explanatory factors of the demand for insurance or even the impact of access to insurance on the resilience of farm households.

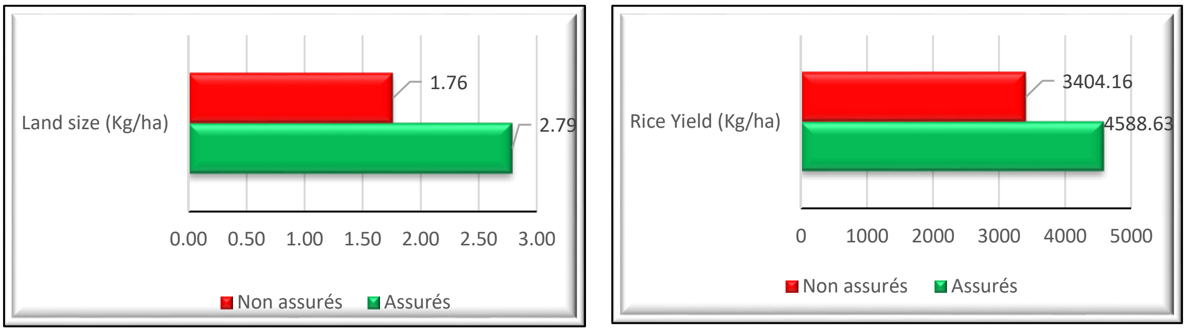
Table 10: Descriptive statistics of the data.

Indicators	Insured households	Uninsured households	Difference	Sample	P-value	Significance
Number of households	129(19%)	539(81%)	515	512 (100%)		
Age of households (years)	52,95	51,79	-1.16	52,02	0,38	
Gender (1 if the capita of household is male)	0,95	0,89	-0.06	0,90	0,07	*
Formal education (1 if the household received formal education)	0,55	0,65	0,09	0,63	0,08	*
Household size (number of persons)	9,00	8,00	-1.00	8,00	0,35	
Total area under cultivation (in hectares)	2,79	1,76	-1.03	3,67	0,27	
Agro-ecological zone (1 if household is located inthe VFS)	0,75	0,73	-0.02	0,74	0,68	
Contract (1 if the household is contractual)	0,16	0,10	-0.06	0,11	0,07	*
Credit (1 if household has access to credit)	0,33	0,15	-0.18	0,18	0,00	***
Organization (1 if household is a member of an organization)	0,41	0,31	-0.09	0,33	0,07	*
Agricultural advice (1 if the household receives agricultural advice)	0,63	0,44	-0.20	0,48	0,00	***
Rice yield (Kg/ha)	4644,52	3343,13	-1301.39	36,05	0,00	***
Log Farm income	14,47	13,36	-1.11	13,64	0,01	***

Note: *Significant 10%, **significant at 5%, ***significant at 1%.

Source: Author's calculations based on AHS survey data, 2017.

Graph 14: Areas under cultivation (ha) and Average rice yield (Kg/ha) of insured and uninsured agricultural households.



Source: Author's calculations based on AHS survey data, 2017.

6. Outcomes of the impact of insurance adoption on farm income

The results of the endogenous switching regression model are shown in Table 11. The ESRM model is estimated using the Full Maximum Likelihood Information (FIML) approach, which jointly derives the selection and outcome equations. In Table 11, the estimate of the participation equation (Eq. 3) shows the determinants of the decision of agricultural households to adopt insurance in response to climatic risks, while the estimation of the outcome equations for insured and uninsured persons is reported in columns Eq.1 and Eq.2 respectively. The equation independence test obtained with the likelihood ratio test is statistically significant at 5%; which justifies the simultaneous estimation of the three equations. Sigma (σ_i) denotes the square root of the variance of the error terms in the result equations (Eq.1) and (Eq.2), respectively; Rho (ρ_i) denotes the correlation coefficient between the error term of the selection equation (Eq.3) and the error term of the result equations (Eq.1) and (Eq.2), respectively. Rho is positive and significant for the insurance market participants scheme and not significant for the non-participant equation; indicating that there is an absolute benefit in terms of adopting agricultural insurance as risk management instruments.

The results of the participation equation indicate that the factors that explain household purchase of agricultural insurance products are related to access to information, access to farm advice, gender and farm status. The access to information variable is positive and significant indicating that knowledge of agricultural insurance is a fundamental aspect for household adoption of insurance products. This makes it possible to understand what insurance is, its importance and especially what it consists of in the context of agricultural risk management.

The farm advisory variable is significant and positively related to access to insurance, showing that access to extension services increases households' likelihood of using insurance. In other words, households that receive advice in their production activities are more likely to use insurance products for better management of agricultural risks. This finding suggests that extension services, through their role in supporting producers, encourage households to adopt much more innovative practices by encouraging them to integrate formal risk management mechanisms into their production activities.

The gender variable is significant and its positive sign shows that men are relatively more likely to participate in the insurance system compared to women. This result reflects the statistics of the data used revealing that of the 19% of rice farmers who have access to insurance, only 1% represent women.

When it comes to planning status, households with private development are less likely to use insurance compared to those with public operations.

The estimation of the outcome equations (Eq. 1 and Eq. 2) indicates that variables such as gender, area and farm advice are significant and positive for both the log income of insured households and the uninsured. These results imply that, regardless of the status of the household – insured or not – the income of the household improves when it had benefited in advance from agricultural advice, but this increase in income is relatively more favorable among households capitated by a man than those capitated by a woman. The positive and significant impact of the area farmed shows that, the larger the size of the holding, the more the household is able to produce more and increase its agricultural turnover. Access to credit is significant and positive only for the outcome equation of non-participants in the insurance system, meaning that in the non-participant group, households with access to credit are more likely to have an income gain compared to those without.

However, the contract variable has opposite signs for both groups; It is significant and positive in equation 1 for insurance system participants while it is significant and negative in equation 2 for non-participants. These results show that households with agricultural insurance find their income increased if they have entered into a contract to sell their product. On the other hand, even if the latter are contractual, the effect of this contractualization on income appears negative when they do not secure their production activities by insurance (See Table 11).

Table 11: Endogenous switching regression model (ESRM) estimation result.

Logarithm of Farm Income	Eq.1 - Insured persons	Eq.2 - Uninsured	Eq.3 Participation
Fertilizer price (in FCFA)	-0.003	0.001	
	(0.002)	(0.002)	
Age (in years)	0.012	-0.004	-0.0104
	(0.014)	(0.016)	(0.008)
Male-capitated household	1.645*	1.186*	1.165*
	(0.912)	(0.682)	(0.486)
Formal education (1 if household has received it)	-0.663	0.492	-0.211
	(0.478)	(0.470)	(0.237)
Area farmed (in hectares)	0.300***	0.259***	0.052
	(0.088)	(0.0565)	(0.049)
Contractual (1 if the household has a contractual relationship)	1.096***	-2.248***	-0.031
	(0.410)	(0.467)	(0.199)
Access to credit (=1 if household has access)	-1.236	1.885***	0.261
	(0.757)	(0.461)	(0.270)
Risk of drought (1 if the household has experienced a drought)	-1.218	-0.293	-0.154
	(1.197)	(1.463)	(0.682)
Access to farm advice (1 if I have benefited from it)	1.925***	0.897**	0.574**
	(0.630)	(0.430)	(0.251)
Constant	8.736***	11.556***	-2.214***
	(1.698)	(1.037)	(0.666)
Access to information from the existence of insurance			0.879***
			(0.216)
Status of the holding (1 if private)			-0.726**
			(0.371)
Sigma (σ)	1,673**	2.237***	
	(0.398)	(0.191)	
Rho (ρ)	0.929***	0.017	
	(0.052)	(0.268)	
LR test of Independent equations. : chi2(2) = 6.49 Prob > chi2 = 0.0389			

Note: *Significant at 10%, **significant at 5%, ***significant at 1%. The values in parentheses are standard deviations.

7. Conclusion

Strengthening farmers' ability to withstand extreme climate risks is of paramount importance in modern agriculture. Knowing that any climatic event (drought or flood) could seriously affect the livelihoods of farming households, especially their income and food, it is therefore important to define policies to support resilience to climate change. To this end, financial risk management instruments seem to be essential to meet this need and are often seen by policymakers as a response to the problem. However, promoting the extension of such an adaptation measure should first require an in-depth study to assess its impact and, above all, the key levers that encourage its adoption. It is in this sense that this research examines agricultural insurance as a means of risk management and assesses its impact on the income of rice farmers in Senegal. The data used came from a survey by the Ministry of Agriculture and Rural Equipment of Senegal's Agricultural Policy Support Project. The applied endogenous switching regression methodology shows that the adoption of insurance can positively affect the expected usefulness of farmers in case of risk. Agricultural insurance is a good risk management tool because it can reduce farmers' risk of loss. However, despite the positive impact of agricultural insurance, its uptake by farmers is still low. To this end, to promote its practice, policymakers should proceed by strengthening household capacities through extension services such as agricultural advice, while insurance institutions such as the National Agricultural Insurance Company (CNAAS) should do more communication so that farmers can access information on insurance products.

GENERAL CONCLUSION AND POLICY IMPLICATIONS

1. Introduction

This chapter concludes the study by synthesizing the main research findings in relation to the research objectives and questions and discussing the value and contribution of these. It also reviews the economic policy implications of the study and will suggest opportunities for future research.

2. Overview of the research: Main issues revisited

While climate change can have considerable negative impacts on the economy and especially on rural farming communities, countries like Senegal are failing to tackle this problem earlier despite the urgency it deserves. Although Senegal is at the beginning of the development of its national adaptation plan (NAP), there is however little solid scientific knowledge that can justify the impact of climate change on agriculture and the vulnerability of farming communities. Climate risk management solutions are also weakly controversial, which does not allow decision makers to apply measures appropriate to the needs of farmers who have limited possibilities of choice to adapt to climate change. The objective of this research was to examine the impact of climate change on rice production in Senegal and the means of financing agricultural risks. As the impact of climate change can be studied at different scales, this research starts with a macroeconomic analysis to see the repercussions on the agricultural gross domestic product and then measures vulnerability and risk management mechanisms at the microeconomic level, particularly among farming households.

The results show that the effects of climatic parameters on the gross domestic product (GDP) of the rice sector are positive. In the short term, a 1% increase in precipitation increases GDP per capita by 0.54%, all other things being equal. The same is true for temperatures; an additional unit of degree Celsius will increase the wealth from rice cultivation by 3.52%, ceteris paribus. On the other hand, a decrease in rainfall could lead to a decrease in the GDP of rice cultivation. The cross-analysis of the normalized precipitation index (SPI) and the evolution of GDP per capita has shown that droughts are unfavorable to agricultural growth. Indeed, the per capita GDP of rice growing would have increased by 1.10% if CO_2 emissions increased by 1%.

Although the macroeconomic analysis provided insight into the response of rice GDP growth to climate change, an analysis focused on agricultural households provided a very specific insight into the vulnerability status of the rice sector. in Senegal. Starting from an integrated approach combining a set of economic, demographic, social and environmental variables, the results show that among the 33 municipalities studied, two (2) (Sare coly sale and Ouro sidy) are at a very high level of vulnerability from 0.61 to 0.70, six (6) (Kolda, Ndendory, Kandia, Orkadiere, Medina cherif, Diobe, and kabendou) are in a state of high vulnerability of 0.53 and 0.60 and six others (6) (Dabia obedji, Kandiaye, Nabadji civol, Bokidiawe, Dobel, and Walalde) are in a relatively moderate situation (0.46 to 0.52). In general, the most vulnerable rice-growing communities are found in southern Senegal, in the Anambé basin of the Kolda region and in eastern Senegal in the Senegal River valley, particularly in the Matam region. The results revealed that these localities are very exposed to climate change given the changes in temperature, precipitation and especially the frequency of meteorological events such as floods and droughts. They are also sensitive to climatic risks because being characterized on the one hand, by a relatively high relief, therefore less favorable to the development of rice growing and on the other hand, by the fact that these localities are dominated by a child age group and therefore, quite vulnerable to shocks. Adaptive capacity is low in localities for several reasons.

- First, their economic capacity is not strong enough to cope with climate change because their access to risk management instruments, in particular insurance, is very limited; the share of irrigated land is very minimal and agricultural income levels are relatively low or even nil for some.
- Second, their institutional capacity is very weak because they lack access to important infrastructure such as roads; to basic services such as health and electricity; and financial services including agricultural credit.
- Third, their human capacity is mediocre due to the low rate of access to education and the fact that they do not have a young population likely to contribute to the economy or to meet the substance of families.
- Fourthly, their social capacity is weak, which is marked by a lack of organization for some of these localities where rice farmers are not grouped into cooperatives or producer organizations and are also marginalized from agricultural extension services, particularly agricultural advice.

The analysis of the impact of the adoption of agricultural insurance on the income of rice farmers revealed that agricultural insurance is a good financial instrument for managing climate risks. Rice farmers who have used insurance as a means of risk management earn relatively higher incomes than their counterparts who do not participate in the system. Access to agricultural information and advice are two of the factors that influence household subscription to agricultural insurance products. In addition, men and households with public farms are more likely to use agricultural insurance.

In sum, this research has provided insight into the impact of climate change on the rice sector in Senegal and identified the need for adaptation policy measures to reduce the vulnerability of rural communities and improve their resilience. The results provide insights for better targeting and prioritization of national adaptation policies for the agricultural sector and inform an important climate risk management mechanism, in particular agricultural insurance. Indeed, some economic policy implications are formulated to address the issue of vulnerability and risk management.

3. Implications of economic policies

Two main policy implications emerge from this research: strengthening economic capital and strengthening institutional capital.

3.1. Strengthening economic capital

Strengthening economic capital through the intervention of the insurance company in these localities to promote and encourage the adoption of agricultural insurance products by rice farmers could reduce their vulnerability to climate change. Moreover, helping rice farmers to become aware of insurance as a good financial instrument for managing climate risks can be done through the following mechanisms:

- Given that access to information is a key determinant of uptake of agricultural insurance products, communication about insurance and its benefits in terms of loss coverage would encourage farm households to use this coping strategy;
- Capacity building of farm households through extension services such as farm advisory services facilitates understanding and encourages farm households to use insurance for climate risk management.

Furthermore, strengthening economic capital through irrigation development would allow rice farming communities to reduce drought-related losses, improve productivity and increase incomes. Moreover, the economic potential itself could be accelerated by a favorable institutional climate, as follows.

3.2. Strengthening institutional capital

Improving institutional capital through the development of infrastructure, basic social services, and financial institutions are the fundamental policy measures to reduce vulnerability and improve the resilience of the farming communities studied. To this end, in Senegal, policies for adapting the agricultural sector to climate change should be oriented towards the following levers:

- Strengthening human capital through education and training of farm households through the provision of agricultural advisory services, which would help raise awareness of climate change and understanding of appropriate adaptation options.
- Development of health infrastructure to facilitate access to health care;
- Construction of roads to facilitate farm households' access to markets for the supply and sale of their crops;
- Strengthening the presence of credit and insurance institutions, particularly CNAAS, to offer farmers more options for adapting to climate change.
- Encouraging farmer communities to better structure themselves into producer organizations, which would help avoid marginalization and at the same time facilitate interventions, particularly with regard to the extension services offered.

BIBLIOGRAPHIC REFERENCES

Acquah, H. D.-G. (2011). *Farmers perception and adaptation to climate change: A willingness to pay analysis*.

Adams, R. M. (1989). Global climate change and agriculture: An economic perspective. *American Journal of Agricultural Economics*, *71*(5), 1272–1279.

Adams, L., 2018: *Unlocking the potential of enhanced rainfed agriculture*. SIWI, Stockholm. Available at: https://www.siwi.org/wp content/uploads/2018/12/ Unlocking-the-potential-of-rainfed-agriculture-2018FINAL.pdf (accessed 31/01/2022).

Adger, W. N. (1999). Social vulnerability to climate change and extremes in coastal Vietnam. *World Development*, *27*(2), 249–269.

Adger, W. N., Brooks, N., Bentham, G., Agnew, M., & Eriksen, S. (2004). New indicators of vulnerability and adaptive capacity (Vol. 122). *Norwich: Tyndall Centre for Climate Change Research*.

Adger, W. N., Brown, I., & Surminski, S. (2018). Advances in risk assessment for climate change adaptation policy. In *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* (Vol. 376, Issue 2121, p. 20180106). The Royal Society Publishing.

Agence Nationale de la Statistique et de la Démographie (ANSD). (2015). *Pauvreté et conditions de vie des ménages*. http://www.ansd.sn/ressources/publications/PAUVRETE%20ET%20CONDITION%20DE%20VIE%20DES%20MENAGES-DEF-VRC-VF.pdf

Agossou, D. S. M., Tossou, C. R., Vissoh, V. P., & Agbossou, K. E. (2012). Perception des perturbations climatiques, savoirs locaux et stratégies d'adaptation des producteurs agricoles béninois. *African Crop Science Journal*, *20*, 565–588.

Ali, S. (2012). Climate change and economic growth in a rain-fed economy: How much does rainfall variability cost Ethiopia? *Available at SSRN 2018233*.

Allen, K. (2003). Vulnerability reduction and the community-based approach: A Philippines study. In *Natural disaster and development in a globalizing world* (pp. 186–200). Routledge.

Alvar-Beltrán, J., Dao, A., Dalla Marta, A., Heureux, A., Sanou, J., & Orlandini, S. (2020). Farmers' perceptions of climate change and agricultural adaptation in Burkina Faso. *Atmosphere*, *11*(8), 827.

Apata, T. G., Samuel, K. D., & Adeola, A. O. (2009). *Analysis of Climate Change Perception and Adaptation among Arable Food Crop Farmers in South Western Nigeria.*

Arouri, M., Nguyen, C., & Youssef, A. B. (2015). Natural disasters, household welfare, and resilience: Evidence from rural Vietnam. *World Development*, *70*, 59–77.

Aryal, J. P., Sapkota, T. B., Rahut, D. B., Krupnik, T. J., Shahrin, S., Jat, M. L., & Stirling, C. M. (2020). Major climate risks and adaptation strategies of smallholder farmers in coastal Bangladesh. *Environmental Management*, *66*(1), 105–120.

Asante, F. A., & Amuakwa-Mensah, F. (2014). Climate change and variability in Ghana: Stocktaking. *Climate*, *3*(1), 78–101.

Ayanlade, A., & Jegede, M. O. (2016). Climate change education and knowledge among Nigerian university graduates. *Weather, Climate, and Society*, *8*(4), 465–473.

Ayinde, O. E., Muchie, M., & Olatunji, G. B. (2011). Effect of climate change on agricultural productivity in Nigeria: A co-integration model approach. *Journal of Human Ecology*, *35*(3), 189–194.

Bang, H., Miles, L., & Gordon, R. (2019). Evaluating local vulnerability and organisational resilience to frequent flooding in Africa: The case of Northern Cameroon. *Foresight*, *21*(2), 266–284.

Barnett, B. J., Barrett, C. B., & Skees, J. R. (2008). Poverty traps and index-based risk transfer products. *World Development*, *36*(10), 1766–1785.

Basupi, L. V., Quinn, C. H., & Dougill, A. J. (2019). Adaptation strategies to environmental and policy change in semi-arid pastoral landscapes: Evidence from Ngamiland, Botswana. *Journal of Arid Environments*, *166*, 17–27.

Besley, T. (1995). Savings, credit and insurance. *Handbook of Development Economics*, *3*, 2123–2207.

Brooks, N. (2003). Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for Climate Change Research Working Paper*, *38*(38), 1–16.

Brooks, N., Adger, W. N., & Kelly, P. M. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change*, *15*(2), 151–163.

Cabral, F. J. (2014). Rainfall and economic growth and poverty: Evidence from Senegal and Burkina Faso. *African Growth and Development Policy*, *8*(3), 1–34.

Callo-Concha, D. (2018). Farmer perceptions and climate change adaptation in the West Africa Sudan savannah: Reality check in Dassari, Benin, and Dano, Burkina Faso. *Climate*, *6*(2), 44.

Campbell, D. J. (1999). Response to drought among farmers and herders in southern Kajiado District, Kenya: A comparison of 1972-1976 and 1994-1995. *Human Ecology*, *27*(3), 377–416.

Carter, M., De Janvry, A., Sadoulet, E., & Sarris, A. (2015). Index-based weather insurance for developing countries: A review of evidence and a set of propositions for up-scaling. *Revue d'economie Du Developpement*, *23*(1), 5–57.

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies*, *42*(2), 178–199.

Ceesay, E. K., & Fanneh, M. M. (2022). Economic growth, climate change, and agriculture sector: ARDL bounds testing approach for Bangladesh (1971-2020). *Economics, Management and Sustainability*, *7*(1), 95–106.

Chandio, A. A., Jiang, Y., & Magsi, H. (2018). *Climate change impact on rice production in Pakistan: An ARDL-bounds testing approach to cointegration*.

Chandio, A. A., Jiang, Y., & Rehman, A. (2019). Using the ARDL-ECM approach to investigate the nexus between support price and wheat production: An empirical evidence from Pakistan. *Journal of Asian Business and Economic Studies*, *26*(1), 139–152.

Chandio, A. A., Jiang, Y., Rehman, A., & Rauf, A. (2020). Short and long-run impacts of climate change on agriculture: An empirical evidence from China. *International Journal of Climate Change Strategies and Management, 12*(2), 201–221.

Chaudhary, R. C., Nanda, J. S., & Van Tran, D. (2003). *Guide d'identification des contraintes de terrain à la production de riz*. Food & Agriculture Org.

Chaudhuri, S., Jalan, J., & Suryahadi, A. (2002). *Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia*.

Christensen, J.H., B. Hewitson, A. Busuioc, A. Chen, X. Gao, I. Held, R. Jones, R.K. Kolli, W.-T. Kwon, R. Laprise, V. Magaña Rueda, L. Mearns, C.G. Menéndez, J. Räisänen, A. Rinke, A. Sarr and P. Whetton, 2007: Regional Climate Projections. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA Available at: https://www.ipcc.ch/site/assets/uploads/2018/02/ar4-wg1-chapter11-1.pdf (accessed 31/01/2022).

Cline, W. R. (2007). *Global warming and agriculture: Impact estimates by country*. Peterson Institute.

Cobb, C. W., & Douglas, P. H. (1928). *A theory of production*.

Colacito, R., Hoffmann, B., & Phan, T. (2018). Temperatures and growth: A panel analysis of the United States. *Journal of Money, Credit, and Banking*, *51*(2–3), 2019.

Cook, K. H., & Vizy, E. K. (2015). Detection and analysis of an amplified warming of the Sahara Desert. *Journal of Climate*, *28*(16), 6560–6580.

Cutter, S. L., Mitchell, J. T., & Scott, M. S. (2012). Revealing the vulnerability of people and places: A case study of Georgetown County, South Carolina. In *Hazards Vulnerability and Environmental Justice* (pp. 111–142). Routledge.

Dasgupta, A., & Baschieri, A. (2010). Vulnerability to climate change in rural Ghana: Mainstreaming climate change in poverty-reduction strategies. *Journal of International Development*, *22*(6), 803–820.

Derbile, E. K., & File, D. J. (2016). Community risk assessment of rainfall variability under rain-fed agriculture: The potential role of local knowledge in Ghana. *Ghana Journal of Development Studies*, *13*(2), 66–83.

Deressa, T., Hassan, R. M., & Ringler, C. (2008). *Measuring Ethiopian Farmers' Vulnerability to Climate Change Across Regional ... - Temesgen Deressa, Rashid M. Hassan, and Claudia Ringler—Google Livres*.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, *19*(2), 248–255.

Dfid, D. (1999). Sustainable Livelihoods Guidance Sheets: Framework Introduction Vulnerability Transforming. *Context*, *26*.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846.

Di Falco, S., Yesuf, M., Kohlin, G., & Ringler, C. (2012). Estimating the impact of climate change on agriculture in low-income countries: Household level evidence from the Nile Basin, Ethiopia. *Environmental and Resource Economics*, *52*, 457–478.

Dinar, A. (1998). *Measuring the impact of climate change on Indian agriculture* (Vol. 402). World Bank Publications.

Dolan, A. H., Smit, B., Skinner, M. W., Bradshaw, B., & Bryant, C. R. (2001). Adaptation to climate change in agriculture: Evaluation of options. *Occasional Paper*, *26*.

Dosio, A. (2017). Projection of temperature and heat waves for Africa with an ensemble of CORDEX Regional Climate Models. *Climate Dynamics*, *49*(1–2), 493–519.

Dosio, A., Jury, M. W., Almazroui, M., Ashfaq, M., Diallo, I., Engelbrecht, F. A., Klutse, N. A., Lennard, C., Pinto, I., & Sylla, M. B. (2021). Projected future daily characteristics of African precipitation based on global (CMIP5, CMIP6) and regional (CORDEX, CORDEX-CORE) climate models. *Climate Dynamics*, *57*(11–12), 3135–3158.

Du Toit, M., Du Toit, S. H. C., & Hawkins, D. M. (2001). *Interactive LISREL: User's guide*. Scientific Software International.

Elum, Z. A., Modise, D. M., & Marr, A. (2017). Farmer's perception of climate change and responsive strategies in three selected provinces of South Africa. *Climate Risk Management*, *16*, 246–257.

Eriksen, S. H., & Kelly, P. M. (2007). Developing credible vulnerability indicators for climate adaptation policy assessment. *Mitigation and Adaptation Strategies for Global Change*, *12*, 495–524.

Evariste, F. F., Jean, S. D., Victor, K., & Claudia, M. (2018). Assessing climate change vulnerability and local adaptation strategies in adjacent communities of the Kribi-Campo coastal ecosystems, South Cameroon. *Urban Climate*, *24*, 1037–1051.

Falco, S. D., Adinolfi, F., Bozzola, M., & Capitanio, F. (2014). Crop insurance as a strategy for adapting to climate change. *Journal of Agricultural Economics*, *65*(2), 485–504.

Faye, B., Webber, H., Naab, J. B., MacCarthy, D. S., Adam, M., Ewert, F., Lamers, J. P., Schleussner, C.-F., Ruane, A., & Gessner, U. (2018). Impacts of 1.5 versus 2.0 C on cereal yields in the West African Sudan Savanna. *Environmental Research Letters*, *13*(3), 034014.

Field, C. B., & Barros, V. R. (2014). *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press.

Fisher, A. C., Hanemann, W. M., Roberts, M. J., & Schlenker, W. (2012). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: comment. *American Economic Review*, *102*(7), 3749–3760.

Forner, C. 2006. *An introduction to the impacts of climate change and vulnerability of forests*. Background document for the South East Asian meeting of the Tropical Forests and Climate Change Adaptation (TroFCCA) project. Bogor, West Java (May 29–30).

Fosu-Mensah, B. Y., Vlek, P. L., & MacCarthy, D. S. (2012). Farmers' perception and adaptation to climate change: A case study of Sekyedumase district in Ghana. *Environment, Development and Sustainability*, *14*, 495–505.

Frimpong Magnus, J., & Oteng-Abayie, E. F. (2006). Bounds testing approach: An examination of foreign direct investment, trade, and growth relationships. *American Journal of Applied Sciences, Forthcoming*.

Fritzsche, K., Schneiderbauer, S., Bubeck, P., Kienberger, S., Buth, M., Zebisch, M., & Kahlenborn, W. (2014). *The vulnerability sourcebook: Concept and guidelines for standardised vulnerability assessments*.

Fuessel, H.-M. (2005). *Vulnerability in climate change research: A comprehensive conceptual framework*.

Fuller, T. L., Clee, P. R. S., Njabo, K. Y., Tróchez, A., Morgan, K., Meñe, D. B., Anthony, N. M., Gonder, M. K., Allen, W. R., & Hanna, R. (2018). Climate warming causes declines in crop yields and lowers school attendance rates in Central Africa. *Science of the Total Environment*, *610*, 503–510.

Füssel, H.-M. (2007). Vulnerability: A generally applicable conceptual framework for climate change research. *Global Environmental Change*, *17*(2), 155–167.

Füssel, H.-M. (2010). How inequitable is the global distribution of responsibility, capability, and vulnerability to climate change: A comprehensive indicator-based assessment. *Global Environmental Change*, *20*(4), 597–611.

Füssel, H.-M., & Klein, R. J. (2006). Climate change vulnerability assessments: An evolution of conceptual thinking. *Climatic Change*, *75*(3), 301–329.

Garrido, A., Bielza, M., Rey, D., Mínguez, M. I., & Ruiz-Ramos, M. (2011). 19 Insurance as an adaptation to climate variability in agriculture. *Handbook on Climate Change and Agriculture*, 420.

Gbetibouo, G. A., Ringler, C., & Hassan, R. (2010). Vulnerability of the South African farming sector to climate change and variability: An indicator approach. *Natural Resources Forum*, *34*(3), 175–187.

Gebre, G. G. (2021). Prevalence of household food insecurity in East Africa: Linking food access with climate vulnerability. *Climate Risk Management*, *33*, 100333.

Giorgi, F., Raffaele, F., & Coppola, E. (2019). The response of precipitation characteristics to<? Xmltex$\backslash$break?> global warming from climate projections. *Earth System Dynamics*, *10*(1), 73–89.

Habou, Z. A., Boubacar, M. K., & Adam, T. (2016). Les systèmes de productions agricoles du Niger face au changement climatique: Défis et perspectives. *International Journal of Biological and Chemical Sciences*, *10*(3), 1262–1272.

Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2018). Do risk preferences change? Evidence from the great east japan earthquake. *American Economic Journal: Applied Economics*, *10*(2), 298–330.

Harris, I., Osborn, T. J., Jones, P., & Lister, D. (2020). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, *7*(1), 109.

Harttgen, K., & Günther, I. (2007). *Estimating vulnerability to covariate and idiosyncratic shocks*. Ibero-America Institute for Economic Research.

Hasegawa, T., Wakatsuki, H., Ju, H., Vyas, S., Nelson, G. C., Farrell, A., Deryng, D., Meza, F., & Makowski, D. (2022). A global dataset for the projected impacts of climate change on four major crops. *Scientific Data*, *9*(1), 58.

He, Y., Zhou, C., & Ahmed, T. (2021). Vulnerability assessment of rural social-ecological system to climate change: A case study of Yunnan Province, China. *International Journal of Climate Change Strategies and Management*, *13*(2), 162–180.

Heitzmann, K., Canagarajah, R. S., & Siegel, P. B. (2002). Guidelines for assessing the sources of risk and vulnerability. *WB Social Protection Discussion Paper*, *218*.

Hess, U., & Syroka, J. (2005). *Weather-based insurance in Southern Africa: The case of Malawi*.

Hoddinott, J., & Quisumbing, A. (2010). *Methods for microeconometric risk and vulnerability assessment*. Springer.

Hoddinott, J., & Quisumbing, M. A. R. (2003). *Data sources for microeconometric risk and vulnerability assessments*. World Bank, Social Protection.

Huynh, L. T. M., & Stringer, L. C. (2018). Multi-scale assessment of social vulnerability to climate change: An empirical study in coastal Vietnam. *Climate Risk Management*, *20*, 165–180.

IPCC, 2014a: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C. B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (ed.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1132 pp. Available at: https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-PartA_FINAL.pdf. (accessed 16/08/2022).

IPCC, 2021: *Summary for Policymaker*s [MassonDelmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Pean, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B.

R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekci, R. Yu and B. Zhou (ed.)]. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, **In press**, Cambridge University Press. Available at: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SPM.pdf (accessed 16/08/2022).

Iizumi, T., Shiogama, H., Imada, Y., Hanasaki, N., Takikawa, H., & Nishimori, M. (2018). Crop production losses associated with anthropogenic climate change for 1981–2010 compared with preindustrial levels. *International Journal of Climatology*, *38*(14), 5405–5417.

Islam, M. M., Alharthi, M., & Murad, M. W. (2021). The effects of carbon emissions, rainfall, temperature, inflation, population, and unemployment on economic growth in Saudi Arabia: An ARDL investigation. *Plos One*, *16*(4), e0248743.

Juana, J. S., Kahaka, Z., & Okurut, F. N. (2013). Farmers' perceptions and adaptations to climate change in sub-Sahara Africa: A synthesis of empirical studies and implications for public policy in African agriculture. *Journal of Agricultural Science*, *5*(4), 121.

Kaiser, H. M., Riha, S. J., Wilks, D. S., Rossiter, D. G., & Sampath, R. (1993). A farm-level analysis of economic and agronomic impacts of gradual climate warming. *American Journal of Agricultural Economics*, *75*(2), 387–398.

Kaly, U., Briguglio, L., McLeod, H., Schmall, S., Pratt, C., & Pal, R. (1999). *Environmental Vulnerability Index (EVI) to summarise national environmental vulnerability profiles*. SOPAC.

Kaly, U., & Pratt, C. (2000). Environmental vulnerability index: Development and provisional indices and profiles for Fiji, Samoa, Tuvalu and Vanuatu. *Phase II Report for NZODA. SOPAC Technical Report*, *306*, 89.

Kelly, P. M., & Adger, W. N. (2000a). Theory and practice in assessing vulnerability to climate change andFacilitating adaptation. *Climatic Change*, *47*(4), 325–352.

Kelly, P. M., & Adger, W. N. (2000b). Theory and practice in assessing vulnerability to climate change andFacilitating adaptation. *Climatic Change*, *47*(4), 325–352.

Kelly, P. M., & Adger, W. N. (2000c). Theory and practice in assessing vulnerability to climate change andFacilitating adaptation. *Climatic Change*, *47*(4), 325–352.

Klein, R. J., & Nicholls, R. J. (1999). Assessment of coastal vulnerability to climate change. *Ambio*, 182–187.

Kuntiyawichai, K., Plermkamon, V., Jayakumar, R., & Van Dau, Q. (2015). Climate change vulnerability mapping for the Greater Mekong Sub-region. *Bangkok, Thailand: Asia and Pacific Regional Bureau for Education of United Nations Educational, Scientific and Cultural Organization*.

Kurukulasuriya, P., & Mendelsohn, R. O. (2007). Crop selection: Adapting to climage change in Africa. *World Bank Policy Research Working Paper*, *4307*.

Leichenko, R. M., & O'brien, K. L. (2002). The dynamics of rural vulnerability to global change: The case of southern Africa. *Mitigation and Adaptation Strategies for Global Change*, *7*(1), 1–18.

Lelieveld, J., Proestos, Y., Hadjinicolaou, P., Tanarhte, M., Tyrlis, E., & Zittis, G. (2016). Strongly increasing heat extremes in the Middle East and North Africa (MENA) in the 21st century. *Climatic Change*, *137*(1), 245–260.

Loko, Y. L., Dansi, A., Agre, A. P., Akpa, N., Dossou-Aminon, I., Assogba, P., Dansi, M., Akpagana, K., & Sanni, A. (2013). Perceptions paysannes et impacts des changements climatiques sur la production et la diversité variétale de l'igname dans la zone aride du nord-ouest du Bénin. *International Journal of Biological and Chemical Sciences*, *7*(2), 672–695.

Lokonon, B. O. K. (2019). Farmers' vulnerability to climate shocks: Insights from the Niger basin of Benin. *Climate and Development*, *11*(7), 585–596.

Luers, A. L., Lobell, D. B., Sklar, L. S., Addams, C. L., & Matson, P. A. (2003). A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. *Global Environmental Change*, *13*(4), 255–267.

Lv, C., Huang, Y., Sun, W., Yu, L., & Zhu, J. (2020). Response of rice yield and yield components to elevated [CO2]: A synthesis of updated data from FACE experiments. *European Journal of Agronomy*, *112*, 125961.

Mahmood, N., Ahmad, B., Hassan, S., & Bakhsh, K. (2012). Impact of temperature ADN precipitation on rice productivity in rice-wheat cropping system of Punjab province. *J. Anim. Plant Sci*, *22*, 993–997.

Mahmood, R., Jia, S., & Zhu, W. (2019). Analysis of climate variability, trends, and prediction in the most active parts of the Lake Chad basin, Africa. *Scientific Reports*, *9*(1), 6317.

Mammo, B. T. (2022). *Climate Change and its Impact on Agricultural GDP Growth in Ethiopia: A Time Series Analysis*.

Martens, P., Kovats, R. S., Nijhof, S., De Vries, P., Livermore, M. T. J., Bradley, D. J., Cox, J., & McMichael, A. J. (1999). Climate change and future populations at risk of malaria. *Global Environmental Change*, *9*, S89–S107.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., & Gomis, M. I. (2021). Climate change 2021: The physical science basis. *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, *2*.

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., & Pidcock, R. (2018). Global warming of 1.5 C. *An IPCC Special Report on the Impacts of Global Warming Of*, *1*(5), 43–50.

McCarthy, J. J., O. F. Canziani, N. A. Leary, D. J. Dokken, and K. S. White (eds.). 2001. *Climate change 2001: Impacts, adaptation and vulnerability*. Cambridge, UK: Cambridge University Press.

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, *17*(22), 179–183.

Mcleman, R., & Smit, B. (2006). Vulnerability to climate change hazards and risks: Crop and flood insurance. *Canadian Geographer/Le Géographe Canadien*, *50*(2), 217–226.

Mechler, R., Singh, C., Ebi, K., Djalante, R., Thomas, A., James, R., Tschakert, P., Wewerinke-Singh, M., Schinko, T., & Ley, D. (2020). Loss and Damage and limits to adaptation: Recent IPCC insights and implications for climate science and policy. *Sustainability Science*, *15*, 1245–1251.

Mendelsohn, R. (2009). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research*, *1*(1), 5–19.

Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: A Ricardian analysis. *The American Economic Review*, 753–771.

Mendelsohn, R., & Williams, L. (2004). Comparing forecasts of the global impacts of climate change. *Mitigation and Adaptation Strategies for Global Change*, *9*, 315–333.

Mertz, O., Mbow, C., Reenberg, A., & Diouf, A. (2009). Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. *Environmental Management*, *43*, 804–816.

Metzger, M. J., & Schröter, D. (2006). Towards a spatially explicit and quantitative vulnerability assessment of environmental change in Europe. *Regional Environmental Change*, *6*, 201–216.

Morardet, S., Mailhol, J.-C., Vidal, A., Garin, P., & Gleyses, G. (1998). Sécheresse et demande en eau d'irrigation: Éléments de réflexion. *Sciences Eaux & Territoires*, *13 Ingénieries-EAT*, 15–28.

Morrow, B. H. (1999). Identifying and mapping community vulnerability. *Disasters*, *23*(1), 1–18.

Moss, R., A. Brenkert, and E. Malone. 2001. *Vulnerability to climate change, A quantitative approach*. https://www.researchgate.net/publication/240403615_Vulnerability_to_Climate_Change_A_Quantitative_Approach Accessed February 18, 2022.

Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M. T., & Liang, L. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. *Journal of Water and Climate Change*, *12*(6), 2256–2270.

Nematchoua, M. K., Orosa, J. A., & Reiter, S. (2019). Climate change: Variabilities, vulnerabilities and adaptation analysis-A case of seven cities located in seven countries of Central Africa. *Urban Climate*, *29*, 100486.

Nguyen, Y. T. B., & Leisz, S. J. (2021). Determinants of livelihood vulnerability to climate change: Two minority ethnic communities in the northwest mountainous region of Vietnam. *Environmental Science & Policy*, *123*, 11–20.

Nhemachena, C., & Hassan, R. (2007). *Micro-level analysis of farmers adaption to climate change in Southern Africa*. Intl Food Policy Res Inst.

Nikiema, P. M., Sylla, M. B., Ogunjobi, K., Kebe, I., Gibba, P., & Giorgi, F. (2017). Multi-model CMIP5 and CORDEX simulations of historical summer temperature and precipitation variabilities over West Africa. *International Journal of Climatology*, *37*(5), 2438–2450.

o'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., Javed, A., Bhadwal, S., Barg, S., & Nygaard, L. (2004). Mapping vulnerability to multiple stressors: Climate change and globalization in India. *Global Environmental Change*, *14*(4), 303–313.

Odusola, A., & Abidoye, B. (2015). Effects of temperature and rainfall shocks on economic growth in Africa. *Available at SSRN 3101790*.

Ojo, T. O., & Baiyegunhi, L. J. S. (2020). Determinants of climate change adaptation strategies and its impact on the net farm income of rice farmers in south-west Nigeria. *Land Use Policy*, *95*, 103946.

Organization for Economic Co-operation and Development (OECD), J. R. C.-E. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD publishing.

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., & Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, *11*(4), 306–312.

Parry, M., Evans, A., Rosegrant, M. W., & Wheeler, T. (2009). *Climate change and hunger: Responding to the challenge*. Intl Food Policy Res Inst.

Parry, M. L., Canziani, O., Palutikof, J., Van der Linden, P., & Hanson, C. (2007). *Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC* (Vol. 4). Cambridge University Press.

Pauw, W. P., & Klein, R. J. (2021). Beyond ambition: Increasing the transparency, coherence and implementability of Nationally Determined Contributions. In *Making Climate Action More Effective* (pp. 1–10). Routledge.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326.

Polsky, C., & Easterling III, W. E. (2001). Adaptation to climate variability and change in the US Great Plains: A multi-scale analysis of Ricardian climate sensitivities. *Agriculture, Ecosystems & Environment*, *85*(1–3), 133–144.

Pörtner, H.-O., Roberts, D. C., Adams, H., Adler, C., Aldunce, P., Ali, E., Begum, R. A., Betts, R., Kerr, R. B., & Biesbroek, R. (2022). *Climate change 2022: Impacts, adaptation and vulnerability*. IPCC Geneva, Switzerland:

Preston, B. L., Westaway, R., Dessai, S., & Smith, T. F. (2009). Are we adapting to climate change? Research and methods for evaluating progress. *Greenhouse 2009: Abstracts*, 58.

Pritchett, L., Suryahadi, A., & Sumarto, S. (2000). *Quantifying vulnerability to poverty: A proposed measure, with application to Indonesia*.

Ranasinghe, R., Ruane, A. C., Vautard, R., Arnell, N., Coppola, E., Cruz, F. A., Dessai, S., Saiful Islam, A. K. M., Rahimi, M., & Carrascal, D. R. (2021). *Climate change information for regional impact and for risk assessment*.

Rankoana, S. A. (2016). Perceptions of climate change and the potential for adaptation in a rural community in Limpopo Province, South Africa. *Sustainability*, *8*(8), 672.

Ravindranath, N. H., Rao, S., Sharma, N., Nair, M., Gopalakrishnan, R., Rao, A. S., Malaviya, S., Tiwari, R., Sagadevan, A., & Munsi, M. (2011). Climate change vulnerability profiles for North East India. *Current Science*, 384–394.

Ray, D. K., West, P. C., Clark, M., Gerber, J. S., Prishchepov, A. V., & Chatterjee, S. (2019). Climate change has likely already affected global food production. *PloS One*, *14*(5), e0217148.

Rosenzweig, C., & Parry, M. L. (1994). Potential impact of climate change on world food supply. *Nature*, *367*(6459), 133–138.

Rothschild, M., & Stiglitz, J. (1978). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. In *Uncertainty in economics* (pp. 257–280). Elsevier.

Salik, K. M., Jahangir, S., & ul Hasson, S. (2015). Climate change vulnerability and adaptation options for the coastal communities of Pakistan. *Ocean & Coastal Management*, *112*, 61–73.

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, *3*(3), 430–439.

Schimmelpfennig, D., & Yohe, G. (1999). Vulnerability of crops to climate change: A practical method of indexing. In *Global Environmental Change and Agriculture* (pp. 193–218). Edward Elgar Publishing.

Schröter, D., Cramer, W., Leemans, R., Prentice, I. C., Araújo, M. B., Arnell, N. W., Bondeau, A., Bugmann, H., Carter, T. R., & Gracia, C. A. (2005). Ecosystem service supply and vulnerability to global change in Europe. *Science*, *310*(5752), 1333–1337.

Sehgal, V. K., Singh, M. R., Jain, N., & Pathak, H. (2017). Climate change and variability: Mapping vulnerability of agriculture using Geospatial Technologies. *Agriculture under Climate Change: Threats, Strategies and Policies*, *1*, 74–79.

Sequeira, T. N., Santos, M. S., & Magalhães, M. (2018). Climate change and economic growth: A heterogeneous panel data approach. *Environmental Science and Pollution Research*, *25*, 22725–22735.

Skees, J. R., & Barnett, B. J. (2006). Enhancing microfinance using index-based risk-transfer products. *Agricultural Finance Review*, *66*(2), 235.

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, *16*(3), 282–292.

Sonwa, D. J., Dieye, A., El Mzouri, E.-H., Majule, A., Mugabe, F. T., Omolo, N., Wouapi, H., Obando, J., & Brooks, N. (2017). Drivers of climate risk in African agriculture. *Climate and Development*, *9*(5), 383–398.

Stern, N. (2008). The economics of climate change. *American Economic Review, 98*(2), 1–37.

Sujakhu, N. M., Ranjitkar, S., He, J., Schmidt-Vogt, D., Su, Y., & Xu, J. (2019). Assessing the livelihood vulnerability of rural indigenous households to climate changes in Central Nepal, Himalaya. *Sustainability*, *11*(10), 2977.

Sultan, B., Defrance, D., & Iizumi, T. (2019). Evidence of crop production losses in West Africa due to historical global warming in two crop models. *Scientific Reports*, *9*(1), 12834.

Svoboda, M., Hayes, M., & Wood, D. (2012). *Standardized precipitation index: User guide*.

Tessema, I., & Simane, B. (2019). Vulnerability analysis of smallholder farmers to climate variability and change: An agro-ecological system-based approach in the Fincha'a sub-basin of the upper Blue Nile Basin of Ethiopia. *Ecological Processes*, *8*, 1–18.

Theodrose, S. (2016). Vulnerability of smallholder farmers to climate change at Dabat and West Belesa Districts, North Gondar, Ethiopia. *Journal of Earth Science & Climatic Change*, *7*(8).

Thornton, P. K., & Herrero, M. (2015). Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa. *Nature Climate Change*, *5*(9), 830–836.

Tjoe, Y. (2016). Measuring the livelihood vulnerability index of a dry region in Indonesia: A case study of three subsistence communities in West Timor. *World Journal of Science, Technology and Sustainable Development*.

Townsend, R. M. (1994). Risk and insurance in village India. *Econometrica: Journal of the Econometric Society*, 539–591.

Tran, P. T., Vu, B. T., Ngo, S. T., Tran, V. D., & Ho, T. D. (2022). Climate change and livelihood vulnerability of the rice farmers in the North Central Region of Vietnam: A case study in Nghe An province, Vietnam. *Environmental Challenges*, *7*, 100460.

Traore, B., Corbeels, M., Van Wijk, M. T., Rufino, M. C., & Giller, K. E. (2013). Effects of climate variability and climate change on crop production in southern Mali. *European Journal of Agronomy*, *49*, 115–125.

UNFCCC Paris Agreement, 2015: *Adoption of the Paris Agreement*. United Nations Climate Change Secretariat (UNFCCC), Bonn, Germany. Available at: http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf. (accessed 31/01/2022).

Waldinger, M. (2013). The Long Term Effects of Climatic Change on Economic Growth: Evidence from the Little Ice Age, 1500–1750. *THE ECONOMIC HISTORY SOCIETY*, 262.

Wang, J., Wang, C., Chen, N., Xiong, Z., Wolfe, D., & Zou, J. (2015). Response of rice production to elevated [CO 2] and its interaction with rising temperature or nitrogen supply: A meta-analysis. *Climatic Change*, *130*, 529–543.

Wehner, M., Seneviratne, S., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., & Kossin, J. (2021). Weather and climate extreme events in a changing climate. *AGU Fall Meeting Abstracts*, *2021*, U13B-11.

Wiréhn, L., Danielsson, Å., & Neset, T.-S. S. (2015). Assessment of composite index methods for agricultural vulnerability to climate change. *Journal of Environmental Management*, *156*, 70–80.

Xiao, X., Melillo, J. M., Kicklighter, D. W., McGuire, A. D., Tian, H., Pan, Y., Vörösmarty, C., & Yang, Z. (1997). *Transient climate change and potential croplands of the world in the 21st century*.

Yesuf, M., Di Falco, S., Deressa, T., Ringler, C., & Kohlin, G. (2008). *The impact of climate change and adaptation on food production in low-income countries: Evidence from the Nile Basin, Ethiopia*. Intl Food Policy Res Inst.

Zarafshani, K., Sharafi, L., Azadi, H., & Van Passel, S. (2016). Vulnerability assessment models to drought: Toward a conceptual framework. *Sustainability, 8*(6), 588.

Zebisch, M., Schneiderbauer, S., Fritzsche, K., Bubeck, P., Kienberger, S., Kahlenborn, W., Schwan, S., & Below, T. (2021). The vulnerability sourcebook and climate impact chains–a standardised framework for a climate vulnerability and risk assessment. *International Journal of Climate Change Strategies and Management*.

Zeleke, T., Beyene, F., Deressa, T., Yousuf, J., & Kebede, T. (2021). Vulnerability of smallholder farmers to climate change-induced shocks in East Hararghe Zone, Ethiopia. *Sustainability*, *13*(4), 2162.

Žurovec, O., Čadro, S., & Sitaula, B. K. (2017). Quantitative assessment of vulnerability to climate change in rural municipalities of Bosnia and Herzegovina. *Sustainability, 9*(7), 1208.

Appendix 1: SPI-1

Year	Jan	Feb	Tue	Apr	May	June	July	August	September	October	November	December
1990	1,4	0,5	NA	0,8	-1,2	-0,7	-0,1	-0,7	-1,3	-0,2	-0,2	0,6
1991	0,9	0,5	NA	0,6	0,1	-1,0	0,0	-1,8	-0,6	0,8	-0,5	0,6
1992	1,1	1,8	NA	0,6	1,2	0,1	-0,3	-0,9	-0,9	-0,3	0,2	0,7
1993	0,8	1,2	NA	2,1	-0,7	-0,4	0,5	-0,8	-0,6	-0,7	0,9	1,7
1994	0,4	0,5	NA	0,1	0,2	-0,3	0,4	1,0	0,0	0,8	1,6	0,6
1995	0,4	0,5	NA	-0,1	-0,1	-0,2	0,3	0,6	-0,5	-0,2	-0,2	0,7
1996	0,4	0,6	NA	-0,8	-0,1	-0,8	0,3	-0,6	-1,0	0,1	0,6	0,6
1997	0,6	0,5	NA	-0,1	1,5	1,4	-1,9	-0,5	-0,2	-0,5	-0,2	0,6
1998	0,4	0,5	NA	-0,4	-0,5	-1,4	-0,6	0,0	1,4	-1,0	-1,0	0,7
1999	0,4	0,5	NA	1,1	0,3	-0,1	0,4	1,4	0,3	2,2	0,2	1,2
2000	0,8	0,5	NA	-0,1	-1,1	-0,1	0,8	-0,3	-0,8	1,4	0,9	0,6
2001	0,4	0,5	NA	-0,4	-0,9	1,3	0,4	-2,1	-0,4	-1,1	2,6	0,6
2002	2,4	0,5	NA	0,3	-0,3	-0,4	-2,7	-1,9	-1,4	0,7	-1,0	1,2
2003	0,4	0,8	NA	0,7	-1,5	0,6	0,5	0,8	0,8	1,0	0,5	0,6
2004	1,5	0,9	NA	-0,1	0,4	0,7	0,7	-0,7	-0,8	-2,6	0,7	0,6
2005	0,4	1,6	NA	-0,4	1,4	1,3	1,9	0,5	0,6	-0,1	-0,2	0,6
2006	0,6	0,6	NA	-0,8	-0,5	1,1	-0,9	0,3	-0,1	-0,1	-1,0	0,6
2007	0,4	0,5	NA	-0,8	-0,2	-1,6	0,2	0,0	0,0	-0,8	1,3	0,6
2008	0,4	2,0	NA	-0,8	1,0	1,6	1,1	0,6	-0,1	0,3	-1,0	0,6
2009	0,4	0,5	NA	-0,8	0,4	0,2	0,9	1,3	0,5	-0,9	-0,2	0,6
2010	0,4	0,5	NA	1,1	0,3	0,9	1,3	0,5	2,1	0,2	0,3	0,6
2011	0,4	0,5	NA	-0,8	-0,1	-0,3	-0,5	0,8	-0,8	-0,8	-1,0	0,6
2012	0,4	0,5	NA	1,6	1,3	1,1	0,8	0,8	1,2	0,2	0,0	1,2
2013	1,1	0,5	NA	0,3	0,1	-0,6	-0,4	0,7	0,9	0,1	0,9	2,2
2014	0,4	0,5	NA	-0,8	2,0	-0,7	-0,7	-0,3	-0,7	0,8	-0,1	0,6
2015	0,4	0,9	NA	0,1	-1,1	-2,3	-0,7	2,0	-0,5	1,3	-0,7	0,7
2016	0,4	0,5	NA	0,3	0,0	-1,1	1,7	-0,7	0,9	-2,0	-0,1	0,6
2017	0,4	0,5	NA	-0,4	1,3	1,7	0,4	0,8	-1,2	-1,0	-0,3	0,6
2018	0,4	0,5	NA	-0,4	-1,4	0,1	-0,6	-1,3	1,0	0,7	0,1	0,6
2019	0,6	1,0	NA	0,9	0,5	0,2	-1,4	0,4	-0,2	1,4	0,6	0,6
2020	0,4	0,5	NA	1,7	-1,2	-0,1	-1,9	0,2	2,3	0,5	0,1	0,6

Appendix 2: SPI-3

Year	Jan	Feb	Tue	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1990	NA	NA	0,9	0,6	-1,1	-0,9	-0,6	-0,8	-1,1	-1,2	-1,3	-0,2
1991	-0,1	0,2	0,3	0,2	0,1	-0,9	-0,5	-1,4	-1,2	-1,0	-0,2	0,7
1992	-0,3	1,8	1,8	1,7	1,2	0,4	0,0	-0,7	-1,1	-1,1	-1,0	-0,4
1993	0,3	1,0	1,0	1,9	-0,4	-0,5	0,0	-0,4	-0,5	-1,0	-0,8	-0,6
1994	0,9	0,2	-0,2	-0,3	0,1	-0,2	0,1	0,7	0,6	0,7	0,4	1,0
1995	1,5	-0,3	0,0	-0,3	-0,1	-0,3	0,1	0,4	0,1	-0,1	-0,6	-0,2
1996	-0,3	0,1	0,2	-0,5	-0,2	-0,8	-0,2	-0,5	-0,7	-0,9	-0,8	0,1
1997	0,5	-0,1	0,0	-0,5	1,5	1,6	-0,2	-0,7	-1,2	-0,6	-0,5	-0,6
1998	-0,4	-0,3	-0,2	-0,7	-0,6	-1,4	-1,1	-0,8	0,5	0,5	0,8	-1,2
1999	-0,9	-0,1	-0,2	0,7	0,4	0,0	0,2	1,0	1,0	1,6	1,4	2,2
2000	0,3	0,3	0,2	-0,5	-1,2	-0,4	0,4	0,2	-0,2	-0,1	0,1	1,5
2001	0,8	-0,3	-0,2	-0,7	-1,0	0,9	0,7	-0,5	-1,0	-1,7	-0,6	-0,5
2002	2,7	1,6	1,6	-0,1	-0,3	-0,5	-2,2	-2,7	-2,8	-1,5	-0,8	0,6
2003	-0,7	0,5	0,3	0,6	-1,4	0,2	0,4	0,9	1,0	1,1	1,1	1,0
2004	0,7	1,2	1,2	0,3	0,4	0,7	0,8	0,1	-0,5	-1,5	-1,6	-2,5
2005	0,6	1,3	1,4	1,2	1,4	1,5	2,1	1,8	1,4	0,5	0,4	-0,2
2006	-0,2	0,1	0,2	-0,7	-0,6	0,8	-0,2	0,1	-0,3	0,0	-0,2	-0,2
2007	-1,3	-0,3	-0,2	-1,3	-0,3	-1,4	-0,5	-0,4	0,1	-0,3	-0,3	-0,7
2008	1,2	1,8	1,7	1,4	1,0	1,6	1,6	1,4	0,7	0,3	-0,1	0,2
2009	-1,3	-0,3	0,0	-0,7	0,4	0,2	0,7	1,3	1,3	0,7	0,0	-1,0
2010	-0,4	-0,3	-0,2	0,7	0,3	0,8	1,3	1,2	1,9	1,5	1,8	0,1
2011	0,2	-0,3	-0,2	-1,3	-0,2	-0,4	-0,6	0,1	-0,2	-0,2	-1,1	-0,9
2012	-1,3	-0,3	-0,2	1,1	1,4	1,3	1,3	1,2	1,3	1,1	1,1	0,2
2013	0,2	0,6	0,4	-0,1	0,0	-0,5	-0,6	0,0	0,6	0,9	0,8	0,2
2014	0,9	0,3	-0,2	-1,3	2,0	0,4	-0,3	-0,9	-0,9	-0,3	-0,2	0,8
2015	-0,2	0,3	0,4	0,3	-1,1	-2,3	-1,6	0,3	0,5	1,2	0,2	1,2
2016	-0,7	-0,1	-0,2	-0,1	0,0	-1,0	0,9	0,3	1,0	-0,3	0,1	-2,0
2017	-0,2	-0,3	-0,2	-0,7	1,3	1,7	1,2	1,2	0,0	-0,5	-1,6	-1,0
2018	-0,4	-0,3	-0,2	-0,7	-1,5	-0,3	-0,7	-1,2	-0,3	0,2	1,1	0,7
2019	0,0	0,7	0,8	1,0	0,5	0,3	-0,9	-0,4	-0,5	0,5	0,5	1,4
2020	0,5	-0,3	-0,2	1,2	-0,8	-0,4	-1,6	-0,9	0,7	1,6	2,2	0,5

Appendix 3: SPI-6

Year	Jan	Feb	Tue	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1990	NA	NA	NA	NA	NA	-0,8	-0,6	-0,8	-1,3	-1,3	-1,3	-1,1
1991	-1,2	-1,3	-0,2	-0,2	0,0	-0,9	-0,5	-1,4	-1,4	-1,1	-1,1	-0,9
1992	-1,0	-0,1	0,8	0,5	1,3	0,5	0,0	-0,6	-0,9	-1,0	-1,1	-1,1
1993	-1,1	-1,0	-0,3	0,9	-0,3	-0,5	0,1	-0,5	-0,6	-0,8	-0,8	-0,7
1994	-1,0	-0,8	-0,6	0,7	0,0	-0,3	0,1	0,6	0,5	0,6	0,7	0,8
1995	0,9	0,5	0,9	1,4	-0,2	-0,3	0,0	0,3	0,0	-0,1	-0,1	0,0
1996	0,0	-0,6	-0,2	-0,7	-0,3	-0,8	-0,2	-0,6	-0,9	-0,9	-0,8	-0,7
1997	-0,9	-0,8	0,1	0,2	1,5	1,6	-0,2	-0,5	-0,5	-0,6	-0,8	-1,3
1998	-0,6	-0,5	-0,6	-0,8	-0,7	-1,4	-1,2	-0,9	0,1	-0,2	-0,2	0,2
1999	0,5	0,9	-1,1	-0,4	0,3	0,0	0,2	1,0	0,9	1,5	1,5	1,6
2000	1,8	1,6	2,2	0,0	-1,2	-0,4	0,4	0,1	-0,3	0,1	0,2	0,2
2001	0,0	0,2	1,4	0,5	-1,1	0,8	0,7	-0,5	-0,7	-0,9	-0,7	-1,1
2002	-1,5	-0,6	-0,4	2,7	-0,2	-0,4	-2,2	-2,7	-2,8	-2,4	-2,4	-2,4
2003	-1,6	-0,8	0,6	-0,4	-1,3	0,2	0,4	0,8	0,9	1,1	1,2	1,2
2004	1,2	1,3	1,0	0,6	0,4	0,7	0,8	0,2	-0,3	-0,7	-0,7	-0,9
2005	-1,5	-1,7	-2,3	0,8	1,4	1,5	2,1	1,9	1,7	1,6	1,5	1,3
2006	0,6	0,5	-0,1	-0,7	-0,7	0,8	-0,2	0,0	0,0	-0,1	-0,1	-0,4
2007	0,1	-0,2	-0,2	-1,8	-0,4	-1,5	-0,5	-0,4	-0,3	-0,5	-0,5	-0,2
2008	-0,2	-0,2	-0,6	1,4	1,0	1,6	1,6	1,5	1,1	1,1	1,0	0,6
2009	0,3	0,0	0,2	-1,5	0,3	0,2	0,7	1,3	1,2	0,9	0,9	1,0
2010	0,8	0,1	-1,0	-0,2	0,2	0,8	1,3	1,2	1,9	1,9	1,9	1,8
2011	1,6	2,0	0,1	-0,3	-0,3	-0,4	-0,7	0,0	-0,3	-0,6	-0,5	-0,5
2012	-0,2	-1,2	-0,9	-0,1	1,4	1,3	1,3	1,4	1,6	1,6	1,5	1,3
2013	1,2	1,2	0,2	-0,1	0,0	-0,5	-0,6	0,0	0,4	0,4	0,4	0,6
2014	1,0	0,9	0,2	0,6	2,0	0,4	-0,3	-0,5	-0,7	-0,5	-0,8	-0,6
2015	-0,3	-0,2	0,8	-0,3	-1,1	-2,3	-1,6	0,2	-0,1	0,3	0,3	0,8
2016	1,3	0,3	1,2	-0,8	-0,1	-1,0	0,9	0,3	0,7	0,3	0,3	0,5
2017	-0,3	0,2	-2,0	-0,7	1,2	1,7	1,2	1,3	0,5	0,3	0,2	-0,3
2018	-0,5	-1,6	-1,0	-0,9	-1,6	-0,3	-0,7	-1,3	-0,4	-0,2	-0,2	-0,2
2019	0,2	1,3	0,7	0,3	0,5	0,3	-0,9	-0,4	-0,4	0,0	-0,1	-0,1
2020	0,6	0,6	1,4	0,7	-0,9	-0,4	-1,6	-1,0	0,5	0,6	0,7	0,8

Appendix 4: SPI-9

Year	Jan	Feb	Tue	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1990	NA	NA	NA	NA	NA	NA	NA	NA	-1,3	-1,3	-1,3	-1,4
1991	-1,3	-1,2	-1,1	-1,2	-1,4	-1,1	-0,5	-1,4	-1,4	-1,1	-1,1	-1,1
1992	-1,1	-1,1	-0,9	-1,0	0,2	0,9	0,0	-0,6	-0,9	-0,9	-1,0	-1,0
1993	-0,9	-1,1	-1,1	-1,1	-1,1	-0,9	0,0	-0,5	-0,6	-0,8	-0,8	-0,8
1994	-0,8	-0,7	-0,6	-1,0	-0,9	-0,9	0,1	0,6	0,5	0,6	0,7	0,7
1995	0,7	0,7	0,8	0,9	0,5	0,4	0,1	0,3	0,0	-0,1	-0,1	-0,1
1996	-0,1	0,0	0,1	0,0	-0,7	-1,0	-0,2	-0,6	-0,9	-0,9	-0,9	-0,9
1997	-0,8	-0,8	-0,6	-0,9	-0,5	1,4	-0,2	-0,5	-0,5	-0,6	-0,7	-0,7
1998	-0,6	-0,8	-1,3	-0,6	-0,6	-1,8	-1,2	-0,9	0,1	-0,2	-0,2	-0,2
1999	-0,2	-0,1	0,2	0,5	0,9	-1,0	0,2	1,0	0,9	1,5	1,5	1,5
2000	1,5	1,5	1,6	1,8	1,4	1,6	0,3	0,0	-0,3	0,1	0,1	0,1
2001	0,1	0,2	0,3	0,0	0,0	1,8	0,7	-0,6	-0,7	-0,9	-0,8	-0,8
2002	-0,7	-0,7	-1,1	-1,5	-0,7	-0,9	-1,8	-2,7	-2,8	-2,4	-2,4	-2,4
2003	-2,4	-2,4	-2,4	-1,6	-1,0	0,5	0,4	0,7	0,9	1,1	1,1	1,1
2004	1,1	1,2	1,2	1,2	1,3	1,2	0,8	0,1	-0,2	-0,7	-0,7	-0,7
2005	-0,7	-0,7	-0,9	-1,5	-1,3	0,2	2,1	1,9	1,7	1,6	1,6	1,6
2006	1,6	1,5	1,3	0,6	0,4	0,5	-0,2	0,0	0,0	-0,1	-0,1	-0,1
2007	-0,1	0,0	-0,3	0,1	-0,3	-1,5	-0,6	-0,5	-0,3	-0,6	-0,5	-0,5
2008	-0,5	-0,4	-0,1	-0,2	-0,1	1,0	1,6	1,5	1,1	1,1	1,1	1,1
2009	1,1	1,0	0,7	0,3	0,0	0,2	0,6	1,2	1,2	0,9	0,9	0,9
2010	0,9	0,9	1,0	0,8	0,1	-0,1	1,3	1,2	1,9	1,9	1,9	1,9
2011	1,9	1,9	1,8	1,6	2,0	-0,4	-0,7	0,0	-0,4	-0,6	-0,6	-0,6
2012	-0,5	-0,5	-0,4	-0,2	-0,8	0,5	1,2	1,3	1,6	1,6	1,6	1,6
2013	1,6	1,5	1,3	1,2	1,2	-0,5	-0,6	0,0	0,4	0,4	0,4	0,4
2014	0,4	0,4	0,6	1,0	1,4	0,3	-0,3	-0,5	-0,7	-0,5	-0,5	-0,5
2015	-0,5	-0,7	-0,6	-0,3	-0,4	-1,1	-1,7	0,2	-0,1	0,3	0,3	0,3
2016	0,3	0,4	0,8	1,3	0,3	0,2	0,9	0,3	0,6	0,3	0,2	0,2
2017	0,3	0,3	0,6	-0,3	0,4	0,5	1,2	1,3	0,5	0,3	0,3	0,3
2018	0,3	0,2	-0,3	-0,5	-1,9	-1,2	-0,7	-1,3	-0,4	-0,3	-0,3	-0,3
2019	-0,2	-0,1	-0,1	0,2	1,3	0,6	-0,9	-0,4	-0,4	0,0	0,0	0,0
2020	0,0	0,0	-0,1	0,6	0,5	0,8	-1,6	-1,0	0,5	0,6	0,6	0,6

Appendix 5: SPI-12

Year	Jan	Feb	Tue	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1990	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-1,3
1991	-1,3	-1,3	-1,3	-1,3	-1,3	-1,3	-1,3	-2,0	-1,6	-1,2	-1,2	-1,2
1992	-1,1	-1,1	-1,1	-1,1	-1,0	-0,7	-0,9	-0,6	-0,8	-1,0	-1,0	-1,0
1993	-0,9	-0,9	-0,9	-0,9	-1,1	-1,2	-0,9	-1,0	-0,9	-0,9	-0,9	-0,8
1994	-0,8	-0,8	-0,8	-0,8	-0,8	-0,7	-0,8	0,1	0,3	0,6	0,6	0,7
1995	0,7	0,7	0,7	0,7	0,7	0,7	0,7	0,5	0,2	-0,1	-0,1	-0,1
1996	-0,1	-0,1	-0,1	-0,1	-0,1	-0,2	-0,2	-0,9	-1,1	-1,0	-1,0	-0,9
1997	-0,9	-0,9	-0,9	-0,9	-0,7	-0,1	-0,9	-0,9	-0,6	-0,7	-0,7	-0,7
1998	-0,6	-0,6	-0,6	-0,6	-0,9	-1,6	-1,2	-1,1	-0,2	-0,3	-0,3	-0,2
1999	-0,2	-0,2	-0,2	-0,2	-0,1	0,1	0,5	1,3	0,6	1,4	1,4	1,5
2000	1,5	1,5	1,5	1,5	1,4	1,4	1,6	0,9	0,4	0,0	0,0	0,1
2001	0,1	0,1	0,1	0,1	0,1	0,5	0,3	-0,4	-0,3	-1,0	-0,8	-0,8
2002	-0,7	-0,7	-0,7	-0,7	-0,7	-1,2	-2,4	-2,6	-3,1	-2,4	-2,5	-2,4
2003	-2,4	-2,4	-2,4	-2,4	-2,5	-2,2	-1,0	0,2	1,1	1,1	1,1	1,1
2004	1,1	1,1	1,1	1,1	1,3	1,3	1,4	0,8	0,0	-0,8	-0,8	-0,7
2005	-0,7	-0,7	-0,7	-0,7	-0,6	-0,4	0,3	0,8	1,4	1,6	1,6	1,6
2006	1,6	1,6	1,6	1,6	1,5	1,4	0,3	0,2	-0,2	-0,2	-0,2	-0,1
2007	-0,1	-0,1	-0,1	-0,1	-0,1	-0,7	-0,3	-0,5	-0,5	-0,6	-0,6	-0,5
2008	-0,5	-0,5	-0,5	-0,5	-0,4	0,4	0,8	1,1	0,9	1,1	1,1	1,1
2009	1,1	1,1	1,1	1,1	1,0	0,6	0,6	1,0	1,2	0,9	0,9	0,9
2010	0,9	0,9	0,9	0,9	0,9	1,1	1,3	1,0	1,8	1,9	1,9	1,9
2011	1,9	1,9	1,9	1,9	1,9	1,6	0,9	1,2	-0,4	-0,6	-0,6	-0,6
2012	-0,6	-0,6	-0,6	-0,5	-0,4	0,0	0,6	0,6	1,4	1,5	1,6	1,6
2013	1,6	1,6	1,6	1,6	1,5	1,1	0,6	0,6	0,4	0,3	0,4	0,4
2014	0,4	0,4	0,4	0,4	0,7	0,6	0,6	0,1	-0,8	-0,5	-0,6	-0,5
2015	-0,5	-0,5	-0,5	-0,5	-0,8	-1,1	-1,2	0,0	0,1	0,2	0,2	0,3
2016	0,3	0,3	0,3	0,3	0,3	0,5	1,6	0,4	1,0	0,2	0,2	0,2
2017	0,3	0,3	0,3	0,3	0,4	1,0	0,5	1,2	0,1	0,2	0,2	0,3
2018	0,3	0,3	0,3	0,3	0,1	-0,4	-0,8	-2,0	-0,8	-0,3	-0,3	-0,3
2019	-0,2	-0,2	-0,2	-0,2	-0,1	-0,1	-0,3	0,4	-0,4	-0,1	-0,1	0,0
2020	0,0	0,0	0,0	0,0	-0,1	-0,2	-0,3	-0,5	0,9	0,6	0,6	0,6