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RESILIENCE TO FOOD INSECURITY OF RURAL HOUSEHOLDS IN THE SENEGALESE GROUNDNUT BASIN IN A CONTEXT OF CLIMATE CHANGE

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RESILIENCE TO FOOD INSECURITY OF RURAL HOUSEHOLDS IN THE SENEGALESE GROUNDNUT BASIN IN A CONTEXT OF CLIMATE

DOCTORAL DISSERTATION

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DEDICATION

To

Almighty God for my life, for His guidance, blessings, love, and care, and for giving me wisdom, knowledge, and understanding during this Ph.D. study.

My parents, I hope that this achievement will complete the dream that you had for me, when you chose to give me the best education you could.

My siblings and husband.

I dedicate this Ph.D. Thesis.

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ABSTRACT

This study analyzed the resilience to food insecurity of rural households in the Senegalese Groundnut Basin in response to climate-related risks. Cross-sectional data from the National Food Security, Nutrition, and Resilience Survey conducted by the Executive Secretariat of the National Council for Food Security of Senegal, covering 3,100 households from 19 departments of the Groundnut Basin, were obtained in addition to relevant climate variables derived from CHIRPS and ERA5 datasets from 1991-2020. The study employs three key methodologies: the Marginal Treatment Effect (MTE) approach to assess the impact of crop diversification on food security and welfare, the Resilience Index Measurement Analysis (RIMA-II) to measure household resilience, and Two-Stage Least Squares (2SLS) combined with the Dose-Response Function to estimate the relationship between resilience and food security outcomes. The results indicate that total seasonal precipitation and maximum temperatures positively influence the yields of groundnuts, millet, and maize, with other weather factors exerting varied effects across the Groundnut Basin. Crop diversification significantly improves household welfare and mitigates climate-related risks. Access to essential services, assets, and adaptive capacity are key resilience determinants. Also, higher Resilience Capacity Index (RCI) positively influences food and nutrition security indicators (Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS)). Female-headed households demonstrate greater resilience than male-headed households. The analysis further reveals that these households benefit more from resilience-building efforts but face higher vulnerability when such measures are absent. The findings recommend enhancing climate adaptation strategies, promoting crop diversification, and strengthening female-headed households' access to resources to improve resilience and food security outcomes.

Keywords: climate-related risk, welfare, agriculture, resilience, Senegal

RÉSUMÉ

Cette étude a analysé la résilience à l'insécurité alimentaire des ménages ruraux du Bassin Arachidier sénégalais face aux risques climatiques. Des données issues de l'Enquête nationale sur la sécurité alimentaire, la nutrition et la résilience, réalisée par le Secrétariat Exécutif du Conseil National à la Sécurité Alimentaire du Sénégal et couvrant 3 100 ménages répartis dans 19 départements du Bassin Arachidier, ont été utilisées, en complément de variables climatiques pertinentes dérivées des bases de données CHIRPS et ERA5 sur la période 1991-2020. L'étude mobilise trois principales méthodologies : l'approche de l'Effet Marginal du Traitement (MTE) pour évaluer l'impact de la diversification des cultures sur la sécurité alimentaire et le bien-être, l'outil d'analyse de la mesure de la résilience (RIMA-II) pour mesurer la résilience des ménages, et la méthode des Moindres Carrés en Deux Étapes (2SLS) combinée à la fonction de dose-réponse pour estimer la relation entre la résilience et les résultats en matière de sécurité alimentaire. Les résultats indiquent que la précipitation totale saisonnière et les températures maximales influencent positivement les rendements de l'arachide, du mil et du maïs, tandis que d'autres facteurs climatiques exercent des effets variés selon les zones du Bassin. La diversification des cultures améliore significativement le bien-être des ménages et atténue les risques liés au climat. L'accès aux services de base, aux actifs et la capacité d'adaptation apparaissent comme des déterminants clés de la résilience. En outre, un indice de capacité de résilience (RCI) plus élevé améliore positivement les indicateurs de sécurité alimentaire et nutritionnelle, tels que le Score de Consommation Alimentaire (SCA) et le Score de Diversité Alimentaire des Ménages (HDDS). Les ménages dirigés par des femmes se révèlent plus résilients que ceux dirigés par des hommes. L'analyse montre également que ces ménages bénéficient davantage des actions de renforcement de la résilience mais restent plus vulnérables en l'absence de telles mesures. Les résultats recommandent de renforcer les stratégies d'adaptation au changement climatique, de promouvoir la diversification des cultures et d'améliorer l'accès des ménages dirigés par des femmes aux ressources pour renforcer leur résilience et améliorer la sécurité alimentaire.

Mots clés : risque climatique, bien-être, agriculture, résilience, Sénégal

LIST OF ABBREVIATIONS

ABS: Access to Basic Services

AC: Adaptive Capacity

AIC: Akaike Information Criterion

ANSD: Agence Nationale de la Statistique et de la Démographie

AR: Assessing Resilience

ASS: Asset

ATE: Average Treatment Effects

ATENT: Average Treatment Effect on the Untreated

ATET: Average Treatment Effect on the Treated

ATT: Average Treatment on the Treated

ATUT: Average Treatment on the Untreated

BRACED: Building Resilience and Adaptation to Climate Extremes and Disasters

CDD: Consecutive Dry Days

CHIRPS: Hazards Center Infrared Precipitation with Stations

COBRA: Community Resilience Assessment and Action

CWD: Consecutive Wet Days

DAPSA: Direction de l'Analyse de la Prévision et des Statistiques Agricoles

DFID: Department For International Development

Drew: Dynamic Resilience Wheel

DRF: Dose Response Function

ENSANR: Enquête Nationale de Sécurité Alimentaire et de Résilience

ESR: Endogenous Switching Regression

FAO: Food and Agriculture Organization

FCS: Food Consumption Score

FHH: Female-Headed Households

GDP: Gross Domestic Product

AGIR: Alliance Global pour l'Initiative Resilience au Sahel

HDDS: Household Dietary Diversity Score

IPAR: Initiative Prospective Agricole Et Rurale

IPCC: Intergovernmental Panel on Climate Change

MHH: Male-Headed Households

MIMIC: Multiple Indicators and Multiple Causes

ML: Maximum Likelihood

MTE: Marginal Treatment Effect

PNASAR: Programme National d'Appui à la Sécurité Alimentaire et à la Résilience

PNIASAN: National Investment Plan for Agriculture, Food, and Nutrition Security

PRACAS : Programme d'Accélération de la Cadence de l'Agriculture Sénégalaise

PRTE: Policy-Relevant Treatment Effects

PSE: Plan Sénégal Emergent

RCI: Resilience Capacity Index

RCSI: Reducing Coping Strategies Index

RGPHAE: Recensement Général de la Population et de l'Habitat, de l'Agriculture et de l'Elevage

RIMA: Resilience Index Measurement Analysis

SDII: Simple Daily Intensity Index

SE: Standard Error

SECNSA: Secrétariat Exécutif du Conseil National de Sécurité Alimentaire

SNSAR: Stratégie Nationale de Sécurité Alimentaire et de Résilience

SPI: Standardized Precipitation Index

SSA: Sub-Saharan Africa

SSN: Social Safety Nets

2SLS: Two-Stage Least Squares

UNDP: United Nations Development Program

UNFCCC: United Nations Framework Convention on Climate Change

WMO: World Meteorological Organization

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CHAPTER 1: GENERAL INTRODUCTION

1.1 Research problem

Recent studies highlight the growing concern of climate change as a significant threat to global food security and economic development, particularly in developing countries (Toromade *et al.*, 2024). Climate change is at the center of the attention of scientific actors, policymakers, NGOs, think tank companies and key economic stakeholders, as it constitutes one of the many obstacles to human development (Dahan, 2014). Climate change leads to an increase in average temperature, higher rainfall variability and the occurrence of extreme conditions such as floods and droughts (Ebi *et al.*, 2020). Agricultural production faces increasing difficulties because of climatic hazards (Chanzy, 2015; Shah *et al.*, 2021). Climate change is modifying the conditions under which agricultural activities are conducted (Singh, 2016). Climate variability directly impacts agricultural production, as farming systems are partly dependent on the nature of the climate (Ayanlade *et al.*, 2017). This impact is particularly important in developing countries where rainfed agriculture dominates, affecting almost 93% of cultivated land, employment rates and incomes of most of the population (Amare *et al.*, 2018; Sultan *et al.*, 2015).

Exposure to climate hazards can trigger shocks to agricultural production and food availability, with risks of market disruptions and increases in agricultural commodity prices (food and feed), impacting the accessibility and stability of food supplies for the entire population (Singh, 2016). Climate change affects food security in several different, often very complex ways. It affects food availability through its impacts on crop yields and livestock productivity. For many net food-purchasing households, crop yields and livestock productivity declines can often translate into reduced access to food due to higher prices (Furtak & Wolińska, 2023).

In addition, the increased frequency of extreme weather events under changing climatic conditions, such as droughts, floods and heat waves, could undermine the stability of food systems and exacerbate existing food and nutrition security problems, posing particularly severe risks to the most vulnerable social groups (Saleem *et al.*, 2024). Extreme weather events, intensified by climate change, conflicts and low economic growth, are the leading causes of growing food insecurity, particularly in developing countries (Engel, 2021). Despite its incredible natural resource potential, Africa struggles to achieve food security. The most direct implications of climate change for food security are through its impacts on food production worldwide (Wollenberg *et al.*, 2016). Climate change could push an additional 78 million people into hunger by 2050 if no adaptive measures are taken (UNEP, 2023).

For several years, Africa has been identified as the continent most vulnerable to climate change (Jarraud & Steiner, 2014). The Intergovernmental Panel on Climate Change (IPCC) confirms that Africa remains the most vulnerable continent to climate change’s effects (Trisos *et al.*, 2022). Considerable work has been undertaken to address climate change and food security challenges in Africa, particularly by organizations such as AGRA, FARA, and ICRAF. These institutions provide crucial knowledge, innovations, and strategic frameworks to enhance agricultural productivity and resilience. They have highlighted the urgent need to build climate-resilient agricultural systems to ensure food security and sustainable development. For instance, AGRA’s Africa Agriculture Status Report emphasizes the importance of scaling up climate-smart agricultural practices, such as drought-resistant crops and improved water management, to enhance productivity and resilience (AGRA, 2023). Similarly, FARA’s strategic frameworks advocate for increased agricultural research and innovation investment to address the dual challenges of climate change and food insecurity (FARA, 2021). The Malabo Declaration (2014) and the CAADP framework provide a roadmap for achieving food security and agricultural transformation in Africa. The Malabo Declaration commits African governments to allocate at least 10% of their national budgets to agriculture and to enhance resilience to climate variability by promoting sustainable farming practices. These policy frameworks align with the broader goals of the African Union’s Agenda 2063, which envisions a prosperous and climate-resilient Africa.

These continental efforts complement national strategies, such as Plan Senegal Emergent (PSE) and the PRACAS program in Senegal, which aim to tackle climate-related food security challenges at the country level. Senegal's economic development vision, as outlined in its PSE, strongly emphasize plans to achieve food security. This priority is also reflected in the Programme d’Accélération de la Cadence de l’Agriculture Sénégalaise (PRACAS), the agricultural strategy under the PSE. Additionally, the country's National Strategy for Food Security and Resilience (*Stratégie Nationale de Sécurité Alimentaire et de Résilience,* SNSAR) further solidifies its commitment to addressing food and nutrition insecurity, aiming to ensure sustainable food systems and resilience to external shocks (Hathie *et al.*, 2017). Consequently, several programs have been launched to encourage agricultural activities in Senegal. These programs strongly focus on agriculture because of its importance in the country’s economy. Despite all these efforts, Senegal, like most Sahelian countries, faces a relatively difficult food situation. The gap between national production and the population's growing needs has widened steadily over the years. The problem is particularly acute in cereals, the staple food for rural and urban populations. Cereal production (millet, sorghum, maize and rice) has averaged around 2,000,000 T over the last ten seasons (DAPSA 2024), with marked fluctuations depending on the year and rainfall. Local cereal production can only cover about half of basic food needs, and the deficit is comprised of massive imports of white rice (LARTES, 2021). The shortfall in agricultural production, dependence on foreign trade, and the fragility of the Sahelian ecosystem, exacerbated by climate change, human pressure and over-fishing, are the main determinants of the country's food insecurity.

From time immemorial, living things have depended on food for survival. The availability, accessibility, affordability, and utilization of sufficient nutritious food led to a productive and healthy life. According to universal human rights principles (United Nations General Assembly, 1968), every human being has the right to adequate food and the fundamental right to be free from hunger (Spies *et al.*, 2024). States must respect, protect and fulfil the right to food, facilitate its enjoyment and provide for its realization (Ayala & Meier, 2017; OHCHR, 2006). Despite these universal rights, several households cannot meet their nutrition needs for several reasons, such as poverty, which has long-term impacts on the ability of families, communities, and countries to develop and prosper (Siddiqui *et al.*, 2020). Prolonged undernourishment stunts growth, slows cognitive development, and increases susceptibility to illness.

Low agricultural productivity is frequently reported in rural communities. Regrettably, the Senegalese Groundnut Basin has faced severe food insecurity recently. In 2019, the National Food Security, Nutrition and Resilience Survey (ENSANR 2019) revealed that food insecurity rates were above the national average by around 8% (SE/CNSA, 2019). In four departments of the Groundnut Basin, alarming food insecurity rates of between 20 and 35% were recorded: Koumpentoum (32.4%), Nioro du rip (27.7%), Guinguinéo (21.7%) and Kaolack 20.4%.
Consequently, agriculture, especially crop production, is highly encouraged to reduce the rate and number of farming households that go to bed hungry every night and improve their livelihoods. This improvement is necessary as the majority of the people in the Senegalese Groundnut Basin earn their livelihoods through farming and pastoralism, which is highly vulnerable to climatic changes and socio-economic shocks. Based on this, this research is intended to contribute to a better understanding of the resilience of rural households in the Groundnut Basin to climate change-related phenomena for sustainable food security.

Conflict/insecurity, climate extremes and economic shocks are generally the three main drivers of food insecurity. However, these factors are often interrelated and mutually reinforcing, making it challenging to identify a single trigger or driver for each food crisis (FSIN, 2021). In the Sahelian zone, food crises were recorded, particularly from 2005 to 2021, and the limits of policies aimed at achieving food and nutritional security have been revealed. Since the 1970s, the most significant food crises that have required recourse to international food aid (1974, 1984-1985, 1992 and 2002) are entirely or partly due to climate variations (Dilley *et al.*, 2005). As a Sahelian country, Senegal has suffered from the adverse effects of these major crises due to its unfavorable biophysical and economic situation, which has been weakened by climatic deterioration. Thus, facing the effects of climate change and increasing fear of the capacity of agriculture to meet food needs, food insecurity remains an increasing preoccupation for many Senegalese households, particularly in rural areas. In Senegal, the majority of the population (54.8%) resides in rural areas, and one out of every two households (49.5%) practices agriculture (ANSD, 2014). Most farming households (61%) are involved in pluvial agriculture and animal breeding. According to a study realized in 2007 by the Initiative Prospective Agricole et Rurale (IPAR), families engaged in agriculture represent 95% of farms and cover 87.9% of Senegalese families. Family farming is more vulnerable to climate change. This vulnerability is remarkable because family farms are usually unproductive, poor and under-equipped (FDI, 2015). The analysis of the resilience of rural households appears as a key issue in the fight against poverty, food insecurity and malnutrition.

Furthermore, assessing whether rural households are sufficiently resilient to food insecurity due to climate change-related effects is important. Thus, this study focuses on rural households living in the Groundnut Basin, an agro-ecological zone covering seven regions of Senegal (Fatick, Kaolack, Diourbel, Kaffrine, Thiès, Louga and Tambacounda). The rural environment of this area is strongly influenced by climatic conditions, given that the main activity remains agriculture RGPHAE 2013 (ANSD, 2014). Indeed, in the Groundnut Basin, agricultural production activities predominate during the rainy season. However, constraints related to soil degradation, climatic risks and poor cultivation practices are all factors that negatively affect agricultural activity and the food security of the population, particularly in rural areas. Consequently, the prevalence of food insecurity in Senegal is twice as high among rural households (11.7%) compared to urban households (4.8%). The double vulnerability of the rural areas of the Groundnut Basin justifies the choice of this part of Senegal as the study area.

Moreover, it is necessary to understand the resilience of communities, i.e. the capacities and strategies they develop to fight against food insecurity faced by climate shocks. This study will inform the decisions of governments and their partners about developing food security policies. It will enable development and humanitarian actors to better target agricultural policies and fight against chronic food insecurity, particularly in rural areas.

The study of resilience to food insecurity among rural households in the Senegalese Groundnut Basin within the context of climate change addresses significant research gaps, particularly given the increasing challenges posed by climatic variability and changes. First, while general climatic parameters are often studied, the impact of localized microclimates within the Senegalese Groundnut Basin has not been thoroughly investigated. Second, increasing research on crop diversification has been gaining attention in recent times, and most studies have tended to focus on the drivers and impacts of the adoption of crop diversification under covariate climate shocks i.e., shocks that affect entire communities or regions such as droughts or floods, without investigating their impacts under individual-specific idiosyncratic shocks which affect individual households (e.g., illness, job loss or death). Finally, studies analyzing resilience do not examine the impact of varying levels of resilience capacity on food and nutrition security, providing a detailed understanding of how incremental changes in resilience influence outcomes. By addressing these gaps, this study deepens our understanding of the resilience of rural households to climate shocks. It provides practical recommendations to policymakers to enhance food security and climate adaptation strategies in Senegal.

1.2 Theoretical framework

1.2.1 Climate Change and Food System Vulnerabilities in Senegal

Uncontrolled greenhouse gas emissions are intensifying global warming, driving changes in temperature, precipitation, and the frequency of extreme weather events (Bolan *et al.*, 2024). In Senegal, these shifts are already altering the dynamics of the entire climate system. Projections indicate that average annual temperatures could rise by 1 to 3°C by the 2060s, accompanied by a marked increase in the number of hot days and nights (USAID, 2017). Although rainfall patterns remain uncertain, heavier and more erratic precipitation is anticipated, exacerbating both droughts and floods. Rising sea levels, potentially up to one meter by 2100, further threaten the country’s ecosystems, especially in coastal zones where the salinization of soils is already reducing land productivity (USAID, 2017). These environmental pressures directly impact Senegal's ecosystems, including its land, water, and ocean resources. In agricultural regions, erratic and declining rainfall has reduced soil fertility and diminished crop yields (Sultan *et al.*, 2013). Recurrent droughts in the northern and central regions have led to substantial losses in staple crops like millet, sorghum, groundnuts, and maize (Ahmed *et al.*, 2021). In addition, ocean warming and rising sea levels negatively affect marine ecosystems. Fisheries, a vital source of protein and income, are at risk from overexploitation and declining fish stocks due to changing ocean temperatures (Katikiro & Macusi, 2012). The salinization of coastal aquifers and farmland further undermines agricultural productivity and increases dependency on food imports. These ecological shifts cascade into the food system, where climate impacts disrupt every stage, from production to consumption. In Senegal, food production is dominated by smallholder farmers practicing rainfed agriculture, making them highly vulnerable to fluctuating weather patterns (Toure *et al.*, 2020). Losses are further exacerbated by inadequate post-harvest infrastructure, leading to significant food loss and waste across value chains (Enete, 2013). Livestock and fisheries, key food system components, are also threatened by prolonged droughts, water scarcity, and declining ocean productivity.

Senegal's socio-economic system, shaped by rapid population growth, rural poverty, and limited access to resilient technologies, amplifies the challenges faced by the food system. Agriculture, livestock, and fisheries account for about 20% of GDP and employ most of the workforce, yet their high dependence on climatic conditions underscores the fragility of livelihoods (D'Alessandro *et al.*, 2015). The rural exodus observed during the prolonged droughts between 1970 and 2000 reflects the socio-economic impacts of declining agricultural productivity. Today, smallholder farmers face heightened risks from shortened planting seasons, unpredictable rainfall, and crop failures (World Bank, 2020). The resulting socio-economic impacts manifest as reduced food availability, fluctuating food prices, and weakened household incomes, further threatening food security, particularly in rural and coastal communities. The rising cost of staple foods like rice and millet, driven by climate-induced production shocks, deepens food insecurity (FAO, 2021). Meanwhile, Senegal's coastal zones, home to 67% of the population and 90% of industrial production, are increasingly vulnerable to sea-level rise, coastal erosion, and saline intrusion, threatening agricultural and urban systems.

This interconnected system converges on the outcome of food security and human well-being, which are under growing threat from the combined stresses of climate change and socio-economic pressures. This situation highlights the urgent need to adopt integrated resilience strategies at all local and national levels.

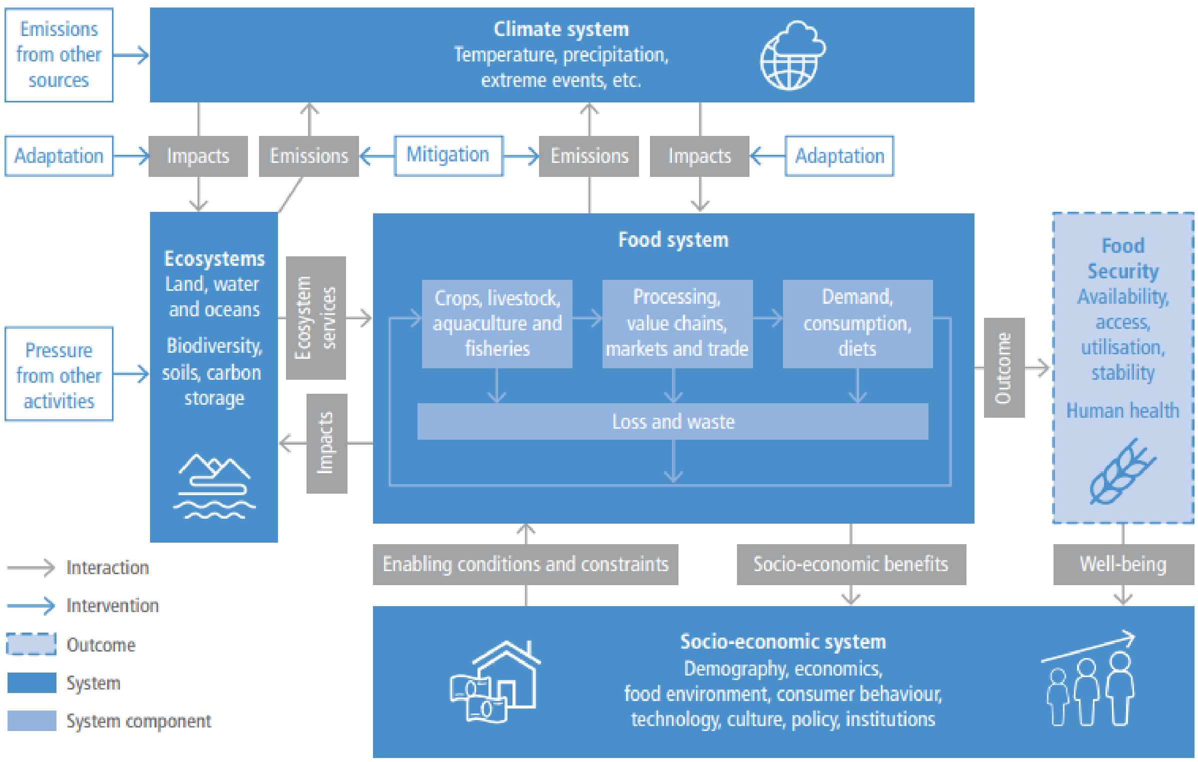


Figure 1- 1: Interlinkages between the climate system, food system, ecosystems (land, water and oceans) and socio-economic system (IPCC, 2019)

1.2.2 Climate Change and Food Security: Challenges

While climate change disrupts the entire ecological and food systems in Senegal, its most immediate and tangible impact is seen in the food security of rural populations. According to the Food and Agriculture Organization (FAO), climate change influences all four dimensions of food security: availability, access, utilization, and stability. The connection between climate change and food security is most evident in the relationship between climate variables and agriculture (Obwocha *et al.*, 2022). Studies have shown that agriculture is the human activity most dependent on climatic conditions (Grigorieva *et al.*, 2023; Nugroho *et al.*, 2023). Globally, 75% of the poor and food insecure depend on agriculture and natural resources for their livelihoods (Dethier & Effenberger, 2012). Therefore, any poverty reduction strategy must necessarily include the transformation of the agricultural sector into a driver of growth for vulnerable populations. By 2050, agricultural production must increase by 60% to feed a growing and wealthier global population (Fróna *et al.*, 2019). However, climate change threatens this goal, especially in Africa, where much agricultural production is rainfed.

In sub-Saharan Africa, 89% of cereal crops depend on rainfall (Lefe *et al.*, 2024). This strong dependence makes climate a key factor in food security, as highlighted by (Yeboah, 2024). Regions reliant on rainfed agriculture, such as the Senegalese Groundnut Basin, are particularly exposed to the effects of climate variability. The Senegalese Groundnut Basin has historically been a key agricultural zone specializing in groundnut production, a major cash crop. However, the region has become increasingly vulnerable to food insecurity due to climate change and other socio-economic factors. Research highlights the increasing frequency of droughts, erratic rainfall, and land degradation as primary drivers of regional agricultural instability (Lefe *et al.*, 2024). These climate shocks exacerbate poverty, making food systems more fragile and less able to support rural households (D'Alessandro *et al.*, 2015).

A vast body of literature focuses on how climate change affects agriculture in Senegal, particularly in the Groundnut Basin. Studies by Faye *et al.*, 2021; Faye *et al.*, 2018; Ndiaye *et al.*, 2024 describe how climate variability, characterized by irregular rainfall patterns and rising temperatures, directly affects crop yields. Groundnuts, a rainfed crop, are especially vulnerable to drought, and the reduced reliability of rainfall has led to declining productivity. This directly influences household food security by reducing the available income for purchasing food and reducing the direct production of staple crops like millet and maize (Sarr *et al.*, 2015). In addition to declining crop yields, desertification and soil degradation further reduce the viability of agriculture in the region. The depletion of water resources and loss of soil fertility contribute to the long-term challenges facing households (Mbow *et al.*, 2019). Several interrelated factors shape vulnerability in rural households. Socioeconomic conditions, including poverty, limited access to resources (land, water, seeds, and inputs), and market fluctuations, leave households exposed to food insecurity. Assefa Tofu & Wolka, 2023; Schlegel, 2014 note that poor households are more likely to depend on subsistence agriculture and, therefore, are disproportionately affected by climate shocks. Limited crop diversity reduces household resilience and increases reliance on external food sources, further driving food insecurity. Senegal ranks 69th out of 125 countries on the Global Food Security Index (2023), reflecting the nation's ongoing challenges with ensuring food availability, affordability, and quality (Grebmer *et al.*, 2023). Food insecurity in Senegal is exacerbated by climate-related shocks that affect agricultural productivity, food prices, and household incomes. When crops fail, households are forced to purchase imported food, which is often more expensive, increasing vulnerability to food insecurity.

1.2.3 Policy framework for agricultural development

The policy framework for agricultural development in Senegal is supported by a range of strategic initiatives aimed at addressing food security, enhancing agricultural productivity, and adapting to climate change. These initiatives reflect the government's commitment to transforming agriculture into a key driver of economic growth and poverty reduction. Launched in 2014, the Plan Sénégal Emergent (PSE) is Senegal's national development vision. It prioritizes agricultural modernization as a cornerstone for economic growth. The plan emphasizes improving food security through increased production, mechanization, and promotion of high-value crops. As the the agricultural component of the PSE, Programme d'Accélération de la Cadence de l'Agriculture Sénégalaise (PRACAS) focuses on achieving food self-sufficiency, particularly in staple crops like rice and groundnuts. It seeks to modernize the agricultural sector by improving infrastructure, access to credit, and better seeds and technology. However, PRACAS does not comprehensively address crop diversification strategies about the dietary needs of Senegalese households. A more nuanced approach would examine how crop diversification impacts nutrition, ensuring that the food basket aligns with local consumption patterns. Additionally, land use patterns warrant further analysis, particularly the balance between lands allocated for staple food crops and cash crops, predominantly cultivated for export. Land allocation plays a critical role in shaping agricultural outcomes in Senegal. A significant portion of arable land is dedicated to cash crops, such as groundnuts and cotton, which are primarily grown for export (Arce & Arias, 2015). This has raised concerns about the availability of land for staple food production and the implications for national food security. The economic model that relies heavily on cash crop exports has historically aimed to generate revenue that could be reinvested into the agricultural sector or used to import food. However, this approach has not translated into substantial poverty reduction since Senegal's independence. Instead, over-reliance on commodity crops has often led to economic vulnerabilities, particularly when global commodity prices fluctuate (Amolegbe *et al.*, 2021). This raises the question of whether the focus should shift toward a more balanced model that integrates food and cash crops to ensure sustainable food security and economic stability.

The National Investment Plan for Agriculture, Food, and Nutrition Security (PNIASAN 2018-2022) is specifically tailored to boost the agricultural sector, aiming to improve food and nutrition security through strategic investments and initiatives. The National Strategy for Food Security and Resilience (SNSAR 2015-2035) strategy outlines the country's long-term vision for strengthening food security and resilience to climate change. This strategy is implemented by the National Food Security and Resilience Support Program (PNASAR 2018-2022), which is a framework for bringing together and integrating all actions that contribute to achieving food security and the resilience of populations to shocks at all scales. Operationalizing the SNSAR, PNASAR aims to "*contribute to the sustainable improvement of food and nutritional security for households, particularly the most vulnerable, as well as the strengthening of their resilience capacities, by 2022*". It promotes sustainable farming practices, climate-smart agriculture, and improving nutrition outcomes. These frameworks and initiatives are crucial given Senegal's heavy reliance on rainfed agriculture, which makes the sector highly vulnerable to climate variability.

1.2.4 Crop diversification

Farming households in Africa, in their attempt to minimize their exposure to worsening climatic conditions and safeguard their food and nutrition security, are increasingly adopting innovative farming practices such as crop diversification and livelihood diversification. Ellis (1998) defines diversification as "*the process by which households construct a diverse portfolio of activities and social support capabilities to survive and improve their living standards*". Crop diversification, in particular, refers to cultivating more than one variety of crops belonging to the same or different species in a given area (Makate *et al.*, 2016).

It is the process by which rural families build up a diversified portfolio of activities and social support capabilities in their struggle to survive and improve their standard of living. Farmers diversify for risk mitigation and enhancing better financial returns (Boakye *et al.*, 2021). In agriculture, these adaptation measures include using seeds adapted to climatic stress factors (e.g. drought-resistant seeds) and the spreading of risks between different types of crops (Mulwa & Visser, 2020). Other benefits of diversified cropping systems include improved soil fertility and expanded household dietary diversity for better nutrition absorption (Mulwa & Visser, 2020).

Incorporating these seed types into a crop mix can be an important adaptation strategy for resilience.

Climate change, combined with degrading soils due to over-farming, put farming households in the Groundnut Basin in a precarious position (Sall, 2015). When farmers face climate-related risks and depend largely on agricultural production for their sustenance, crop diversification is one remarkable way of developing resilience to stabilize their food stocks and incomes (Mango *et al.*, 2018). In anticipation of covariate shocks such as droughts, poor farming households are particularly inclined to choose less risky technology portfolios to avoid lasting damage (Mulwa & Visser, 2020). Recent studies suggest that the probability of a household remaining poor or vulnerable decreases with the adoption of different complementary technologies and significantly increases the welfare outcomes of farm households (Biru *et al.*, 2020).

1.2.4.1 Crop diversification and food and nutrition security

Applied Economists have reported mixed findings of the impact of crop diversification on food and nutrition security in Africa (Jones *et al.*, 2014). On the one hand, some scholars report increased food and nutrition insecurity when farmers diversify their crop portfolio, arguing that households that diversify crops cannot manage multiple crops and may be less productive. In contrast, households that produce specific crops find it easier to manage their farms effectively to improve productivity (Nkegbe *et al.*, 2017). On the other hand, others report better food and nutrition security outcomes when farmers adopt crop diversification (Adjimoti & Kwadzo, 2018; Mulwa & Visser, 2020).

For example, Adjimoti & Kwadzo, (2018), in their study in Benin, report a positive and statistically significant impact of crop diversification on household food security, arguing that Crop diversification offers the possibility of greater dietary diversity and a reduction in micronutrient deficiencies and malnutrition. In fact, part of the harvest is consumed by the household (Nahar *et al.*, 2024). Similarly, (Goshu *et al.*, 2012) in their study on a sample of farmers in rural Ethiopia find crop diversification to be positively correlated to household food security. Other scholars have reported similar findings in countries such as Zimbabwe, Malawi, Kenya and Tanzania in northern Namibia (Makate *et al.*, 2016; Mango *et al.*, 2018; Mulwa & Visser, 2020).

Cultivating several crop species can help smallholder farmers manage production risk, reduce the cost of risk and increase farm-level crop productivity (Di Falco & Chavas, 2009). Crop diversification can, therefore, be a viable option in reducing the risks associated with food and nutrition insecurity and low incomes from agricultural production.

1.2.4.2 Crop diversification and poverty

Several studies have found a positive relationship between crop diversification and a reduction in the incidence and level of income poverty (Asfaw *et al.*, 2019; Jones, 2017; Makate *et al.*, 2016). The intuition is that crop diversification is an effective strategy for tackling various problems, including poverty. Michler & Josephson, (2017) find that crop diversity has a positive and significant impact on reducing the probability of a household being poor. One explanation for the positive relationship between crop diversification and poverty is that diversified farming systems are more resilient to shocks and stresses. By cultivating a variety of crops, farmers are less vulnerable to the failure of a single crop, which can lead to income loss and increased poverty. Additionally, diversified farming systems can provide a more stable and diverse source of income, reducing reliance on a single source of revenue. In their study on crop diversification, households who cultivate a diversified set of products are less likely to be poor compared to households who specialized in cultivating a single crop. Thus, crop diversification may be a viable option for reducing the incidence and level of poverty (Sakho-Jimbira & Benoit-Cattin, 2007).

While some studies find a positive relationship between crop diversification and the incidence and level of income poverty, others report a negative relationship (Harris & Orr, 2014). The observed positive relation has been attributed to factors such as limited market access, the lack of technical knowledge and resources. For example, a study in Uganda by (Coromaldi *et al.*, 2015) found that farmers who diversified their crops had lower incomes compared to those who specialized in a single crop. This was attributed to limited access to markets, knowledge, and resources for diversified crops. Additionally, some farmers may lack the necessary skills and knowledge to effectively manage a diverse range of crops, leading to lower yields and incomes.

1.2.5 Concept definition

1.2.5.1 Climate variability and change

Climate change refers to long-term alterations in the climate system that persist over decades or more, impacting not only temperatures but also rainfall patterns, wind regimes, soil moisture, and the frequency of extreme weather events (IPCC, 2019). According to the IPCC, climate change includes shifts in the mean and variability of these climatic variables. The United Nations Framework Convention on Climate Change (UNFCCC) differentiates between "climate change," which is attributed directly or indirectly to human activities altering the composition of the global atmosphere, and "climate variability," which refers to natural fluctuations over time (UNFCCC, 1992). In Senegal, long-term climate change and short-term climate variability present major challenges, particularly for sectors such as agriculture, livestock, and fisheries that are highly sensitive to climatic conditions (USAID, 2017). The agricultural sector is particularly vulnerable as more than 95% of the total cultivated land depends on rain-fed systems, with most farmers engaged in subsistence agriculture (Khouma *et al.*, 2013).

Senegal's agricultural production is affected by several forms of climate variability. These include delayed onset of rains, which affects planting schedules and crop establishment; early cessation of rains, which shortens the growing season; prolonged intra-seasonal dry spells, leading to soil moisture deficits; interannual variability in rainfall totals; and erratic distribution of rainfall during the rainy season (D'Alessandro *et al.*, 2015; Jalloh *et al.*, 2013). Since the 1960s, average temperatures in Senegal have risen by approximately 0.9°C, with stronger warming in the northern regions (USAID, 2017). These trends have intensified evapotranspiration rates and soil moisture depletion, resulting in adverse impacts on crops and pasturelands (ANACIM *et al.*, 2013).

Historically, Senegal has been marked by persistent droughts, particularly in the 1970s and 1980s, which severely disrupted ecosystems and agricultural productivity in the drier northern parts of the country (Gonzalez *et al.*, 2012). Between 1986 and 2003, average annual rainfall in many departments in Senegal was consistently below the long-term average (World Bank, 2009). Major droughts in 2002 and 2007 caused substantial declines in total crop production by 35% and 25% respectively (World Bank, 2009). The 2002 drought alone affected approximately 284,000 people (ANACIM *et al.*, 2013). The primary cause of crop losses during this period was drought, affecting nearly 30% of rain-fed farmers, followed by locust infestations, reported by 16% of farmers (EMAP, 2004). The 2011/2012 cropping season experienced another severe drought, which was followed by floods in 2012, impacting nearly 850,000 people (GIIF, 2017). In 2007, drought was again identified as the main factor behind decreased agricultural production, with cereal and groundnut yields declining by 12% and 7%, respectively, compared to the previous season (World Bank, 2009). More recently, low and delayed rainfall patterns were observed during the 2013 and 2014 rainy seasons, negatively impacting agricultural productivity (GIIF, 2017).

Multiple studies have underscored the strong link between climatic shocks and agricultural losses in Senegal. For instance, approximately 40% of crop yield variability is attributed to fluctuations in annual rainfall (D'Alessandro *et al.*, 2015). Groundnut, Senegal's primary cash crop, is highly sensitive to rainfall variability, with precipitation explaining nearly 39% of yield fluctuations (IMF, 2007). Between 1980 and 2012, Senegal experienced production losses equivalent to 4.82 million metric tons, translating to approximately US$1.38 billion, or an average of US$41.7 million per year, corresponding to around 3.9% of agricultural GDP (Collins-Sowah, 2021). Furthermore, agriculture in Senegal typically faces losses exceeding 10% of gross production value in one out of every five to six years due to unmanaged climate-related risks (Collins-Sowah, 2021). The most significant cause of these losses is drought and erratic rainfall, responsible for approximately 50% of crop yield reductions, followed by pests and diseases, especially locust outbreaks, which account for about 25% of losses (D'Alessandro *et al.*, 2015).The severity of impacts often escalates when multiple risks occur concurrently, such as when droughts are followed by pest infestations (D'Alessandro *et al.*, 2015). Maize production is particularly vulnerable regarding risk frequency, whereas groundnut production accounts for nearly 45% of aggregate crop losses (D'Alessandro *et al.*, 2015).

Looking toward the future, projections suggest that Senegal will face continued rainfall declines, even as the intensity of rainfall events may increase (Jalloh *et al.*, 2013; USAID, 2017). These trends, combined with rising temperatures and sea-level rise, will continue to place significant pressure on Senegal's agricultural systems. Increased soil salinization, driven by both sea-level rise and saltwater intrusion, is further degrading agricultural land in coastal areas (ANACIM *et al.*, 2013; IFAD, 2019).

1.2.5.2 Food Security, Food Insecurity, and Resilience

Food security, food insecurity, and resilience are deeply interconnected concepts, especially within climate-sensitive contexts such as Senegal. The concept of food security emerged in the 1970s, initially defined by the UN in 1975 as the global capacity to maintain the supply of essential food commodities while ensuring price stability (UN, 1975). Over time, the definition evolved to focus more on the individual level. The World Bank (1986) highlighted the importance of continuous access to sufficient food for a healthy, active life (Troubat & Sajala, 2014). The FAO's 1996 and 2009 definitions further incorporated aspects of food quality, safety, and the social dimensions of access (FAO, 1996; CFS, 2012). Today, food security is widely accepted as resting on four key dimensions: (i) availability of sufficient food; (ii) physical, economic, and social access; (iii) stability of both availability and access over time; and (iv) proper utilization, including nutritional quality and safety (Bindraban *et al.*, 1999; Sanni, 2017). In contrast, food insecurity occurs when individuals or households face limited or uncertain access to nutritionally adequate and safe food (Ahmad *et al.*, 2021; Anderson & Cook, 1999). It is often linked to poverty and manifests when households are forced to deplete their savings, sell productive assets, or rely on external aid (Demery & Addison, 1987). Acute food insecurity, as noted by (Issoufou, 2020), can reach life-threatening levels, especially when compounded by shocks such as droughts, floods, or pest outbreaks. The concept of resilience originally drawn from ecology and engineering has been widely adopted in development and humanitarian contexts, particularly after the crises of the late 2000s (Barrett *et al.*, 2021; UN, 2020b). It refers to the ability of individuals, households, and systems to anticipate, absorb, recover from, and adapt to shocks without long-term setbacks (FAO, 2016) (UNISDR, 2009; FAO, 2016; AGIR, 2012). In food systems, resilience is critical to mitigating the adverse effects of climate variability and change, such as droughts and erratic rainfall, which directly influence food availability and access (D'Alessandro *et al.*, 2015; USAID, 2017).

In Senegal, where rainfed agriculture predominates, resilience plays a pivotal role in mediating food security outcomes. For instance, recurrent droughts, delayed rainfall onset, or extreme flooding frequently disrupt food production and markets, driving households into food insecurity (ANACIM *et al.*, 2013; GIIF, 2017). However, households with higher resilience characterized by diversified income sources, access to social safety nets, and adaptive agricultural practices are better able to withstand such shocks and maintain food security (Barrett *et al.*, 2021; FAO *et al.*, 2018). Empirical evidence further illustrates that resilience is not merely a protective factor but also a determinant of long-term food security. For example, the FAO (2016) emphasizes that building resilience in agricultural livelihoods enhances both the availability and stability of food supplies. Additionally, studies show that climate shocks, when coupled with low resilience, have cascading effects on household nutrition, health, and poverty levels (Sanni, 2017). Thus, rather than treating food security and resilience as separate analytical categories, understanding their causal relationship is crucial. Resilience-building measures, such as the adoption of climate-smart agriculture, improved access to credit and insurance, and investments in social protection systems, can directly reduce food insecurity by buffering against the biophysical and socioeconomic drivers of vulnerability (Barrett *et al.*, 2021; FAO, 2016). Ultimately, in regions like Senegal, where climate variability is an ever-present challenge, the interplay between resilience and food security defines how well communities can sustain livelihoods, reduce poverty, and avoid hunger amidst growing environmental and economic uncertainty.

1.2.5.3 Dimensions of Food Security and Senegal's Performance

Food security is framed by four key dimensions: availability, access, utilization, and stability.

Availability refers to the physical presence of sufficient quantities of food, supplied either through domestic production, imports, or food aid. In Sub-Saharan Africa, the average caloric availability is approximately 2580 kcal/capita/day, below the global average of 2985 kcal per person per day in 2022 (FAO, 2023). Senegal performs slightly below the global average, with caloric availability estimated at 2826 kcal/capita/day (FAO, 2023). Across the continent, agricultural yields remain among the lowest globally due to limited mechanization, poor soil fertility, and low adoption of improved inputs (Sam *et al.*, 2021). Food availability is also undermined by post-harvest losses, which in Senegal can account for up to 30% of cereal production (CILSS, 2025).

Access to food is shaped by household income, market prices, and the efficiency of food distribution systems. Africa's dependence on food imports to meet demand continues to grow, with the continent importing approximately 85 million metric tons of cereals in 2022 (FAO, 2023). In Senegal, the food trade deficit widened significantly over the past decade, with rice imports covering over 60% of national consumption (Formiga & Degreenia, 2023). Rural populations, particularly in remote areas of Senegal, face additional constraints due to poor market connectivity, high transportation costs, and price volatility (D'Alessandro *et al.*, 2015). Seasonal lean periods, typically from June to August, exacerbate food access challenges as food stocks dwindle and prices rise, further limiting affordability for vulnerable households (Ilboudo Nébié *et al.*, 2021).

Utilization refers to the proper biological use of food, requiring a diet that meets nutritional needs along with good health and sanitation. In Africa, undernourishment affects around 20.4% of the population, Senegal performs better than some Sahelian neighbors but still faces considerable challenges, with 4.6% of its population classified as undernourished (FAO, 2023). Micronutrient deficiencies remain widespread, especially among children under five, where stunting rates stand at 17% and wasting at 7.5% (UNICEF *et al.*, 2023). Food utilization is further undermined by post-harvest and food loss issues; in Senegal, 20-25% of harvested groundnuts and cereals are lost before reaching markets or households (World Bank, 2017). Additionally, limited dietary diversity and poor access to potable water and sanitation services contribute to malnutrition and poor health outcomes (UNICEF *et al.*, 2023).

Stability, the fourth dimension, captures the reliability of food availability and access over time. In Africa, food systems are highly sensitive to climate variability, conflict, and economic shocks. The Per capita food production variability index in Sub-Saharan Africa averages 25-30%, substantially higher than the global average of 12% (FAO, 2023). In Senegal, variability is driven primarily by climate shocks such as droughts and irregular rainy seasons, which destabilize food production and rural incomes (ANACIM *et al.*, 2013). Insecurity in the Sahel and global supply chain disruptions have also affected Senegal's food stability, amplifying price shocks and reducing household resilience. These fluctuations mainly affect the lean season, during which food insecurity rates typically peak (OCHA, 2023).

Hotspots of food insecurity in Africa are concentrated in the horn of Africa (Somalia, Ethiopia) and parts of the Sahel (Nigeria, Chad, Niger, etc.), where drought, conflict, and displacement exacerbate vulnerability. Senegal, while not in the most extreme hotspot category, exhibits chronic food insecurity pockets in northern and central regions, where food access and production deficits are recurrent (WFP, 2024).

1.2.5.4 Resilience Index Measurement Analysis (RIMA)

Resilience is a topic of interest in the humanitarian and development worlds, as is the need for tools to measure and analyze it in different contexts. To meet this need, several tools for measuring and analyzing resilience have been developed by non-governmental organizations, researchers and donors. However, while some use tools to measure resilience at the individual level, others measure it at the household, community and/or sub-national levels. The analysis and measurement of resilience are made all the more complex by the fact that the definition of the concept of resilience is plural. Thus, international organizations and non-governmental organizations that have made resilience an objective of their interventions seek to measure its effects.

Table 1- 1: Tools to measure and analyze resilience

MEASUREMENT	TOOLS	AUTHORS
COBRA (Community Resilience Assessment And Action)	Community resilience	United Nations Development Programme (UNDP)
BRACED (Building Resilience and Adaptation to Climate Extremes and Disasters)	Disaster resilience	British Cooperation (DFID)
Drew(Dynamic Resilience Wheel)	Characterizing resilience	Lutheran World Relief: charitable organization
The RA manual (Assessing Resilience)	Resilience in socio-ecosystems	Alliance for Resilience
RIMA (Resilience Index Measurement and Analysis)	Resilience to food insecurity	Food and Agriculture Organization of the United Nations (FAO)

Notes: some examples of tools to measure and analyze resilience

Sources: (DFID, 2011; UNDP, 2014, FAO 2016, O'connell *et al.*2016)

Even if we have a lot of tools to measure and analyze resilience, RIMA is the one which is more specific to analyze resilience to food insecurity. In fact, since 2008, the FAO has been developing a resilience measurement and analysis framework (RIMA) to measure people's resilience to food insecurity and assess the effectiveness of interventions aimed at strengthening their resilience (Alinovi *et al.* 2009). RIMA is a quantitative approach that helps explain why and how some households cope with shocks and stressors better than others. It provides a rigorous framework for designing long-term humanitarian and development initiatives to strengthen household food security and resilience, and enables more effective design, implementation, monitoring and evaluation of assistance to poor populations, addressing their priority needs.

In its initial version, the RIMA approach was based on 6 pillars (income and access to food, access to basic services, assets, social safety nets, adaptive capacity and sensitivity). After its application in 10 countries, based on the results obtained, technical improvements were made to the first version of RIMA. In 2015, FAO revised and improved this approach. In the new approach (RIMA II), the model considers four pillars of resilience: access to basic social services, assets, social safety nets and adaptive capacity. The analysis and measurement of resilience through RIMA answers a number of questions: (i) who are the poorest populations? (ii) Where should investments be concentrated geographically? (iii) Which dimensions of resilience should be strengthened? (iv) to what extent have interventions strengthened or reduced the resilience of targeted populations? What types of shocks have the greatest impact on household resilience? Etc.

It uses factor analysis techniques to estimate pillars and a resilience index. The tool thus makes it possible to estimate the level of resilience according to several criteria, and to identify the pillars that contribute most. It is structured in two parts: a descriptive part and an explanatory part. The descriptive part consists of constructing a resilience index that will enable a comparative analysis of household resilience capacities between the country's regions and departments. The explanatory part identifies the factors that enable households to strengthen their resilience.

The pillars of food security resilience are: access to basic social services, assets, social safety nets and adaptive capacity.

- **Access to basic services** reflects a household's ability to meet its essential needs through the effective use of basic services. This dimension groups together variables relating to access to drinking water (the household's main source of drinking water), electricity (the household's main source of lighting), housing characteristics (the main components of housing floors, walls and roofs) and hygienic cooking conditions (the main source of energy for cooking).

- **Assets:** these include productive and non-productive assets. Productive assets are the main elements that enable households to ensure their subsistence by producing consumable and marketable goods (farm equipment, plot size in hectares, number of tropical livestock units). Non-productive assets include housing features and household capital goods.

Social safety nets: this pillar measures households' ability to obtain help from relatives, friends, or the government and to access assistance provided by international organizations or NGOs. It is represented by the amount of transfers received by households, loans/purchases on credit, donations, and food aid.

- **Adaptive capacity:** this is the household's ability to bounce back from a shock and develop new strategies. It encompasses the 10 strategies obtained with the question “Did the household have to resort to any of the following strategies because of food difficulties?”, the number of years of education of the head of household, and income.

1.3 Aim and Objectives of the Study

General Research Question

The fundamental question that emerges from this study is: How does the food security of rural households in the Senegalese Groundnut Basin threatened by the negative effects of climate change?

The specific research questions are as follows:

- What are the major climate-related risks affecting agricultural yield to which the rural households in the Senegalese Groundnut Basin are exposed?
- What is the impact of crop diversification in mitigating climate-related risks and improving household welfare in the Senegalese Groundnut Basin?
- What is the level of resilience to food insecurity of households in the Senegalese Groundnut Basin?

General research objective

This research aims to analyze the resilience to food insecurity of rural households in the Senegalese Groundnut Basin in relation to climate-related risks. The specific objective are to:

SO1: conduct an analysis of climate-related risks and agriculture yield assessment in the Senegalese Groundnut Basin;

SO2: analyze the impact of crop diversification in mitigating climate-related risk and improving welfare in the Senegalese Groundnut Basin;

SO3: measure the resilience to food insecurity of households in the Senegalese Groundnut Basin due to climate-related risks.

Specific research hypothesis

- Climate-related risks have a significant influence on agriculture yields in the Senegalese Groundnut Basin;
- Crop diversification has a positive effect in mitigating climate-related risks and improving household welfare in the Senegalese Groundnut Basin;
- In the Senegalese Groundnut Basin, households with higher levels of resilience are less vulnerable to food insecurity despite exposure to climate-related risks.

Significance of the Study

In the Senegalese Groundnut Basin, climate change adaptation in the agricultural sector has been the subject of several studies (CIAT & BFS/USAID, 2016; Garambois *et al.*, 2024; Sy, 2022). However, little attention has been paid to households' resilience to food insecurity in an unfavorable climatic context (Fall, 2018). This study fills this gap by proposing effective adaptation approaches to strengthen resilience while preserving the livelihoods of rural households. Our research enriches the literature on food security, climate adaptation, and sustainable development in West Africa. It analyzes local socio-economic dynamics and proposes innovative analytical frameworks to enhance understanding of community resilience. Identifying local resilience mechanisms provides valuable insights for guiding public policies on food security and climate adaptation. The thesis utilizes robust empirical data to inform policymakers in formulating adaptation and sustainable agricultural development strategies. It highlights the factors that promote or hinder resilience, enabling the design of targeted programs tailored to local realities. These programs include livelihood diversification, market access improvement, promotion of resilient agricultural practices, and the establishment of early warning systems against climate risks.

The originality of this study lies in its focus on the Groundnut Basin, an area whose socio-ecological specificities make it a relevant field for developing resilience models applicable to other Sahelian regions. The thesis will serve as a reference for national and regional initiatives to strengthen resilience to food insecurity in rural areas. The findings of this research open up prospects for collaborations between researchers, NGOs, government institutions, and international partners in favor of sustainable and resilient agriculture. The conclusions will contribute to global discussions on climate adaptation and food security, supporting the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 13 (Climate Action) assess the impacts of climate parameters for strengthening resilience and adaptive capacity to climate-related risks.

This study proposes concrete solutions to strengthen the resilience of rural households in the Senegalese groundnut basin, thus contributing to building a sustainable future for vulnerable communities. The recommendations from this research will serve as a basis for integrated policies on agriculture, food security, and climate adaptation, tailored to climate risk areas.

1.4 Methodology

1.4.1 Data description

The data used in this study were sourced from the 2019 National Food Security, Nutrition, and Resilience Survey (ENSANR), conducted by the Executive Secretariat of the National Council for Food Security (SE_CNSA). Data collection took place between January and February 2019, utilizing a multistage sampling approach to gather quantitative data from farm households. In the first stage, census districts were selected through a systematic random draw, with probabilities proportional to the population size of the primary units (census districts). This process was conducted independently for each department (or stratum), which was stratified by place of residence (urban or rural). The sample in each department was allocated proportionally between urban and rural areas according to population size. Within each area of residence, the number of census districts was determined using the systematic selection procedure, and in each district, 16 households were chosen through the same method. In the second stage, households within the selected districts were chosen using a systematic random sampling method, applying a sampling step (P), which refers to the number of households separating two selected households. The step size (P) was calculated by dividing the total number of households (N) in each district by the number of households to be surveyed (n). This sampling increment (P) was then used to select the households. ENSANR achieved stratified representativeness at the departmental level and by area of residence for household indicators such as food security and resilience, surveying 7,847 households across all 14 regions and 45 departments of Senegal.

Our focus is on examining resilience to food insecurity among rural households in the Senegalese Groundnut Basin within the context of climate change, we extracted data from 19 departments within the Groundnut Basin. From an initial sample of 7,847 households, we use a sub-sample of 3,100 rural households (both urban and rural) composed of 2442 male-headed households and 568 female-headed households. The survey gathered detailed information on household characteristics, living conditions, agricultural practices, food consumption, income and expenses, shocks, and coping strategies. (cf. appendices N^{0}1 for more details concerning ENSANR metadata).

1.4.2 Data analysis

Various statistical analysis techniques were used depending on the research questions. Across the different chapters, the data was analyzed using multiple regression, trend analysis, and correlation approaches. We first employed a pooled ordinary least squares multiple regression technique to assess the overall relationship between our outcome of interest (i.e., crop yields) and various explanatory variables, primarily agro-climatic variables (rainfall and temperature). Secondly, we use the marginal treatment effect (MTE) approach, which accounts for selectivity bias from both observed and unobserved attributes and heterogeneity in the treatment effects among farming households. Finally, we use the Resilience Index Measurement Analysis (RIMAII), followed by Two-Stage Least Squares (2SLS) and Dose-Response Function methodologies to analyze the Resilience Capacity Index (RCI) and its effects on key food security indicators: Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS). All the data were computed using STATA, MATLAB and R version 4.2.2 software.

1.4.3 Study Area

The Groundnut Basin of 49,500 km2 is densely populated and subject to ecosystem degradation and depletion of land resources (soil fertility and timber resources). It has a human population of 8,640,894, representing about 47% of the national population, according to ANSD (ANSD, 2021). Approximately 60% of the inhabitants live in rural areas, with a youthful demographic and a higher population density in the southern regions of Fatick and Kaolack. It is the area with the fastest and most rapid increase in population numbers. This rapid increase can be explained by the fact that the zone covers a very large area in terms of surface area, as well as the fact that it is home to Senegal's major agricultural centers Kaolack, Diourbel, Kaffrine and major cities such as Thiès and Diourbel, Kaolack, Fatick and Kaffrine.

Table 1- 2: Characteristics of the Groundnut Basin

Administrative division	Demography and surface area	Climatic and environmental description			Types of soil	Agricultural practices	Vulnerability to climate change
		T mean	**Mean rainfall**	**Vegetation**			
Regions of Thies, Diourbel, Fatick and Kaolack and Departments of Louga, Kebemer and Koumpentoum	Densely populated 8,640,894 47% of the national population Surface area 49,500 km2 57% of arable land 60% live in rural areas	29^{0}C	500mm	Dominated by acacias Degradation due to agriculture and drought	Tropical ferruginous soils (dominant); Hydromorphic soils (rare); Lithosols (rare); Mudflats (rare); Ferruginous soils (rare).	Cash crops: groundnut Food crops: millet, maize, sorghum Livestock Small-scale fishing (Mbour, Kayar, Joal) 65% of the population practices rain-fed agriculture occupies	Drought Ecosystem degradation Soil acidification Salinisation of water tables Marine invasion (Saloum River) Destruction of mangroves Coastal erosion.
					Severely degraded soils	**Agro-pastoral systems**	**High vulnerability**

Sources: (ANSD, CSAO-CILLS, ISRA, BM and Diallo, 2016)

1.5 Outline of the thesis

The thesis is organized into chapters. Subsequent chapters 2, 3, and 4 report the empirical findings of the research.

The objective of chapter 2 is to characterize rainfall and temperature variability in the Senegalese Groundnut Basin and to assess the influence of these climatic parameters on the yields of groundnut, millet, and maize. The methodology is based on trend analysis, correlation analysis, and multiple regression models. The data used consists of daily records of rainfall, temperature, and crop yields covering the period from 1991 to 2020 for both the northern and southern zones of the Groundnut Basin. The results show an increase in seasonal rainfall, with higher variability in the southern zone. Both zones are experiencing warming. Regression analysis reveals that total seasonal rainfall and maximum temperature positively and significantly influence crop yields, while other climatic factors have varying effects depending on the zone.

The chapter 3 analyzed the impact of crop diversification on food and nutrition security and poverty among rural households in Senegal. The analysis relies on farmer-level data and employs the Marginal Treatment Effect (MTE) approach to control for both observed and unobserved heterogeneity and selection bias. The data include information on household welfare, food security indicators, and access to markets, with a focus on households exposed to climatic shocks. The key results show that households with a higher propensity to adopt crop diversification experience greater improvements in food security and poverty reduction, even under adverse weather conditions. The findings also highlight that reducing the distance to input markets enhances crop diversification and contributes to better food and nutrition security and poverty alleviation.

The chapter 4 to assess the heterogeneous impact of household resilience on food and nutrition security in Senegal. The analysis uses household-level data and applies the Resilience Index Measurement Analysis (RIMAII), followed by Two-Stage Least Squares (2SLS) and Dose-Response Function methodologies. The data include resilience indicators and food security measures such as the Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS). The key results show that access to basic services, assets, and adaptive capacity are significant determinants of resilience, with female-headed households being more resilient than male-headed ones. The 2SLS results confirm that greater resilience leads to improved food security. The dose-response function reveals a heterogeneous positive impact of resilience, with female-headed households benefiting more from increased resilience capacity but also being more vulnerable when non-treated.

In chapter 5, all empirical findings are discussed in concert and in a broader perspective to conclude and to give the policy implications.

CHAPTER 2: CLIMATE-RELATED RISKS AND AGRICULTURAL YIELD ASSESSMENT IN THE SENEGALESE GROUNDNUT BASIN

Abstract

Climate change and variability pose significant threats to agricultural production, particularly in regions heavily dependent on rainfed agriculture like Senegal. This study examines the impact of climate-related risks on agricultural yields in the Senegalese Groundnut Basin, a key agricultural region. The research objectives are to characterize rainfall and temperature variability between 1991 and 2020 and to assess the influence of these climatic parameters on the yields of key crops (groundnut, millet, and maize). Daily rainfall, temperatures, and yield data were analyzed using multiple regression, trend analysis, and correlation methods. The results indicate an increase in seasonal rainfall (98 mm in the north and 103 mm in the south) with a slower rate of increase in the south. The northern zone exhibits a more predictable growing season, while the southern zone experiences higher variability. Both zones are warming, with the southern zone showing a more pronounced increase in maximum temperatures (+0.7 °C) than to the northern zone (+0.4 °C). Regression analysis revealed that total seasonal precipitation and maximum temperature positively and significantly influence groundnut, millet, and maize yields in both zones. However, other weather-related parameters have varying impacts depending on the zone. These findings highlight the heterogeneity of the Groundnut Basin and the significant role climatic factors play in crop yield variability in the Groundnut Basin. Understanding these influences is crucial for developing targeted agricultural strategies and climate adaptation measures to mitigate risks and enhance regional productivity. The study provides valuable guidance for policymakers and farmers aiming to improve crop resilience and sustain agricultural outputs amidst changing climatic conditions.

Keywords: climate-related risk; agriculture; yield; Groundnut Basin; Senegal

2.1 Introduction

Climate change is no longer a distant threat; it is a present reality, reshaping the world and challenging the foundations of our agricultural systems (Kumar *et al.*, 2021). Agriculture remains the cornerstone of human survival, providing food, livelihoods, and economic stability. However, its ability to meet the growing demands of a rapidly increasing global population is under threat due to the escalating effects of climate change (Velten *et al.*, 2015). One of the most pressing consequences of climate change is the increased frequency and intensity of hydro-climatic and extreme weather events such as floods and droughts. These disruptions significantly impact economies, livelihoods, and the environment, particularly in vulnerable regions like West Africa (Arif *et al.*, 2022; Trisos *et al.*, 2022). West Africa is already experiencing drastic climate variability, with increasing fluctuations in rainfall patterns and the duration of the rainy season coupled with more extreme events (Barry *et al.*, 2018). Adverse weather conditions' frequency, magnitude and duration change with more severe effects observed in the Sahel region (Greenfacts, 2022). The most prominent climate variability challenge in West Africa is the pronounced seasonal and inter-annual fluctuations, often characterized by periods of drought or excessive rainfall and unpredictable shifts in the length of the rainy season (Borona *et al.*, 2016). These fluctuations manifest water stress caused by the late onset of rains, erratic rainfall, early cessation of rains, or prolonged drought (Arce & Arias, 2015). Such instability disrupts agricultural calendars, negatively affecting crop production. Since crop yield is inherently vulnerable to climate variability, temperature and rainfall remain the primary factors influencing agricultural productivity directly and indirectly (Abegaz & Kebede, 2022).

These challenges are evident in Senegal, where agriculture is predominantly rainfed. Wetter years generally correspond to higher food production, while dry years pose an increased risk of food shortages (Faye *et al.*, 2021). Climatic factors such as rainfall and temperature are essential inputs for production, and their variability significantly affects crop yields (Ouikotan *et al.*, 2017). Changes in these climatic indicators are predicted to cause significant production losses, exacerbating food insecurity and increasing the risk of famine (FAO *et al.*, 2018; UN, 2020; WFP, 2018). The decline in staple crop yields in Senegal is primarily attributed to a decrease in total annual rainfall, increasing inter-annual variability, soil degradation, and demographic pressure. Research has shown that more than 40 % of the variation in national crop yields can be directly linked to fluctuations in annual rainfall (Arce & Arias, 2015). In central Senegal, worsening climate variability has been linked to increasing food insecurity (Ilboudo Nébié *et al.*, 2021).

Approximately 60% of Senegalese farms are located in the Groundnut Basin, the country's primary cash crop production region. This area accounts for a significant portion of Senegal's economy, with millet and groundnut covering nearly half of the cultivated land (Davidson, 2015). These crops serve a dual function, acting as a staple food for households and key cash crops that drive economic activity within domestic and regional markets. However, the unpredictability of rainfall patterns, delayed or erratic rainy season onset, and prolonged dry spells have contributed to a steady decline in crop productivity (Huang *et al.*, 2015). Given this reality, climate change presents one of the biggest challenges in increasing or stabilizing food production (Davidson, 2015; Guo *et al.*, 2022). Adverse changes in climate-related variables impact crop growth, yield potential, input supply, and the overall farming system management (Knox *et al.*, 2012). Accurately assessing the impact of climate change on crop yields is, therefore, essential to ensuring food security and sustaining agricultural livelihoods. This study provides a localized analysis of climate-related risks by distinguishing between the northern and southern zones of the Groundnut Basin, thereby capturing spatial heterogeneity often overlooked in broader assessments.

Despite extensive research on the effects of climate variability, localized microclimatic impacts within the Senegalese Groundnut Basin remain underexplored. Many studies focus on general climate trends but do not capture the nuanced, time-specific indicators affecting crop yields in this region. Previous research efforts have analyzed climate impacts on agriculture in different contexts, but their methodologies and geographic focus differ. Knox *et al.* (2012) examined climate impacts on agriculture but did not analyze rainfall indicators in detail. Müller *et al.* (2015) assessed socio-economic models for family farms in Senegal to enhance resilience but did not focus on microclimatic variability. Sultan *et al.* (2013) studied the effects of climate change on dry cereal crop yields, combining multiple climate scenarios and agronomic modelling. This study aims to fill this gap by focusing on rainfall and temperature variability in Senegal's Groundnut Basin. It employs a descriptive approach to examine how these climate indicators influence crop yields. These indicators are crucial as they define key seasonal parameters that significantly affect crop growth, development, and yield outcomes. The central hypothesis of this study is that climate-related risks, particularly variations in rainfall and temperature, significantly affect agricultural yields in the Senegalese Groundnut Basin, with distinct impacts across the northern and southern zones. The study's primary objective is to enhance understanding of climate-related risks and their influence on crop yields in Senegal’s Groundnut Basin. Specifically, it aims to characterize climate-related risks by analyzing rainfall and temperature variability using satellite data (CHIRPS and ERA5) and assess the impact of these climatic variables on crop yields within the region. By addressing these objectives, this study seeks to provide critical insights for policymakers and agricultural stakeholders, helping to build resilience and improve adaptive strategies for farming communities in Senegal. Our findings show that weather patterns reveal a break point in 1998, showing an increase of 100 mm afterward in rainfall in the study area with observed shocks (anomalies) between 15 to 17 according to the zone. Climate variability and extreme weather events significantly affect agricultural yields, thus affecting all rain-fed farming systems in the study area.

2.2 Literature review

The Senegalese Groundnut Basin is highly vulnerable to climate-related risks, primarily driven by variability in rainfall, increasing temperatures, and extreme weather events such as droughts and floods. Climate variability has varying direct and indirect effects on crop yield fluctuation (Osborne & Wheeler, 2013). Studies indicate that climate change is already impacting groundnut and cereal yields, with changes in precipitation patterns and temperature extremes exacerbating water stress and reducing the length of the growing season (Diouf *et al.*, 2019). These rainfed crops are particularly sensitive to rainfall variability, as delayed onset of rains or mid-season dry spells often lead to significant yield losses. Defrance *et al.* (2020) predict that by 2050, yields of key crops such as sorghum, maize, and millet could decline by ranging from 20% to 50% due to climate change. Additionally, rising temperatures are expected to increase weed and pest infestations, further reducing crop productivity and heightening food insecurity. Long-term climate data indicate a decline in annual rainfall and a rising temperature in Senegal since the 1970s, contributing to increased evapotranspiration and soil moisture loss (Funk *et al.*, 2012). Higher temperatures during critical crop development stages, such as flowering and pod formation, have negatively impacted groundnut yields (Hasanuzzaman *et al.*, 2013). Climate projection under scenarios RCP 4.5 and 8.5 indicates further temperature increases and continued irregular patterns, likely aggravating these risks (Faye *et al.*, 2018). The growing unpredictability of weather conditions necessitates urgent adaptive measures to sustain agricultural productivity in the region.

Beyond climate variability, soil degradation and unsustainable land-use practices further amplify climate risks to agriculture in the Senegalese Groundnut Basin. Erratic rainfall patterns and poor agricultural practices have led to soil nutrient depletion and reduced water-holding capacity, thereby decreasing overall productivity (Zizinga *et al.*, 2022). This interplay between climate variability and land degradation underscores the need for integrated approaches to risk assessment and mitigation. On a global scale, climate change is recognized as a major threat to agriculture, with anticipated consequences such as shifts in water availability, soil erosion, and reduced crop productivity (Howden *et al.*, 2007; McCarl, 2010). In Senegal, where rainfed agriculture dominates, rising temperatures and declining precipitation trends not only impact groundnut and cereal production but also threaten food security and economic stability (Asseng *et al.*, 2011; Serdeczny *et al.*, 2017). Weather shocks are among the most significant risk factors, negatively impacting agriculture yields and food security (Chavas *et al.*, 2022). Developing adaptive capacity to cope with these extreme weather shocks is critical for the resilience of farm households in Senegal.

Various adaptation strategies have been explored to mitigate climate-related risks. Traditional and modern adaptive measures such as soil conservation techniques, drought-resistant crop varieties, agroforestry, water harvesting, and adjusted planting dates have been proposed to improve resilience (Douxchamps *et al.*, 2016; Mortimore & Adams, 2001). However, adaptation efforts are often constrained by limited access to climate information, which makes it challenging for farmers to implement effective and locally tailored strategies. This highlighted the need for policy interventions to improve knowledge dissemination and promote sustainable agricultural practices. By analyzing daily rainfall and temperature data using multiple regression, trend analysis, and correlation methods, this study aims to provide a deeper understanding of the relationships between climatic variables and crop productivity. The application of analytical techniques allows for a more precise assessment of the impacts of climate variability on groundnut, millet and maize yields, addressing a critical gap in the literature.

Many previous studies have sought to understand the physical effects of climate variability on crop yield, often relying on crop simulation models. However, small but critical changes in climatic variables, particularly temperature fluctuations, are often excluded (Roberts *et al.*, 2008). Unlike these studies, the present research does not focus on crop physiology or farm management. Instead, it emphasizes seasonal climatic descriptors that influence crop development. Assessing the effects of climate on crop yields remains a key area of research, but every methodology comes with uncertainties and limitations, as Hengl *et al.* (2014) noted. The specificity of this study lies in its in-depth analysis of rainfall indicators, employing a descriptive approach to examine their influence on agricultural yields in Senegal. These indicators define key seasonal parameters that significantly impact crop growth, development, and final yield outcomes. This study contributes to the growing body of literature by investigating how crops causally respond to specific climate variability indicators at the localized level within the Groundnut Basin of Senegal. Furthermore, the study's focus on daily data and advanced analytical methods enhances the accuracy and reliability of its findings, making it a valuable resource for future research and policy formulation. Understanding current climate variability trends and their effects on crop yields is crucial for making informed decisions about crop management and selecting appropriate crop varieties. The importance of this study lies in its ability to provide actionable insights for policymakers and farmers in the Senegalese Groundnut Basin. By understanding past and present climate conditions, stakeholders can better plan for the future and implement effective adaptation strategies to ensure the region's food security and economic prosperity.

2.3 Methodology

2.3.1 Model Estimation

Given the nature of the dataset, having a time and cross-sectional dimension, the paper adopted a model by Belford *et al.*, 2020, Cohen *et al.*, 2003; Wooldridge *et al.* 2010. We used a pooled ordinary least squares multiple regression technique to assess the overall relationship between our outcome of interest (i.e. crop yields) and various explanatory variables, mostly agro-climatic variables (rainfall and temperature). As shown by Cohen *et al.* (2003), the model is written in the following form:

$$Y_{ij} = a + bX_{1j} + cX_{2j} + ... + zX_{ij} + \varepsilon_{ij} \quad (1)$$

where Y_{ij} is the observed variable (crop yields), X_i are the predictor variables, and a, b and z are the estimated values of the parameters associated with the climate-related variables. It must be emphasized that j, as used in the model specification, represents a given department on which the data was collected. **Table 2-1** below shows the different calculated agro-climatic variables and their descriptive statistics.

Table 2- 1: Presentation of agro-climatic variables used

Variables	**Definition**	**Unit**	**Mean**	**Standard deviation**	**Expected sign**	**References**
Climatic	Total seasonal precipitation (TSP) Seasonal total precipitation in wet days (PR >= 1 mm)	mm	505.54	114.61	+	(Toure *et al.*, 2020; Mwenda, 2021)
	Simple daily rainfall intensity index (SDII)) Average daily PR intensity =Annual total PR divided by the number of wet days (when total PR >= 1.0 mm)	mm	11.61	1.36	+	(Hailu *et al.*, 2025; Toure *et al.*, 2020)
	Max 5-day precipitation (RX5days) Maximum 5-day PR total	mm	78.21	13.27	+	(Dubey *et al.*, 2024; Hailu *et al.*, 2025)
	Number of very heavy rain days (R20mm) Number of days when PR ≥ 20mm	day	5.40	1.99	+	(Dubey *et al.*, 2024; Hailu *et al.*, 2025)
	Consecutive wet day (CWD) Maximum seasonal number of consecutive wet days with PR > 1 mm	day	5.49	1.22	+	(Toure *et al.*, 2020; Mwenda, 2021)
	Consecutive dry days (CDD) or length of dry days Maximum seasonal number of consecutive dry days with PR < 1 mm	day	18.27	6.21	_	(Fall, *et al.*, 2021; Toure *et al.*, 2020)
	Seasonal maximum mean temperature (T_{max})	°C	32.69	0.63	_	(Asseng *et al.*, 2011; Toure *et al.*, 2020)
	Seasonal minimum mean temperature (T_{min})	°C	22.22	0.65	+	(Faye *et al.*, 2021)
	Seasonal start date (Onset)	Julien day	192.25	13.34	_	(Dobor *et al.*, 2016; Fall *et al.*, 2021)
	Seasonal end date (Offset)	Julien day	274.82	6.96	_	(Alimagham *et al.*, 2024; Trail *et al.*, 2016)
Agro	Maize yields	Kg/ha	1,067.80	271.44		
	Millet yields	Kg/ha	651.29	233.24		
	Groundnut yields	Kg/ha	771.271	298.175		

Note: This table presents a brief description of all the variables used in our estimation and the descriptive statistics.

Sources: data from CHIRPS, ERA5 and DAPSA

A stepwise multiple regression model is used because it involves comparing several models to determine which model performed the best. When the number of predictors is small, manually comparing the models to select the most appropriate one is easy. However, when the number of independent variables increases, this approach quickly becomes unusable, and it is useful to use an appropriate goodness-of-fit measure. Step-by-step selection based on the Akaike Information Criterion (AIC) is one of the approaches used. This AIC goodness-of-fit measure chooses the model with the lowest AIC value. The following is how Akaike *et al.* (Akaike, 1974) demonstrate how to compute the AIC:

$$AIC = 2 \times \ln(RSS) + 2K AIC = 2 \times \ln(RSS) + 2K \quad (2)$$

where K is the number of independent variables, n is the number of observations, and RSS is the sum of squared residuals. This measure favors the accuracy of predictions and penalizes complexity. When models are compared by AIC, the model with the lowest AIC is the preferred model.

2.3.2 Data Collection

The various data (climate variables and crop yields) were acquired from 1981 to 2020. However, due to gaps in the yield series collected by the Directorate of Analysis, Forecasting and Agricultural Statistics (DAPSA) of Senegal for the various crops, the study focused on 1991-2020. This study period ensures consistency in the data and allows us to identify potential changes observed over the last three decades. Moreover, the period from 1991 to 2020, which corresponds to the latest climatological normal of the World Meteorological Organization (WMO), also coincides with the so-called rainfall return period in the West African Sahel after the two dry decades (1970-1990). This period seems, therefore, more consistent in climatic terms for assessing the agro-climatic characteristics and their relationship to the yields of the various crops considered in this study. The data were computed using MATLAB and R version 4.2.2 software. **Table 2-2** briefly highlights the sources of climatic data used for the current analysis. Rainfall estimation products are highly regarded due to their ability to integrate multiple satellite and ground-based datasets, resulting in improved accuracy and reliability. The CHIRPS-v2 product, for example, combines rain gauge and satellite data to produce a spatiotemporal distribution of rainfall in areas with significant data gaps. This has proven beneficial in all African ecosystems (Dube *et al.*, 2023).

CHIRPS was selected due to its demonstrated accuracy in capturing rainfall variability in semi-arid and sub-Saharan regions, particularly where rain gauge density is low. Additionally, CHIRPS has been widely validated across West Africa, making it a reliable and regionally appropriate choice (Dube *et al.*, 2023; Kouakou *et al.*, 2023).

Table 2- 2: Description of climate data sources used in the overall analysis

Products Name	Variable	Temporal resolution	Spatial resolution	Source	Time coverage
CHIRPS	Precipitation	Daily	0.05°	CHC-UCSB	1991-2020
ERA5	Temperature	Hourly	0.31°	Climate Data Store (CDS)	1991-2020

Note: this table present the climate data source we used for this study

The agro-climatic characterization of the seasons in the study area was based on discretizing the seasons by calculating different agro-climatic variables or indicators. Various statistical parameters, such as the mean, standard deviation, and annual coefficient of variation, were calculated for the different agro-climatic variables in each zone to assess the potential variations observed over the study period.

To analyze trends in the annual series of agro-climatic variables at the level of each agricultural zone, the statistical approach based on the Mann-Kendall test (1975) was applied to the average annual data from 1991-2020. This test is widely used in the literature to detect trends in agro-environmental data (Faour *et al.*, 2016).

The Pettitt test (Pettitt *et al.*, 2024) was chosen for the homogeneity test. It is widely used and is suitable for determining a break in a time series. The Pettitt test is a rank-based nonparametric statistical test used to detect change points present in a data series; derived from the Mann-Whitney test. Its normalization purpose is to detect a break in a time series. Based on this, the null hypothesis of the test states that there is no break in the series. For a time t varying from 1 to N (N being the number in the series), it is assumed that:

The series $\left(x_i\right)$, $i = 1$ to t, and $\left(x_i\right)$, $i = t + 1$ to N, belong to the same population.

Or $D_{ij} = sgn\left(X_i - X_j\right)$, with sign $(X) = 1$ if $X > 0$

$$0 \text{ if } X = 0$$
$$-1 \text{if } X < 0$$

We consider the variable $u_{t,N}$ such as:

$$u_{t,N} = \sum_{i=1}^{t} \sum_{j=t+1}^{N} D_{ij} \tag{3}$$

To assess the potential relationship of climate on yields of different crops (maize, millet and groundnut), a modeling approach based on the analysis of linear relationships between climatic parameters characterizing agricultural seasons and crop yields was applied in each agricultural zone. We normalized the variables of the data set to have an average of 0. The following formula was used to normalize the data of the Groundnut Basin (north and south):

$$\boldsymbol{I_z} = \frac{\boldsymbol{x_i} - \boldsymbol{\bar{x}_i}}{\boldsymbol{\sigma}} \tag{4}$$

where $\boldsymbol{I_z}$ is the normalized value of the parameter in the zone; xi is the ith value in the data set; x is the sample mean, and $\boldsymbol{\sigma}$ is the standard deviation of the sample.

The correlation between the various agro-climatic variables and crop yields was analyzed by calculating the Pearson correlation coefficient. When a change in one variable (i.e. independent) is correlated with a proportionate change in the other (i.e. dependent), the relationship is linear. Comparing the p-value of the estimated coefficient to the significance level gives an indication of whether the estimated relationship truly exists (with a certain level of confidence) or is purely due to chance. For most scientific research, the widely accepted significance level 0.05, indicating that there is a 5% chance of drawing incorrect conclusion that there exist a correlation when none actually exists. This parameter measures the link between two quantitative variables. This step enabled us to assess which variables are strongly related to each other or vice versa. The following formula describes it:

$$r = \frac{\sum(x_i - \bar{x}) - (y_i - \bar{y})}{\sum(x_i - \bar{x})^2 - (y_i - \bar{y})^2} \tag{5}$$

Where r= correlation coefficient
x_i = value of the x-variable in a sample
$\bar{x}$ = mean of the value of the x-variable
y_i =values of the y-variable in a sample
$\bar{y}$ = mean of the values of the y-variable

2.3.3. Study Area

The Groundnut Basin of Senegal, as displayed in Figure 1 below, covers the western and central administrative regions of the country. It comprises the regions of Thies, Diourbel, Fatick, and Kaolack, in addition to the departments of Louga, Kebemer, and Koumpentoum, based on the delineation made by the Ecological Monitoring Centre of Senegal (Beye, 2015).

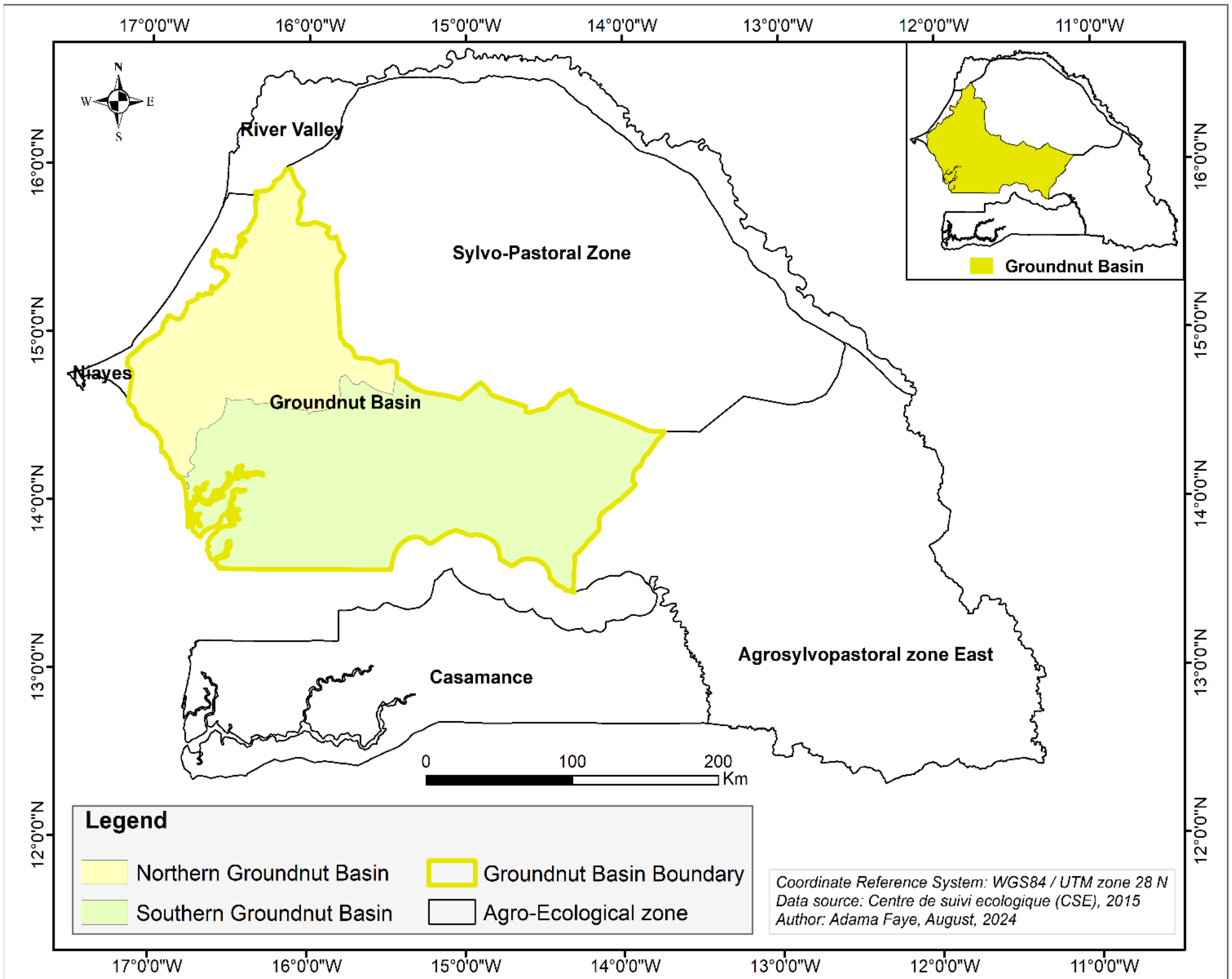


Figure 1. The Agro-Ecological zones of Senegal showing the north and the south of the Groundnut Basin (CSE, 2015)

The zone's administrative departments are divided into two main agricultural zones: the northern and the southern. The distribution of departments in the different agricultural zones is based on studies Sall, 2015 where the Groundnut Basin is split into two zones based on the rainfall gradient. With latitudes 13 ° –15 ° 30 north and longitudes 13 ° –16 ° 30 east, it is in the semi-arid part of the country. Due to disparity and low rainfall that rises from the south to the north, the climate is classified as Sahelian in the north and Sahelo-Sudanian in the south (Traore *et al.*, 2021). The

Groundnut Basin of 49,500 km2 is densely populated and subject to ecosystem degradation and depletion of land resources (soil fertility and timber resources). It has a human population of 8,640,894 representing about, 47% of the national population according to ANSD, 2021. Rainfall in the Groundnut Basin's north is often in the range of 300 to 600 mm. Sahelian agro-pastoral production systems, which rely on dry farming and customary animal keeping, dominate it. Agriculture is predominantly rainfed, with crops such as groundnut, millet and maize being the most commonly cultivated (Faye *et al.*, 2019). However, in the Thies region, cultivation of horticultural crops in market gardening and arboriculture is quite widespread. Rainfall in the Groundnut Basin to the south ranges from 500 to 800 mm. Other crops of economic and consumption importance are sorghum, cotton and cowpeas.

2.4 Results and Discussion

2.4.1 Analyses of Spatial and Inter-annual Rainfall Variabilities

The total rainfall index is shown on the spatial rainfall distribution map, with south-north gradient trends that are upward in the Groundnut Basin, as shown in **Figure 2-1**. The Groundnut Basin recorded fairly variable rainfall patterns over the 1991-2020 period, with cumulative rainfall ranging from 300 mm in the extreme north to 800 mm in the extreme south. Rainfall in Senegal is highly variable with inter-annual and inter-decadal timescales. The southern zone with higher rainfall might be more favorable for rainfed agriculture, supporting crops that require more moisture than the Northern regions with less rainfall may face water scarcity, limiting agricultural productivity and making them more vulnerable to droughts or climate variability. The spatial disparity could lead to inequities in food security across the region.

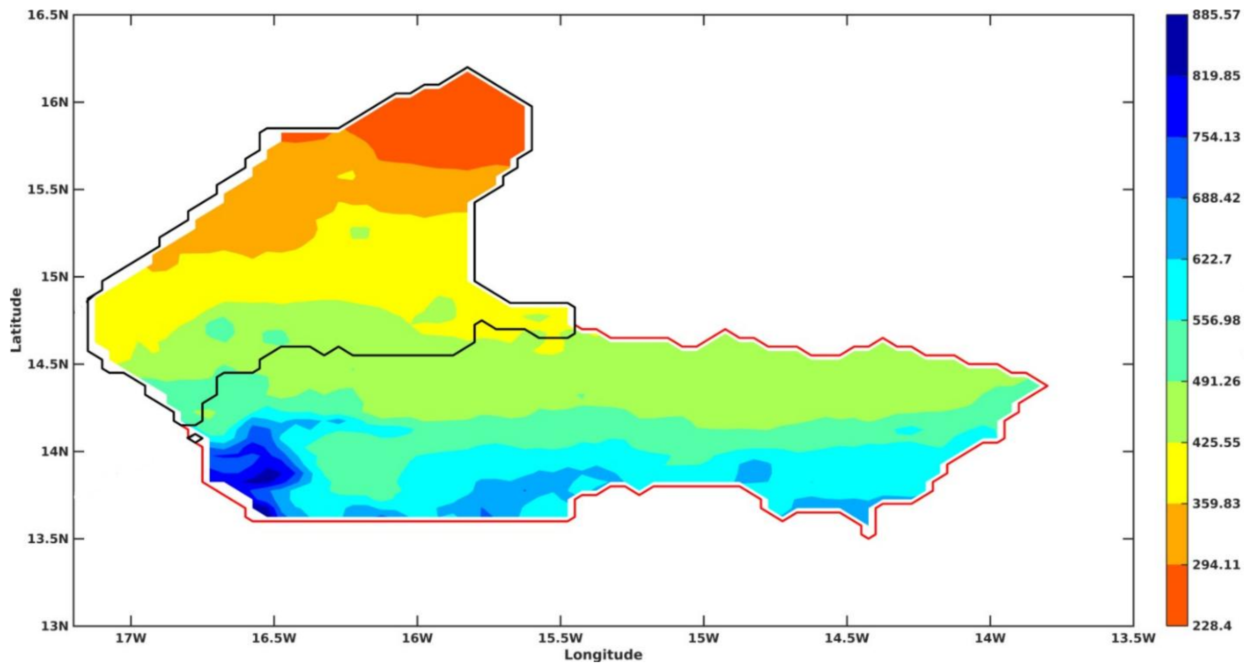


Figure 2- 1: Spatio-temporal representation of the rainfall in the Groundnut Basin of Senegal (CHIRPS, 1991-2020)

However, **Figure 2-3** on both sides indicates a positive trend in total seasonal precipitation with the average ranging from 433.9 mm to 598.8 mm in the northern and southern zones, respectively. This suggests that the overall seasonal precipitation increases over time for both the southern and northern zones. But seasonal precipitation increases at a slower rate in the southern zone compared to the northern. This increase in rainfall is consistent with the findings of Belford *et al.* (2020) and Panthou *et al.* (2014), who conclude that cumulative rainfall in the Sahel has increased since the 2000s. However, it should be noted that the climate in West Africa, including Senegal, is characterized by high inter-annual and inter-decadal variability (Christensen *et al.*, 2013; Daron, 2014).

The shift from the less rainy period to the rainier one is highlighted by the Pettitt test. It shows a break in homogeneity in 1998 in both zones, with mean rainfall (1991-1998) of 362 mm and mean rainfall (1999-2020) of 460 mm in the northern zone and mean rainfall (1991-1998) of 501 mm and mean rainfall (1999-2020) of 604 mm in the southern zone (**Figure 2-2**). A comparison of the two averages using Student's t-test revealed an increase in rainfall of 98 mm in the north and 103 mm in the south for the period 1999 to 2020, meaning that the study area has two major periods: lower rainfall from 1991 to 1998 and a significant increase of rainfall from 1999 to 2020. These observations are similar to those of Sagna *et al.*, 2015, who showed an improvement in rainfall in Senegal from 1999 onwards based on a study carried out on the 1961-2010 series. Similarly, Bodian, 2014 also identified 1999 as the year in which the rains began to return to Senegal.

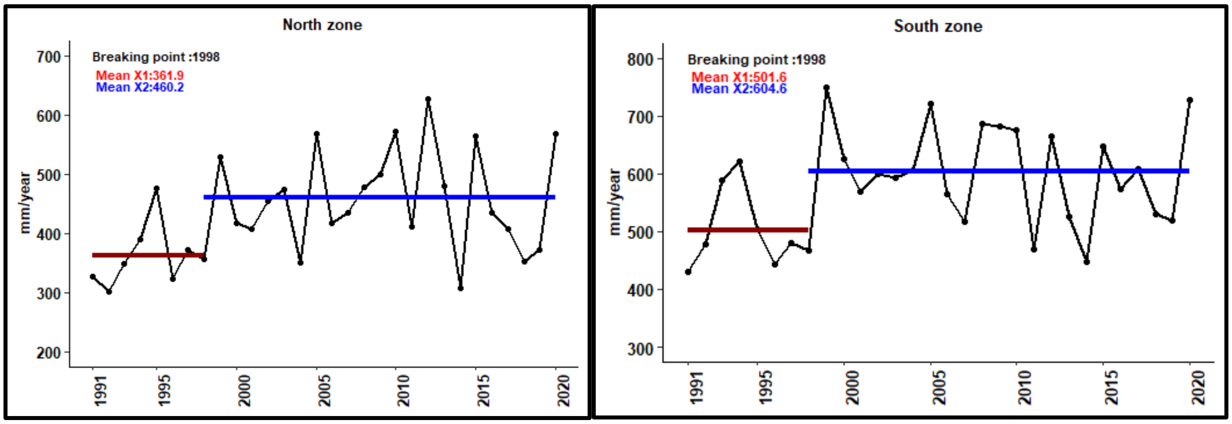


Figure 2- 2: Inter-annual variation of precipitation highlighting the breaking point (CHIRPS, 1991-2020)

Both northern and southern zones show an upward trend in RX5days, suggesting an increase in the intensity of rainfall events over time. Maximum cumulative rainfall over 5 days fluctuated between 20 and 120 mm per year in the different zones. In the northern zone, RX5days averaged 76.9 mm (SD of 14.6 mm) and 79.4 mm in the southern zone (SD of 11.9 mm) (**cf.Table 2- 6**). The slopes of the linear regression lines show that the rate of increase in both RX5days and TSP is higher in the northern zone compared to the southern zone. This means that the northern zone is experiencing a more pronounced increase in both the intensity of heavy rainfall events and total seasonal precipitation.

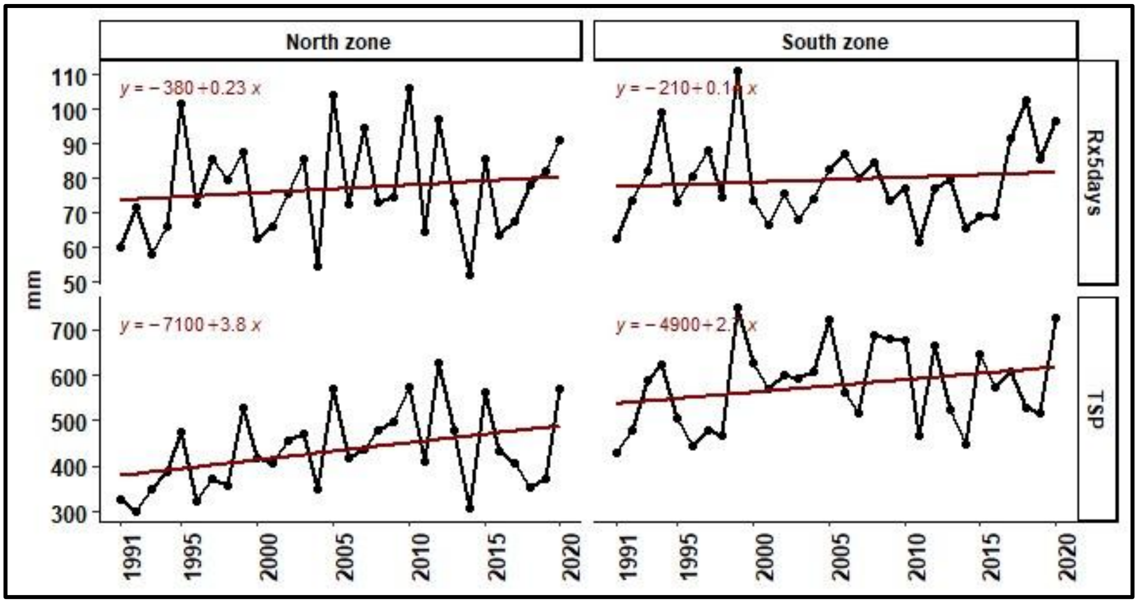


Figure 2- 3: Evolution of total seasonal precipitation and RX5 day (CHIRPS, 1991-2020)

2.4.2. Variability of Standardized Precipitation Index (SPI)

Figure 2-4 shows the evolution of the standardized precipitation index (SPI). The SPI values indicate alternating wet and dry years in both the north and south of the Groundnut Basin. Over the 30 years, there have been 17 dry years (57%) in the north compared with 15 dry years (50%) in the south, with varying degrees of drought from one year to the next. We notice that significant periods of drought (SPI < 0) are observed, particularly during 1991-1993 and 1995-1997 for the north and during 1994-1997 and 2013-2014 for the south. There were only 13 wet years (43%) in the north, with varying degrees of humidity from one year to the next. The remarkable surplus year for the Groundnut Basin corresponds to 1999 in the south and 2012 in the north of the Groundnut Basin, with indices above (1.88 and 2.17, respectively). However, in general, the Groundnut Basin (northern and southern zones) exhibits a pattern of wetter conditions in the 2000s and early 2010s. These findings are confirmed by Mbaye *et al.*, who affirm that in Senegal, the earlier 2000s were marked by a "return of wet conditions" with a multitude of positive rainfall anomalies (Mbaye *et al.*, 2021). In fact, the SPI data provides valuable insights into seasonal precipitation patterns, facilitating the selection of appropriate crop types and optimal planting periods according to projected moisture availability (Ibrahim *et al.*, 2022; Waongo *et al.*, 2015). However, the return of negative SPI anomalies between 2015 and 2020 indicates a resurgence of drought episodes, particularly affecting vulnerable agricultural areas. Physiologically, these water deficits disrupt key stages of crop development, leading to a significant decline in agricultural yields.

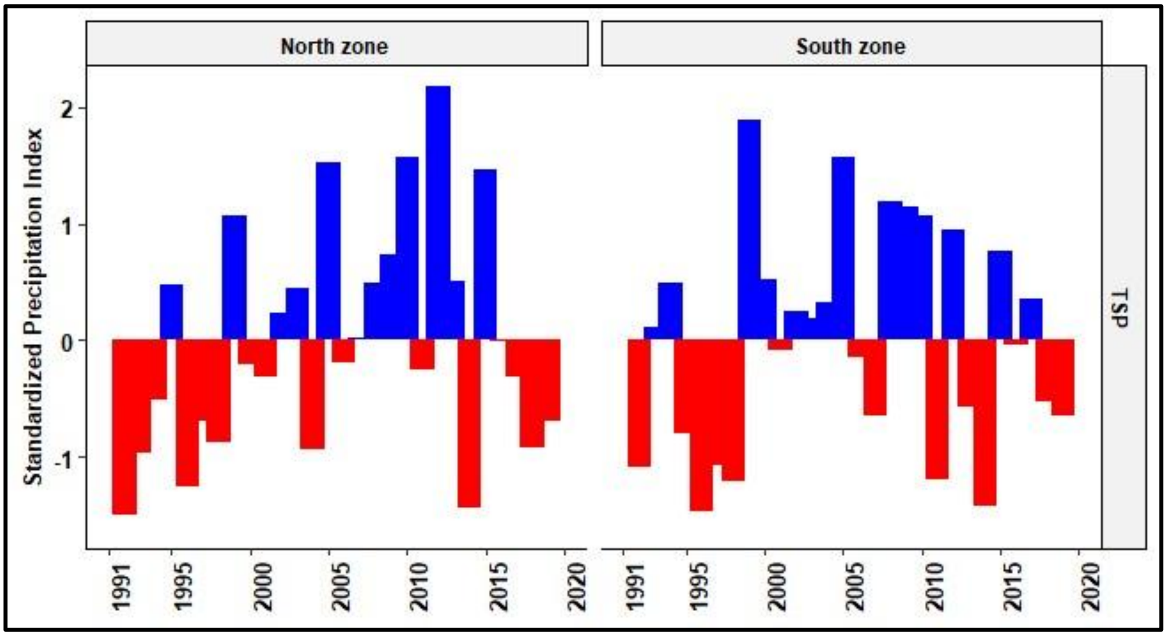


Figure 2- 4: Standardized precipitation index over the 1991-2020 period (CHIRPS, 1991-2020)

2.4.3 Evolution of the Simple Daily Intensity Index (SDII)

Figure 2-5 shows that the variation in SDII is between 8 and 15 mm/day in the Groundnut Basin. In the northern and southern zones, respectively, the average SDII is 11.4 mm/day (SD of 1.5 mm/day) and 11.7 mm (SD of 1.19 mm/day) (**cf.Table 2- 6**). Both zones show a positive trend in SDII, indicating increasing average daily rainfall intensity over time. However, the Mann-Kendall test shows that this increasing trend is not significant. This finding is similar to Mbaye *et al.*, who analyzed past extreme precipitation and evapotranspiration indices over Sub-Saharan countries and noticed no significant trend in rainfall intensity when considering the whole period 1981–2019 (Mbaye *et al.*, 2021). Both zones experience similar fluctuations in SDII, with peaks and troughs occurring around the same years. The variations in SDII are more extreme in the northern zone compared to the southern zone, indicating higher variability in daily rainfall intensity in the north.

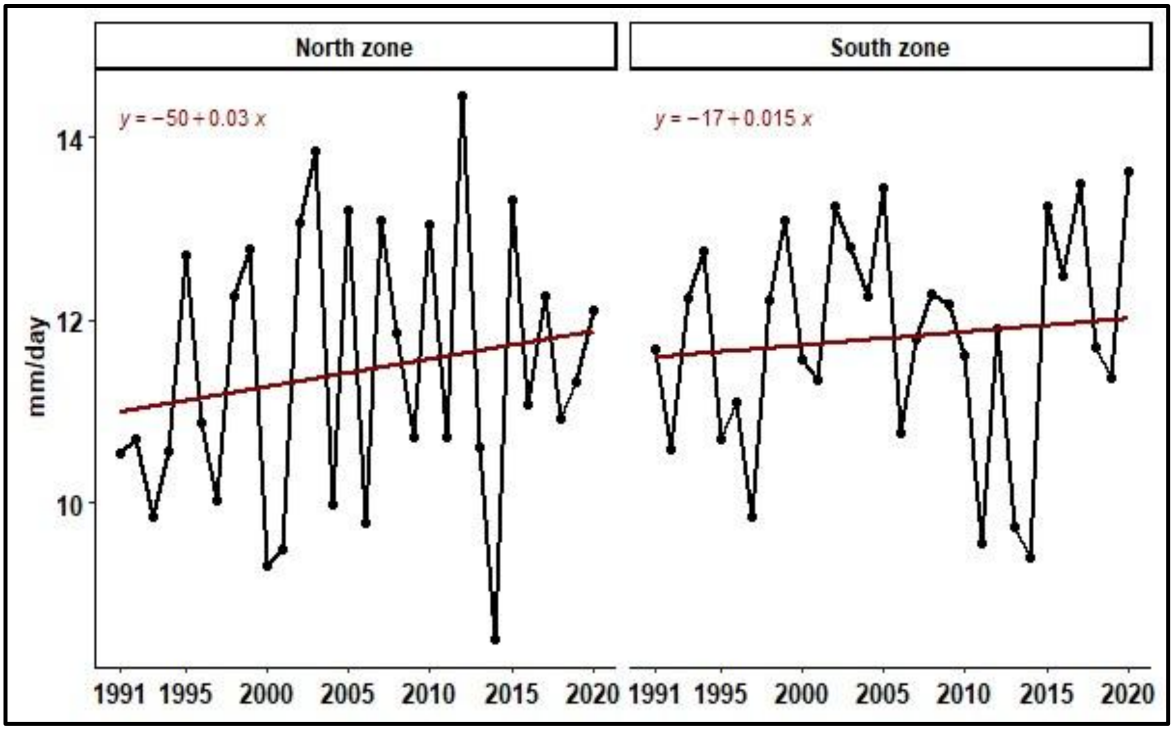
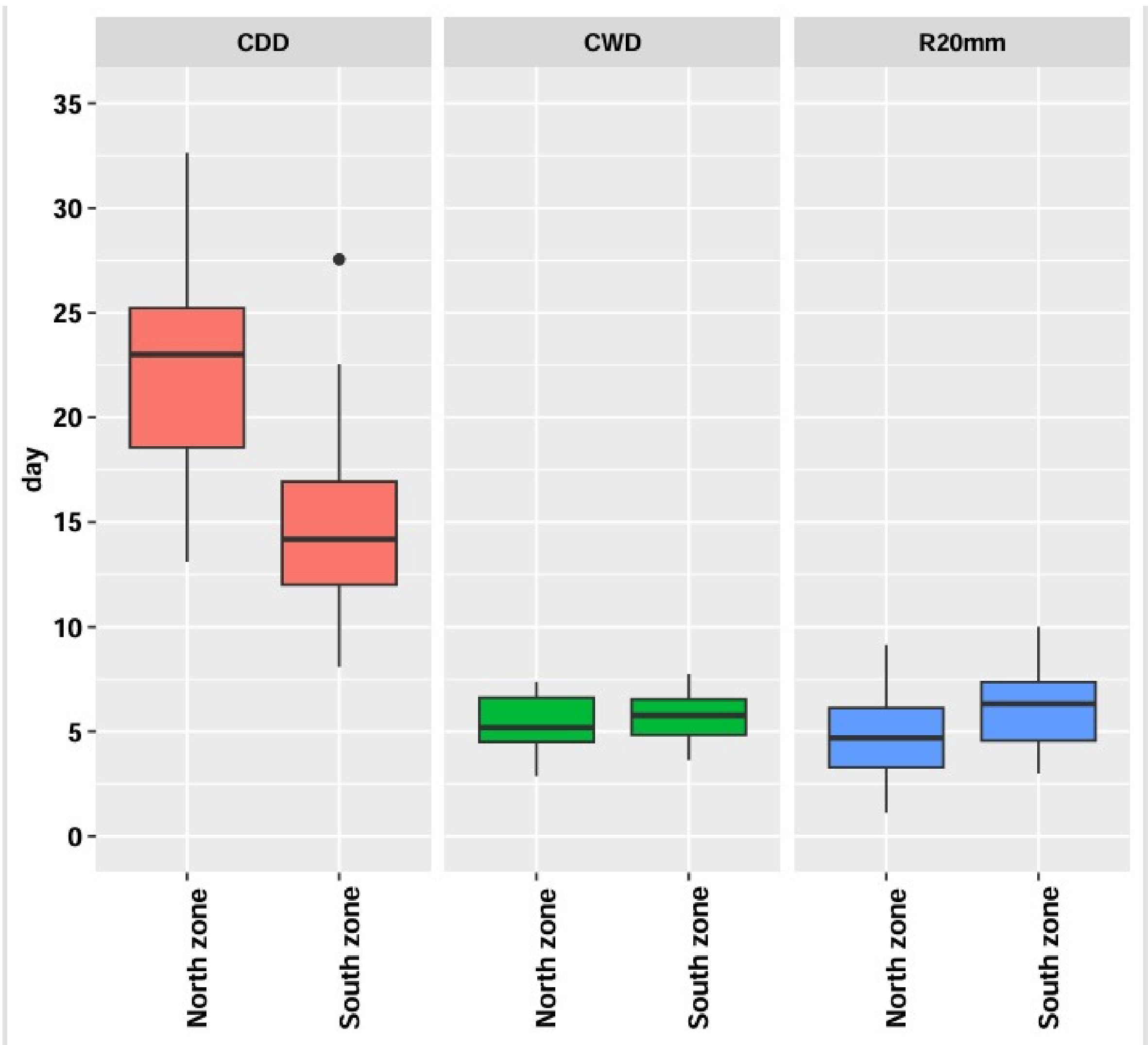


Figure 2- 5: Temporal variation of SDII in the Groundnut Basin (CHIRPS, 1991-2020)

2.4.4 Evolution of Occurrences of Rainy and Dry Days

Figure 2-6 shows that R20mm varies between 1 and 10 days in the season, depending on the zone, with an average of 4 and 6 days in the northern and southern zones, respectively. Concerning consecutive dry days, they varied between 5 and 35 days in the year. In the north, there is an average of 22 CDD (SD of 5 days) compared with 14 days (SD of 4 days) in the south (**cf.Table 2- 6**). Dry spells during the rainy season are widely recognized as a critical limitation to crop growth and productivity (Agbazo *et al.*, 2021; Ibrahim *et al.*, 2022). These prolonged dry periods intensify water deficits during key crop development stages, substantially increasing the risk of yield losses and crop failure (Narasimhan & Srinivasan, 2005). The negative effects are especially pronounced when dry spells coincide with sensitive growth phases (Baffour-Ata *et al.*, 2021). The magnitude of their impact is determined by the timing of occurrence within the growing season, as well as their duration and frequency.

The average number of consecutive wet days is 5 to 6 in the north and south, respectively. The overall statistical trend in the occurrence of wet and dry days is increasing over time, reflecting a trend toward an increase in these parameters. The northern zone is characterized by longer periods of consecutive dry days (CDD) compared to the southern zone. Both zones exhibit similar patterns for consecutive wet days (CWD) and days with heavy rainfall (R20mm), suggesting that these factors have a uniform impact on the agricultural conditions across both zones. These findings are similar to Didi *et al.*, who affirmed an increase in precipitation for Senegal's results, including increase in precipitation frequency as well as the maximum length of wet spells (an increase in CWD) (Didi Sacré Regis *et al.*, 2020). The consistency in wet days and heavy rainfall days between the zones indicates that the difference in crop yields is more likely influenced by the length of dry spells rather than the frequency of wet days or heavy rainfall events.



Note: *The dot represents an outlier.*

Figure 2- 6: Variation in consecutive dry days, consecutive wet days, and R20mm in the Groundnut Basin (CHIRPS, 1991-2020)

2.4.5 Evolution of Start Dates (Onset), End dates of Seasons (Offset) of Seasons

Figures 2-7 and **2-8** provide additional information on the trends in the growing season for the north and south Groundnut Basin. **Figure 2-7** illustrates the trends in the onset and offset of the growing season, while **Figure 2-8** shows the cumulative probability of these onsets and offsets. The results of **Figure 2-7** indicate that in both the north and southern zones, the onset and offset of the rainy season exhibit weak and insignificant trends based on the p-values > 0, 05 (**cf.Table 2- 6**). This suggests that there has not been a clear shift in the timing of the rainy season in recent years, meaning that the start and end of the season have remained relatively stable. Overall, the seasons in the study area start between the first ten days of June and the last ten days of July, depending on the agricultural zone. As for the end of the seasons, they fluctuate between September and October, depending on the agricultural zone. In the northern zone, the seasons begin on average around the end of June each year, compared to the end of May and the beginning of June in the southern zone. Similarly, the seasons end between late September and early October in the northern zone and late October in the southern zone. These findings are consistent with those of Badji *et al.* (2022) and Faye *et al.* (2024).

Balliet *et al.* (2016) emphasize that early- or mid-season droughts may lead to a false start of the growing season or even to the failure of an entire crop year. Furthermore, studies such as Sagna *et al.* (2015), which focus on broader agro-ecological zones in Senegal, have reported significant interannual variability in the cessation of the rainy season. Nonetheless, the trend revealed by this localized study highlights the onset of the season as a key factor influencing agricultural decision-making.

As Schneider *et al.*(2000) point out, a longer rainy season allows farmers to grow crop varieties with longer maturity periods, supporting better grain filling and higher cereal yields. Indeed, both the onset of rainfall and the length of the growing season are critical parameters for agricultural planning, as they determine the timing of essential activities such as land preparation and sowing, as well as the duration crops can benefit from continuous rainfall (Waongo *et al.*, 2015; Wu *et al.*, 2023).

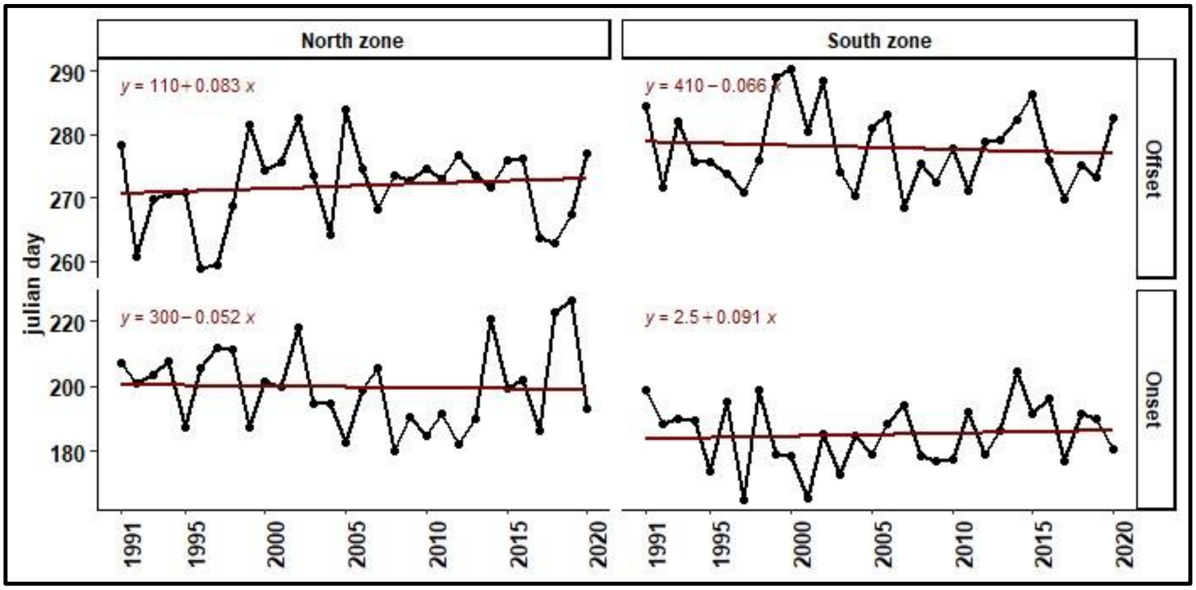


Figure 2- 7: Evolution of Onset, Offset (CHIRPS, 1991-2020)

The cumulative probability curves of **Figure 2-8** illustrate the differences in the growing season dynamics between the northern and southern zones. The northern zone's curve shows a more gradual slope, while the south zone's curve shows more steepness, indicating greater variability. The southern zone has greater variability in terms of the onset and offset of rains compared to the north. The northern zone exhibits more consistent patterns for both the onset and offset of the growing season, as indicated by the gradual slopes of the cumulative probability curves. The southern zone shows more variability in both onset and offset, as indicated by the steeper slopes of the curves. The south-to-north gradient in the onset and offset dates of the rainy season aligns perfectly with the findings of (Faye *et al.*, 2024; Marteau *et al.*, 2011), which showed that the spatial patterns of rainfall accumulation and intensity, as well as the timing of season onset, cessation, and duration, follow a clear gradient from south to north.

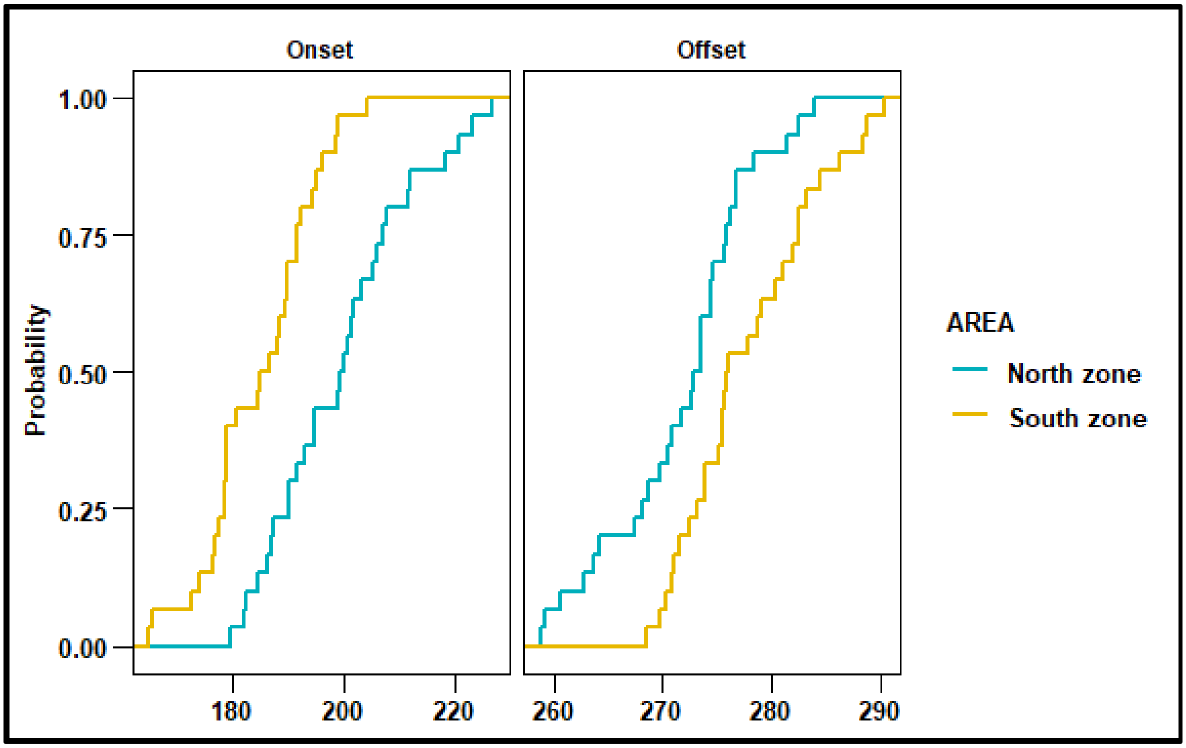


Figure 2- 8: Probability of Onset, Offset in the Groundnut Basin (CHIRPS, 1991-2020)

2.4.6 Evolution of Temperatures

The average maximum temperatures (Tmax) varied between 31 and 34°C depending on the zone **Figure 2-9**.The average Tmax in the northern zone was 32.2°C, compared with 33.1°C in the southern zone. The average minimum temperature (Tmin) varied between 21 and 23.5°C. The increase in Tmax is statistically significant in both zones (North (0.008) and South (6.432e-05)), with the South showing a more pronounced trend. Tmin does not show any statistically significant trend in either zone (p-value >0.05), suggesting relative stability in minimum temperatures. Despite the fluctuations in yearly data points, the trend lines of Tmax indicate a consistent rise in temperatures, suggesting potential long-term climate changes in these regions. An increase in temperature can cause an exponential rise in the saturation vapor pressure of the air, potentially leading to direct damage to plant cells (Lobell *et al.*, 2013). Additionally, higher temperatures have been shown to hinder crop development by inducing environmental stress, which is responsible for over 50% of global yield losses in major crops (Bajguz & Hayat, 2009). Moreover, changes in rainfall patterns combined with rising temperatures may lead to dry spells and shorten the crop maturity period (Antwi-Agyei *et al.*, 2012). The analysis suggests that both the northern and southern zones are experiencing a warming trend. According to Schlenker *et al.* the continuing temperature rise has a greater impact on the inter-annual variations in yield (Schlenker & Lobell, 2010). The potential for decreased yields is due to evaporation from water bodies, evapotranspiration, and soil drying up in both locations; these hazards can also emphasize heat stress, fail to fertilize, require more water, and shorten the cycle (Weber, 2019).

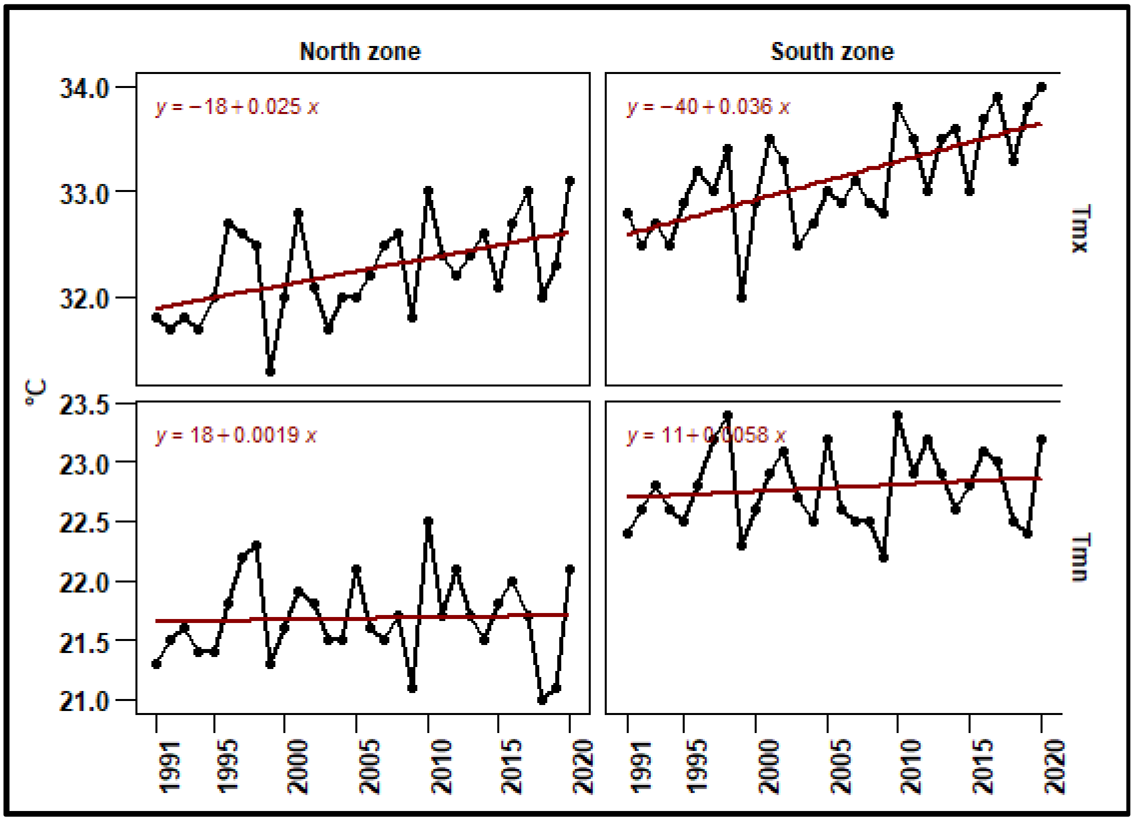


Figure 2- 9: Evolution of temperature min and max in the Groundnut Basin (ERA5, 1991-2020)

2.4.7 Inter-annual Variation in Crop Yields in the Groundnut Basin

Figure 2-10 shows that maize yields fluctuated between 400 and 2000 kg/ha, with an average of 982 and 1153 kg/ha in the northern and southern zones, respectively. Groundnut yields fluctuated between 200 and 1500 kg/ha. On average, yields were 591 and 952 kg/ha in the northern and southern zones, respectively. Finally, millet yields fluctuated between less than 100 kg and 1,300 kg/ha, with averages of 489 and 813 kg/ha in the north and south zones, respectively.

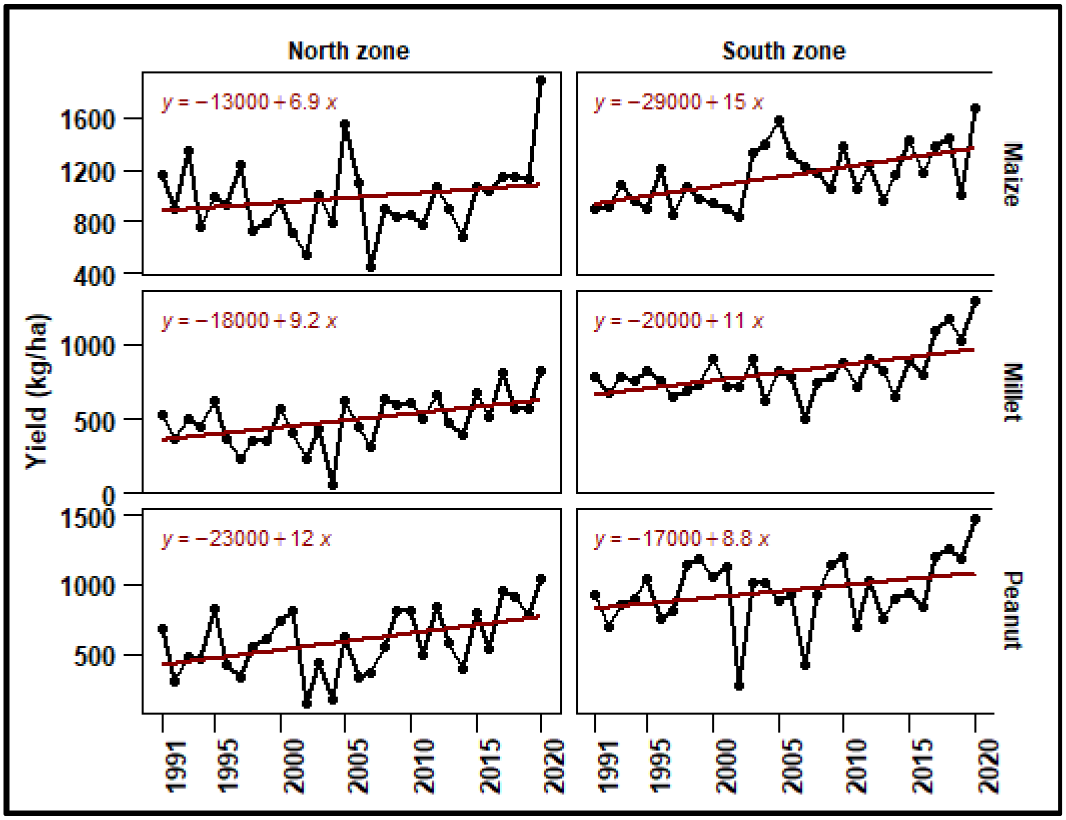


Figure 2- 10: Evolution of yield in the Groundnut Basin (DAPSA, 1991-2020)

Table 2-3 shows a strong positive trend for maize in the north zone (0.51) with a highly significant p-value < 0,001, indicating that the increasing yields trend is not due to chance. The southern zone shows a weak positive and non-significant trend (0.08), indicating no clear trend. For groundnut, the north zone has a moderate positive and significant trend (0.31) with a significant p-value (0.01). The south zone shows a weak positive and significant trend (0.22). However, for millet, both zones exhibit moderate positive trends (north: 0.32, south: 0.33) with a significant p-value in the north (0.01) and a more precise estimate with a lower (SE 30) in both zone. The trends are generally significant in the north zone and nearly significant in the south.

Maize in the north zone performs significantly better in terms of mean yield but has higher variability. Concerning groundnut and millet, the southern zone outperforms the northern zone in terms of mean yields for both crops, though variability is comparable. Over time, maize in the northern zone shows a significant upward trend, suggesting improvements or favorable conditions over time. The south zone shows no significant trend. Both zones show positive trends for maize, groundnut and millet, but these trends are more pronounced and statistically significant in the northern zone. The data suggests that agricultural yields for maize, millet, and groundnut have generally improved over the past three decades in both the north and south zones, with some variations in the rate of improvement between the zones.

Table 2- 3: Mann-Kendall results.

Groundnut Basin		Maize	Groundnut	Millet
North	Mean	982	591	489,3
	Standard error (SE)	52,5	42,4	30,8
	Tau Mann-Kendal	0,51	0,31	0,32
	P-Value	6.432e-05	0,01	0,01
South	Mean	1153	952	813,2
	Standard error (SE)	41,5	44,6	30,4
	Tau Mann-Kendal	0.08	0,22	0,33
	P-Value	0.49	0.08	0,09

Note: This table presents the results of the Mann-Kendall test on maize, groundnut and millet yields.

Source: DAPSA, 2020

Figure 2-11 indicates that, for all three crops (maize, millet, and groundnut), the median yield is higher in the southern zone compared to the north. However, the southern zone has also more outliers indicating greater variability. The southern zone has a higher and less variability in maize yield indicating a more stable production compare to the northern zone with more outliers. For millet, the southern zone also shows a higher median yield but with some outliers above 1000 kg/ha, suggesting exceptionally high production in certain cases. Concerning groundnut, the southern zone again shows a higher median yield with some outliers below 500 kg/ha, suggesting exceptionally low production. The interquartile range (IQR) for all crops is wider in the southern zone compared to the northern zone, indicating more variability in southern zone yields. The southern zone has more outliers for millet and peanut, indicating occasional extreme yield values. The northern zone has fewer outliers, suggesting more stable yield patterns.

The boxplots reinforce the observation that millet and groundnut crop yields are generally higher and less stable in the southern zone compared to the northern zone. The higher variability and frequent outliers in the southern zone suggest that yields are less predictable and more susceptible to fluctuations.

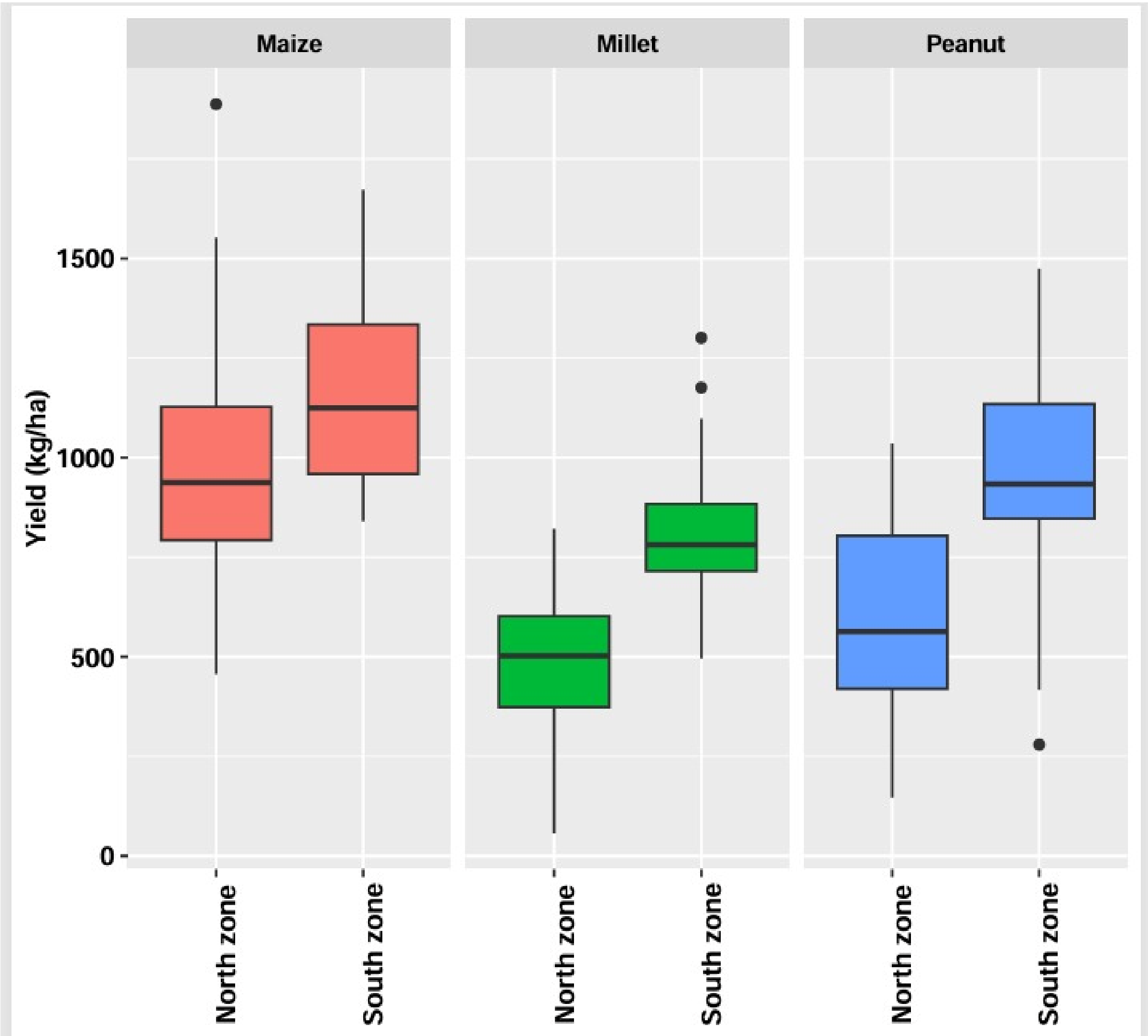


Figure 2- 11: Yield plots in the Groundnut Basin (DAPSA, 1991-2020)

2.4.7.1 Analysis of Relationships between Climatic Variables and Crop Yields

Tables 2-4 and **2-5** are correlation matrices displaying the relationship between agro-climatic variables and crop yields in the northern and the southern zone, respectively.

In the northern zone, the values in **Figures 2-4** show the Pearson correlation coefficient between pairs of variables, number of heavy precipitation days (R20mm) and daily rainfall intensity (SDII), indicating a strong positive correlation (0.92). The maximum (Tmax) and minimum (Tmin) temperatures have a high positive correlation (0.59). The heavy precipitation days (R20mm) and total seasonal precipitation TSP indicate a strong positive correlation (0.8). The rainfall intensity (SDII) and consecutive wet days (R×5days) show a strong correlation (0.78).

Concerning precipitation metrics, TSP, R20mm and SDII generally show positive correlations with crop yields, indicating the importance of adequate rainfall for crop production. Maize does not show strong correlations with any specific variable in the provided matrix, suggesting it may be influenced by a combination of factors rather than any single variable. However, groundnut yields are positively correlation with Tmin and Tmax, implying warmer temperatures are beneficial. Millet yields are positively correlated with SDII, suggesting that consistent and intense rainfall benefits millet yield. Also correlated with Tmax, indicating a preference for higher maximum temperatures. This result aligns with (Mwenda et al, 2021; Salack *et al.*, 2014), who found that rainfall indicators significantly impact crop yields in the West African Sahel. Further studies have emphasized the significant impact of temperature fluctuations on various crops, cereals ((Khanal, 2015), and legumes like groundnuts (Eke *et al.*, 2023).

Table 2- 4: Correlation between variables in the northern Groundnut Basin

	TSP	Rx5 days	CWD	CDD	SDII	R20mm	Onset	Offset	Tmx	Tmn	Maize	Groundnut	Millet
TSP	1												
Rx5 days	0.71***	1											
CWD	0.22	0.13	1										
CDD	-0.31	-0.29	-0.02	1									
SDII	0.71***	0.78***	-0.10	-0.04	1								
R20 mm	0.80***	0.76***	0.07	-0.12	0.92***	1							
Onset	-0.66***	-0.35	-0.15	0.35	-0.40*	-0.49**	1						
Offset	0.64***	0.22	-0.02	-0.09	0.34*	0.39*	-0.34	1					
Tmx	0.06	0.07	0.14	-0.15	-0.04	0.10	-0.03	-0.17	1				
Tmn	0.40*	0.35	0.29	-0.31	0.28*	0.42*	-0.33	0.17	0.59***	1			
Maize	0.25	0.23	-0.02	-0.15	0.07	0.19	-0.17	0.07	0.13	0.20	1		
Peanut	0.45*	0.34	0.14	0.14	0.27	0.24	-0.27	0.17	0.24	0.04	0.47**	1	
Millet	0.51**	0.31	0.13	0.02	0.31	0.35	-0.40*	0.26	0.24	0.09	0.57***	0.84***	1

Note: This table presents the correlation table between agro-climatic variables. **, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

***Sources**: CHIRPS, ERA5 and DAPSA*

In the south zone, R20mm and SDII (0.9) have a very strong positive correlation between the number of heavy precipitation days and daily rainfall intensity. The maximum (Tmax) and minimum (Tmin) temperatures have a moderate positive correlation (0.56). The heavy precipitation days (R20mm) and total seasonal precipitation (TSP) correlate strongly and positively (0.88). The total seasonal precipitation (TSP) and number of rainy days (RX5days) have a moderate correlation (0.42). Both temperature (Tmax and Tmin) show moderate positive correlations with crop yields, suggesting higher temperatures might favor yield increases within the observed range. Precipitation metrics (TSP, R20mm, SDII) generally show strong positive correlations with each other, indicating the importance of adequate rainfall for crop production. For maize, it shows a moderate positive correlation with Tmin, indicating that minimum temperatures may be beneficial. Groundnut has a positive correlation with Tmin, suggesting that minimal temperatures are favorable. Millet is also positively correlated with SDII and Tmax, indicating that consistent and intense rainfall and higher maximum temperatures benefit millet yield. The moderate positive correlations between crop yields and Tmin, as well as SDII, indicate that both temperature and rainfall intensity are critical factors for successful crop yields in the southern zone.

Table 2- 5: Correlation between variables in the southern Groundnut Basin

	TSP	Rx5 days	CWD	CDD	SDII	R20mm	Onset	Offset	Tmx	Tmn	Maize	Groundnut	Millet
TSP	1												
Rx5 days	0.42*	1											
CWD	0.27	0.25	1										
CDD	-0.49**	-0.38*	-0.20	1									
SDII	0.70***	0.34	-0.14	-0.02	1								
R20 mm	0.88***	0.42*	0.08	-0.27	0.90***	1							
Onset	-0.48***	-0.17	-0.22	0.68***	-0.15	-0.31*	1						
Offset	0.33	0.04	-0.19	-0.01	0.23	0.23	0.05	1					
Tmx	-0.16	-0.14	0	0.23	-0.11	-0.07	0.14	-0.14	1				
Tmn	0.11	-0.09	-0.08	-0.02	0.14	0.15	-0.13	0.05	0.56**	1			
Maize	0.43*	0.22	-0.01	-0.03	0.45*	0.53***	0.05	-0.08	0.28	0.28	1		
Peanut	0.38*	0.33	0.27	-0.08	0.25	0.31	-0.29	0.06	0.18	0.01	0.39*	1	
Millet	0.34	0.37*	0.16	0.09	0.37*	0.43*	-0.16	0.14	0.43*	0.17	0.50**	0.67***	1

Note: This table presents the correlation table between agro-climatic variables. **, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

***Sources**: CHIRPS, ERA5 and DAPSA*

A comparative analysis between the north and southern zones (**figure 2-4 and 2-5**) reveals that while both zones share similar patterns in terms of relationships between agro-climatic variables and crop yields, there are notable regional differences. The southern zone tends to have more moderate correlations with Tmin, impacting maize yields, while the northern zone shows stronger inter-correlations among precipitation metrics and a notable impact of TSP on millet yield. In fact, maize yield in the south zone shows a moderate positive correlation with Tmin, whereas no strong correlations are observed in the north zone. Millet yields also in both zones, shows a positive correlation with R20mm and SDII, emphasizing the importance of rainfall intensity. However, the onset and offset of the rainy season in both zones show weak correlations with crop yields, indicating that the timing of the rainy season may not be as critical as the total precipitation and its distribution. The northern zone exhibits a stronger positive correlation between CWD and R×5days compared to the southern zone. The southern zone shows a moderate correlation between maize yield and Tmin, which is not seen in the northern zone. The relationship between total seasonal precipitation and maize in the northern zone shows that there is a positive relationship, which means an increase in precipitation will lead to an increase in maize yield, as can be seen in the scatterplot in Figure **2-12**. Thus, to reinforce the above correlation figures between the northern and southern zones, scatterplots for some yields and selected climate variables with a regression line are illustrated in **figure 2-12** below.

However, it should be pointed out that climatic parameters alone are not sufficient to determine crop yields (Faye *et al.*, 2018). According to Noufe *et al.* (2015) the guarantee of good yield also depends on conditions linked to the proper coordination of cultivation operations (tillage, sowing, weeding, fertilization, use of improved varieties, etc.). They have shown that knowledge of rainfall patterns alone is not enough to explain the yield of a crop such as rainfed maize since a low yield results from either insufficient or excess water. Other parameters, such as soil fertility, seed quality, disease and pests, also need to be taken into account, all of which play a decisive role (Noufé *et al.*, 2011).

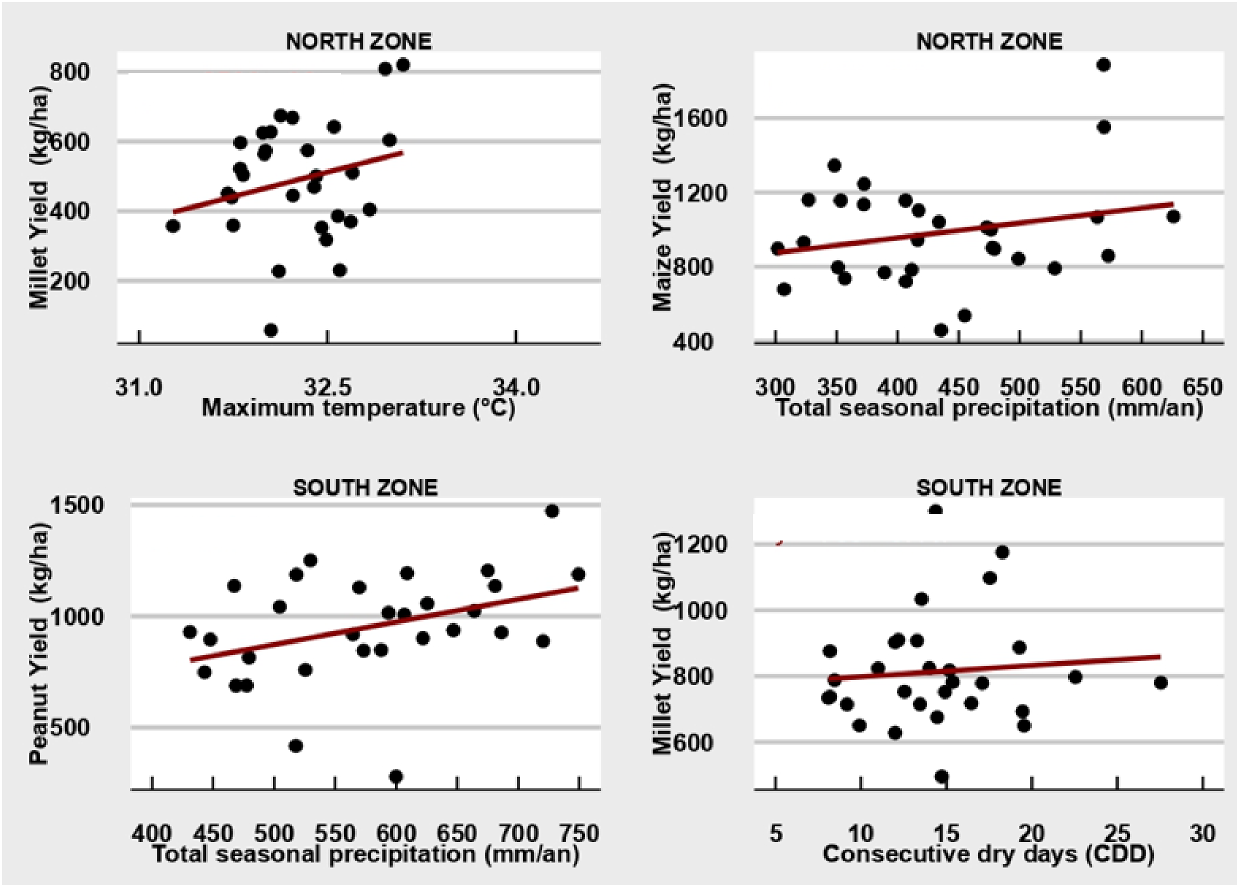


Figure 2- 12: Scatterplots of some yields and selected climate variables (CHIRPS and DAPSA 1991-2020)

Table 2- 6: Mann-Kendall results for climatic variables

Groundnut Basin		Rx 5days	TSP	SDII	CDD	CWD	R 20mm	Offset	Onset	Tmax	Tmin
North	Mean	76,9	433.9	11,4	22	5	4	271	199	32,2	21,6
	Standard deviation (SD)	14,6	88.3	1,5	5	1,3	2	6,5	12,5	0,44	0,36
	Tau of Mann-kendall	0.12	0.28	0,17	0,13	0,07	0,21	0,09	-0,10	0,34	0,09
	P-Value	0.33	0.02	0,18	0 ,3	0,56	0,10	0,46	0,42	0,008	0,45
South	*Mean*	79,4	568.8	11,7	14	6	6	278	184	33,12	22,7
	Standard deviation (SD)	11,9	91,2	1,19	4	1,08	2	6	9,6	0,48	0,32
	Tau of Mann-kendall	0.08	0.17	0,11	0,11	0,13	0,14	-0,04	0,04	0,51	0,11
	P-Value	0.49	0.18	0,39	0,37	0,32	0,26	0,72	0,72	6.432e-05	0,37

Note: This table presents the Mann-Kendall results for climatic variables.

Sources*:* CHIRPS, ERA5 1991-2020

2.4.7.2 Analysis of the Impact of Climate on Yields

Table 2-7 below compares the statistical performance of models predicting crop yields for groundnut, millet, and maize between the northern and the southern zones of the Groundnut Basin, focusing on the implications of climate variables on agricultural production. Precipitation (TSP) has a positive and significant effect on all crop yields, except for maize which is positive, but statistically insignificant in the northern zone. The maximum temperature (Tmx) is also found to positively and significantly impact all crop yields in both zones. On the contrary, minimum temperature (Tmn) negatively impacts yields, in both zones where it's considered. Days with heavy rainfall (R20mm) have mixed effects: negative for groundnut in the north, positive for maize in the north and positive for millet in the south. The start and end of the rainy season (Onset and Offset) significantly influences yields in the southern zone, especially for millet and maize. In the northern zone, the groundnut model demonstrates a better ability to explain yield based on climate variables, as evidenced by a relatively high R-squared of 0.56 and a significant p-value (0.002).

Total Seasonal Precipitation (TSP) and maximum temperature (Tmx) have strong and significant positive impacts on yield, indicating that both rainfall and temperature play crucial roles in influencing groundnut production. The results from model fitted to millet also performs adequately in terms of its explanatory ability, but that fitted to maize in the northern zone is notably weak explanatory power, with low R-squared. In the southern zone, the models show generally stronger explanatory power, particularly for millet, which has the highest R-squared (0.64) and high statistical significance (p-value 0.001), suggesting a robust relationship between climate variables and crop yield. While the model fitted to maize explains has better explanatory value in the north, it shows somewhat moderate predictive power, and the groundnut model is less statistically significant than the north. Overall, the effectiveness of these models highlights the critical role of climate factors, such as temperature, rainfall patterns, and seasonal shifts, in agricultural productivity.

Climate variability has a significant impact on crop yields. In the northern part of the Groundnut Basin, climate parameter variability accounts for approximately 21% to 56% of the variation in total production of groundnut, millet, and maize, compared to 38% to 64% in the southern region. The remaining unexplained variation highlights the influence of other climatic and non-climatic factors not included in the model, such as differences in farm inputs, irrigation techniques, and economic conditions affecting agricultural practices. Despite this, the fact that a substantial portion of yield variability (21% to 56% in the North and 38% to 64% in the South) can be explained by basic measures of rainfall and temperature underscores the strong link between climate parameters and crop production. These findings align with previous global assessments (ANACIM *et al.*, 2013; Lobell & Field, 2007; Toure *et al.*, 2020), reaffirming the significant correlation between climate variability and agricultural output in Senegal. They also suggest that, without adequate adaptation measures, climate change could pose a serious threat to food production in the country. These results highlight the complexity of climate-yield relationships and suggest that different crops and regions require tailored approaches to improve agricultural productivity.

Table 2- 7: Statistical Relationship between Climate and Crop Yield

	North Zone			South Zone		
Climatic variables	Groundnut (1)	Millet (2)	Maize (3)	Groundnut (1)	Millet (2)	Maize (3)
TSP	0.942*** (0.251)	0.655*** (0.170)		0.329 (0.207)		0.857*** (0.186)
CWD			-0.272 (0.204)			-0.224 (0.156)
Rx5days	0.381 (0.227)		0.482 (0.299)	0.292 (0.190)	0.422** (0.153)	
CDD	0.420** (0.158)			0.386 (0.243)	0.501** (0.189)	
R20mm	-0.647** (0.279)		0.999* (0.504)		0.273* (0.154)	
Onset				-0.436* (0.235)	-0.465** (0.184)	0.385** (0.169)
Offset					0.180 (0.135)	-0.381** (0.164)
Tmax	0.499*** (0.176)	0.466** (0.193)		0.398* (0.208)	0.602*** (0.165)	0.318** (0.146)
Tmin	-0.369* (0.199)	-0.444** (0.211)		-0.270 (0.207)	-0.222 (0.164)	
SDII			-1.253** (0.549)			
Constant	0.000 (0.136)	0.000 (0.149)	-0.000 (0.174)	-0.000 (0.160)	-0.000 (0.125)	-0.000 (0.140)
observations	30	30	30	30	30	30
R2	0.563	0.404	0.219	0.388	0.643	0.513
R adjusted	0.449	0.335	0.094	0.228	0.529	0.411
P-value	0.002	0.003	0.169	0,058	0.001	0,003
F Statistic	4.937***	5.878***	1.756	2.426*	5.649***	5.049***

Note: This table presents the Statistical Relationship between Climate and Crop Yield. **, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

***Sources**: CHIRPS, ERA5 and DAPSA 1991-2020*

2.5 Conclusion and Policy Implications

The study of the characterization of climatic risks and the impact of climatic parameters on agricultural yields is still a topical issue in the Sahelian regions. We used climate data to investigate the effects of climate-related variables on yield in the Groundnut Basin of Senegal. Regarding changes in rainfall, both the northern and southern zones show an increasing trend in TSP, with the northern zone experiencing a more pronounced increase. This suggests a general rise in seasonal rainfall over the past three decades. The Pettitt test has enabled the identification of a break that occurred in the Groundnut Basin in 1999 for both zones. The SPI analysis reveals alternating wet and dry periods in both zones, with increased wet conditions in the 2000s and early 2010s and significant droughts in the early 1990s, late 1990s, early 2000s, and late 2010s. The variability shown in SPI, with alternating periods of drought and wet conditions, indicates a high level of climate variability. This unpredictability of climate poses a significant risk to agricultural planning and crop yields. Both zones exhibit a slight increase in RX5days, indicating more intense rainfall events within short periods. The northern zone shows a steeper increase compared to the south. There is a slight increase in SDII in both zones, with the northern zone experiencing a more pronounced increase. This indicates a trend toward more intense daily rainfall. Both the north and south zones exhibit an upward trend in maximum temperatures indicating a general warming pattern over the study period.

The analysis of climatic trends in the Senegalese Groundnut Basin reveals a complex interplay of increasing rainfall intensity, significant variability, and periods of extreme drought and wet conditions. These findings suggest that yields are correlated with rainfall variability, uneven spatiotemporal distribution, and the frequency of wet and dry spells. These climate risks pose substantial challenges to groundnut, millet and maize yields, necessitating for comprehensive adaptation strategies to ensure agricultural sustainability and resilience in changing climate conditions. Implementing effective water management, erosion control, and resilient agricultural practices will be critical in mitigating the impacts of these climatic trends on agricultural production in the Groundnut Basin. Policymakers should prioritize the development of climate-resilient agricultural systems, including the promotion of drought-tolerant crop varieties, improved water management, and soil conservation techniques. Additionally, investment in climate-smart agricultural infrastructure, such as rainwater harvesting systems and irrigation, is crucial to enhance farmers' ability to cope with increasingly unpredictable rainfall patterns. The findings also underscore the importance of enhancing farmers' access to climate information services, enabling them to make informed decisions and adjust farming practices accordingly. By integrating these insights into agricultural policy, decision-makers can mitigate the risks posed by climate variability and promote resilience in farming systems. This will help ensure that farmers in the Groundnut Basin can maintain and even improve yields despite changing climate conditions. Assessing climate-related risks and their impact on agricultural yields in the Senegalese Groundnut Basin highlights the need for adaptive strategies to safeguard food security and farmer livelihoods. This sets the stage for exploring the potential of crop diversification as a viable solution to mitigate climate-related risks and enhance welfare in the region. The upcoming topic will delve into the transformative impact of crop diversification in improving welfare in the Senegalese Groundnut Basin.

CHAPTER 3: IMPACT OF CROP DIVERSIFICATION IN MITIGATING CLIMATE- RELATED RISK AND IMPROVING WELFARE IN THE SENEGALESE GROUNDNUT BASIN

Abstract

This chapter investigates the impacts of crop diversification on food and nutrition security, and poverty among rural households, using farmer level data from Senegal. We use the Marginal Treatment Effect (MTE) approach that does not only account for selectivity bias from both observed and unobserved attributes, but also accounts for heterogeneity in the treatment effects among farming households. The results show that farmers with higher propensity to adopt crop diversification gain more in terms of their food security status and poverty reduction status even under climatic shocks, compared to their lower propensity counterparts. Suggesting that poor farm households can derive significant benefits from adopting crop diversification strategies. The data used in the analysis reveal that even under adverse weather conditions, crop diversification leads to higher household incomes. Crop diversification is an adaptation strategy for farmers to mitigate climate-related risks and to decrease vulnerability. Furthermore, results from our Policy Relevant Treatment Effects (PRTEs) analysis reveal that reducing the distance to the nearest input market is crucial in enhancing crop diversification, which improves household food and nutrition security levels and reduces household poverty levels. Policy measures to improve the productivity of farm households and provide the necessary market infrastructure to stimulate marketing should be implemented given that crop diversification could be leveraged as a climate risk coping strategy in reducing food insecurity and alleviating poverty. Moreover, investing in rural infrastructure to improve access to markets will further incentivize crop diversification and help improve household welfare.

Keywords: crop diversification, climate-related risk, food and nutrition security, poverty

3.1 Introduction

Food insecurity remains a problem for many sub-Saharan African (SSA) countries despite domestic and international efforts made in addressing this problem. For example, in 2022, 12% of SSA's population was projected to be acutely food insecure and suffering from high malnutrition (Baptista & Farid, 2022). The worsening climatic condition has been recognized as one of the fundamental factors intensifying food insecurity throughout SSA, contributing to persistent and negative economic growth and worsened poverty situation (Baptista & Farid, 2022). Available evidence suggests that climate change has had a deleterious impact on agricultural productivity over the past half-century. Sam *et al.* (2021), in a simulation exercise, for example, found that rising temperatures are likely to significantly reduce cereal yields in low-income countries, with a consequent increase in household poverty. A recent report by the Intergovernmental Panel on Climate Change (IPCC, 2022) rightly attributes the increased global humanitarian interventions to worsening climatic conditions. These effects of climate change are expected to increase the incidence of poverty and further widen income inequality (IPCC, 2022). In the absence of relevant policy interventions to address the projected increases in frequency and intensity of climate-related shocks, the livelihoods of billions of smallholder farmers in developing and emerging economies are seriously at risk (Chavas *et al.*, 2022; Issahaku & Abdulai, 2020).

In response to these welfare implications, measures to mitigate and adapt to climate-related risks have become crucial to the extent that they have been mainstreamed into numerous developmental and security policies. Researchers and policymakers have attempted to address climate-related shocks by proposing formal means such as developing agricultural insurance. However, the problem of information asymmetry has led to missing agricultural insurance markets in most developing and emerging economies (Ali *et al.*, 2020). To adapt to climate shocks, many farmers rely on informal means such as crop diversification, change in the cropping calendar (early or late planting), drought-resilient variety, and crop rotation (Adjimoti & Kwadzo, 2018; Mango *et al.*, 2018).

Diversification of crop species is one remarkable strategy widely used by farmers to cope with the vagaries of the climate. By diversifying crops, farming households can spread production and economic risks over a greater number of crops, reducing their economic vulnerabilities from adverse climatic and market conditions (IUCN, 2022). When farming households diversify their crops or income sources, they tend to raise their food and nutrition security level through an increased portfolio of crop varieties (Adem *et al.*, 2018). Adoption of crop diversification is an important means of increasing food security and reducing poverty. A growing body of evidence has reported that crop diversification could be leveraged by smallholder farmers in their climate adaptation strategy to stabilize farm households' incomes (Auffhammer & Carleton, 2018; Moniruzzaman, 2019), Given the increasing relevance of crop diversification as an adaptation strategy as well as the increasing exposure of agriculture in Senegal to worsening climate variability, crop diversification strategy has been highlighted as a major part of the national climate change adaptation strategy (CDN, 2020).

Agriculture in Senegal, like most other SSA countries, is primarily rainfed, with only about 6% of agricultural lands under irrigation (World Bank, 2016). It employs more than 70% of the workforce, contributing about 17% to the national gross domestic product (GDP) (USAID, 2020). The relevant role agriculture plays in Senegal's economy and the poor's livelihoods are seriously threatened by the increasing temperature and erratic rainfall if remedial efforts are not put in place. Further exacerbating the worsening climatic conditions is the increasing population growth rate of about 2.7% per annum and the recent spikes in rural-urban migration's deleterious impact on farming households' welfare (UN, 2020). Between 2014 and 2019, nearly a million farming households were exposed to varying degrees of food and nutrition security. The hostile agro-environment, in addition to other structural economic challenges, has been reported to have driven about 54% of the rural population below the poverty line (ANSD, 2021). Crop diversification could offer the appropriate leverage to address these welfare challenges.

While increasing research on crop diversification has been gaining attention in recent times, most studies have tended to focus on the drivers and impacts of the adoption of crop diversification under covariate climate shocks (Adjimoti & Kwadzo, 2018; Mango *et al.*, 2018; Mulwa & Visser, 2020; Shahzad & Abdulai, 2021) without investigating their impacts under individual-specific idiosyncratic shocks, which affect individual households (e.g., illness, job loss, or death). These shocks require targeted support, such as social safety nets or health insurance, which complement crop diversification. Ignoring idiosyncratic shocks may lead to an incomplete understanding of household vulnerability, as some households may face more acute food insecurity (Béné *et al.*, 2012) or poverty due to personal crises that crop diversification alone cannot solve. Investigating the role of crop diversification under both idiosyncratic and covariate shocks is crucial in informing policy initiatives capable of addressing these shocks holistically because of the overwhelming heterogeneity in the target group and in the extent to which crop diversification could vary in terms of its effectiveness under these different shocks.

Previous studies have investigated the impact of crop diversification on the welfare of rural households using quasi-experimental methods such as propensity score matching (PSM) and endogenous switching regression (ESR) (Ochieng *et al.*, 2020). Although these methods rely on instruments for the purpose of identification, there are some limitations to their application. The PSM approach, for example, does not account for selection bias from unobserved factors (Abdulai, 2016; Khonje *et al.*, 2018). On the contrary, Endogenous Switching Regression (ESR) addresses the selection bias from both observed and unobserved factors but aggregates the unobserved heterogeneity. A major limitation of aggregating the unobserved heterogeneity is our inability to gain insights into the heterogeneous impacts of crop diversification on welfare indicators across farming households (Cornelissen *et al.*, 2016). Applying the marginal treatment effect (MTE) approach accounts for potential endogeneity arising from both observed and unobserved attributes, as well as providing insights into their heterogeneous impacts across farming households. Finally, the MTE framework enables us to simulate the policy-relevant treatment of welfare indicators and important policy implications regarding the distributive effects of crop diversification. By quantifying the impact of crop diversification on farming households' welfare indicators, we are able to provide evidence-based research findings to inform policy decisions and guide the design of targeted interventions to bolster climate resilience and promote sustainable agricultural practices in Senegal.

In this study, we contribute to the empirical literature by investigating the impact of crop diversification on households' food and nutrition security status and poverty indicators. Food and nutrition security indicators such as Household Dietary Diversity Score (HDDS) and Reducing Coping Strategies Index (rCSI) are applied. The level of poverty is measured by poverty headcount and poverty gap. Specifically, we use data on 1,436 farming households collected under the National Food Security, Nutrition and Resilience Survey (ENSANR 2019), conducted by the Executive Secretariat of the National Council for Food Security (SE_CNSA) in Senegal. Our findings reveal that crop diversification significantly improves food and nutrition security of rural households in the Senegalese Groundnut Basin, as measured by dietary diversity and reduced coping strategies. Diversifying crops is also associated with lower poverty headcount and poverty gap levels. These results highlight crop diversification as a key adaptation strategy for mitigating climate-related risks and enhancing household resilience.

3.2 Related literature

In response to increasingly severe climatic challenges, farming households are adopting crop and livelihood diversification strategies. These approaches are increasingly used to minimize their vulnerability to climate shocks and strengthen food and nutritional security in the face of climate unpredictability. According to Ellis (1998), diversification is the process through which households build a diversified set of income-generating activities and social support networks to sustain their livelihoods and enhance their living standards. Farmers engage in diversification not only as a risk mitigation strategy but also to enhance financial returns (Adam & Abdulai, 2024). Adaptation measures in agriculture, such as using drought-resistant seeds and spreading risks across different types of crops, have been found beneficial for improving soil fertility and enhancing household dietary diversity (Mulwa & Visser, 2020). However, despite these efforts, the risks posed by climate variability, both idiosyncratic (household-specific) and covariate (region-wide or systemic), are insufficiently addressed in the literature, limiting a nuanced understanding of how such shocks differentially impact households.

While crop diversification is recognized as a resilience strategy, the literature largely overlooks how households cope with or adapt to idiosyncratic versus covariate shocks. For example, poor farming households, anticipating covariate shocks like droughts, often opt for less risky portfolios to avoid long-term damage (Mulwa & Visser, 2020). The failure to distinguish between these two types of shocks leaves a critical gap in comprehending how diversification protects households against localized risks like illness or crop failure versus widespread risks such as droughts that affect entire communities. Climate change, coupled with soil degradation from over-farming, places households in Senegal's Groundnut Basin in a vulnerable situation. (Sall, 2015), but without proper disaggregation of shock types, the efficacy of adaptation strategies remains unclear.

The mixed findings in the literature on crop diversification and household welfare outcomes further emphasize the need for further research to fill this gap. Some studies report that crop diversification can lead to food and nutrition insecurity, arguing that managing multiple crops may overwhelm households, thus reducing productivity and farm income, leading to food insecurity

(Nkegbe *et al.*, 2017). Conversely, some emphasize its advantages, as crop diversification has been found to positively associate with household food security and dietary diversity. (Adjimoti & Kwadzo, 2018). In countries like Ethiopia and Zimbabwe, crop diversification has been found to reduce production risk and boost household food security (Makate *et al.*, 2016; Mango *et al.*, 2018). However, these studies do not sufficiently differentiate how these outcomes are influenced by the different types of shocks faced by households.

In terms of poverty reduction, studies have shown that crop diversification can reduce the likelihood of poverty by stabilizing incomes and reducing vulnerability to single-crop failures (Asfaw *et al.*, 2019; Jones, 2017). Households cultivating various crops are found to be more resilient to shocks and less likely to fall into poverty (Sakho-Jimbira & Benoit-Cattin, 2007). Nevertheless, negative relationships between diversification and income have also been documented (Coromaldi *et al.*, 2015). Some research attributes lower incomes among diversified households to limited market access and lack of resources to manage multiple crops effectively (Coromaldi *et al.*, 2015). This underscores the need to better understand how crop diversification interacts with specific local contexts, particularly in relation to idiosyncratic and covariate shocks.

Given the mixed and inconclusive evidence and the current gap in understanding the role of different types of shocks, this study makes a crucial contribution to the empirical literature. By explicitly focusing on how idiosyncratic and covariate shocks influence the outcomes of crop diversification in rural Senegal, this research contributes to a more comprehensive understanding of the resilience strategies of rural households. The study aims to fill this gap by exploring how these shocks impact household welfare and to what extent crop diversification can offer some resilience against these distinct types of shocks. Doing so will contribute to more effective policy interventions tailored to the specific needs of households facing localized and systemic unfavorable production conditions.

3.3 Methodology

3.3.1 Analytical framework

We present a simple framework to illustrate how the adoption of crop diversification impacts welfare using the marginal treatment effect (MTE) model. As widely acknowledged in the empirical literature, potential endogeneity arising from selection bias presents a major challenge to research that relies on observational data. The MTE framework does not only address potential endogeneity arising from selection bias, but also accounts for both observed and unobserved heterogeneity. We consider a risk-neutral farmer who derives some benefits from diversifying their crop production. Similarly, there is an associated benefit if the farmer decides not to diversify crop production. A farmer will only diversify if the benefit from diversify exceeds that from not diversifying.

Let the benefit associated with a farmer's decision to adopt crop diversification be represented by ϑ_{Di} and that from non-diversification by ϑ_{Ni}.

The expected net benefit from diversifying D_i^* can be expressed as the difference in the benefits from diversification and non-diversification as:

$$\vartheta_{Di} - \vartheta_{Ni} = D_i^* \tag{6}$$

The farmer will only adopt when the net benefit is positive: $D_i^*>0$

The expected net benefit of diversification is, however, not observed; what is observed is whether the farmer diversified her crop portfolio or not. The expected net benefits which are captured by the latent variable D_i^* can be expressed as a function of observed characteristics $\left(X_i\right)$ such as sex, age, education level of the farmer, household size, etc., in equation 7 below:

$$D_i^* = \beta_D\left(X_i\right) - V_i \tag{7}$$

D_i =1 if $D_i^* \geq 0$ and D_i =0 otherwise

D_i, is a treatment indicator, taking the value of 1 for adopters and 0 for non-adopters. In the MTE literature, the error term V_i which represents the resistance to the adoption of crop diversification, enters the selection equation with a negative sign, as shown in equation (7). A higher value of the unobserved resistance to the treatment, V_i decreases the expected net benefit from participation, suggesting that farmers will be less likely to adopt crop diversification.

In the potential outcome equations, we can express Y_{0i}, and Y_{1i} respectively as outcomes for adopters and non-adopters of crop diversification as:

$$Y_{0i} = \beta_0(X_i) + \delta_{0i} \qquad Y_{1i} = \beta_1(X_i) + \delta_{1i} \tag{8}$$

where δ_{0i} and δ_{1i} are unobserved characteristics and $\beta_0(X_i)$ represent observed characteristics. Using observational data in estimating equation 7 will produce biased and inconsistent estimates because the error terms of the selection equation 1 and the outcome equation 8 are likely to be correlated, given that farmers were not randomly assigned to the treatment (i.e. crop diversification adoption). Those who adopted crop diversification are likely to be systematically different from those who did not adopt, leading to potential endogeneity problems from sample selection bias. If not properly addressed, this can lead to biased and inconsistent estimates.

To address that, we use the instrumental variable approach. To properly identify the causal impact, we used distance from the household to the nearest input market and a dummy variable that indicates household ownership of motorcycles.

We argue that distance to the nearest input market is likely to influence the decision to diversify, because of the lower transaction costs in purchasing farm inputs such as seeds, fertilizer to increase crop diversification. However, market access constraints can compromise the ability of the poorest to sell their agricultural production (Schneider & Gugerty, 2011) due to the cost of transporting produce and the difficulty of controlling trading partners.

Similarly, owning a motorcycle, facilitates travel to another household in the neighborhood to potentially obtain seeds to increase the tendency to diversify. According to Karema & Irandu, 2017 motorcycles are extremely important in an agriculturally productive area by transporting both farm inputs and farm products.

From equation (7) $D_i = 1[D_i^* \geq 0] = 1[\beta(X) > V_i]$ we apply the cumulative density function (CDF) on $\beta(X)$ to obtain $P(X) = P(D=1|Z) = \phi(U(x)) \qquad D = 1[D_i^* > 0] = 1[P(X) \geq U_D]$ (9)

where P(X) is the propensity score, U_D is the quantile of resistance to adoption of crop diversification, $\varnothing$ is the CDF function of V used for the transformation. The MTE is based on conditional differences in outcomes between farmers who diversify and farmers who do not.

$$MTE(x,u) = E(Y_1 - Y_0 | X = x, U_D = u) = x(\beta_1 - \beta_0) + E(U_1 - U_0 | U_D = u) \tag{10}$$

where $x(\beta_1 - \beta_0)$ represents heterogeneity in observable characteristics and $E(U_1 - U_0 | U_D = u)$ the heterogeneity in unobservable. The $MTE(x,u)$ is expressed as the conditional expectation of the outcome variable on the set of observable characteristics X = x and in the U_D =u quantile of the V distribution; which is indifferent between diversification and non-diversification with a propensity score $P(Z)$ equal to U_D and unobservable variables.

The heterogeneous returns to diversification would be reflected in a non-linear curve for the MTE along the U_D in equation (11) below:

$$MTE(x,u)=\frac{\partial E(Y|x,p)}{\partial p}=(\beta_1-\beta_0)x+\frac{\partial K(p)}{\partial p}=(\beta_1-\beta_0)x+E(U_1-U_0|U_D=u) \quad (11)$$

It is the derivative of the expected value of the outcome conditional on the observed and unobserved characteristics and the propensity score (probability distribution).

There are two stages to the estimation procedure. We first obtain propensity score estimates from a first-stage probit estimation from the selection equation (1) and then proceed to estimate p $E(U_1-U_0\,|\,U_D\le \text{p})$ as a parametric polynomial in *p* of degree K = 2, as the baseline specification. We also conduct robustness check analysis to test the sensitivity of the results to specification and estimation choices, which generally confirms the main conclusions.

As shown in (Heckman & Vytlacil, 2005) , the MTE can be aggregated over U_D in different ways to obtain average treatment effects (ATE), average treatment effects on the treated (ATT) and average treatment effects on the untreated (ATUT). In order to analyze the impact of policy intervention on crop diversification, we use policy-relevant treatment effects (PRTE) to simulate baseline and alternative policies to estimate the aggregate effects of such policy changes (Heckman & Vytlacil, 2005). The PRTE measures the benefit of crop diversification for a farmer who is encouraged to change his decision to diversify in response to specific policies. In the present study, the policy variables include distance to the nearest input market and motorcycle ownership. The formula used is as follows:

$$PRTE(X)=\frac{E\left[Y_i|X_i=x,alternate\ policy\right]-E[Y_i\,|\,X_i=x,baseline\ policy]}{E\left[A_i|X_i=x,alternate\ policy\right]-E[A_i\,|\,X_i=x,baseline\ policy]} \quad (12)$$

3.3.2 Variable descriptions

3.3.2.1 Household dietary diversity Score (HDDS)

HDDS measures the food utilization dimension and intake of micronutrients (Mulwa & Visser, 2020). It is a qualitative measure of food consumption that reflects a household's access to a variety of foods. HDDS represents the number of foods or groups of foods consumed by households during the last seven days before the survey. Dietary diversity has been studied by several authors with different approaches in terms of the reference period and/or the number of food groups considered (Issoufou, 2020; Workicho *et al.*, 2016). However, two widely used recall periods are the 24-hours and the 7-days recall periods. In this study, we follow the 7-days recall period which gives more representative information of the food consumption patterns of the households relative to the 24-hours recall. The food items were divided into twelve food groups: cereals, tubers, vegetables, fruits, eggs, meat, fish, legumes, milk, oil, sugar, and other foods (condiments). The lowest scores imply less diversified sources , while higher scores are linked to greater diversity and imply improved food and nutrition security (Amolegbe *et al.*, 2021). HDDS is computed as:

$$\text{HDDS} = \sum P_i$$

where P_i =1 if the food group is consumed and 0 otherwise

3.3.2.2 Reducing coping strategies index (rCSI)

The reduced Index of Coping Strategies is an indicator of food access. It considers both the frequency and severity of five pre-selected coping strategies that households used in the seven days prior to the survey (Maxwell, 2008). The rCSI is based on many possible answers to one single question: "What do you do when you don't have adequate food, and don't have the money to buy food?" The higher the score, the higher the number of coping strategies used in addressing food insecurity. The maximum value of 56 represents the highest level of food insecurity, with high frequency of consuming less food and severity due to insufficient access to food.

3.3.2.3 Poverty headcount ratio and poverty GAP

The poverty headcount ratio measures the proportion of the population that is counted as poor. The poverty Gap measures the extent to which individuals fall below the poverty line. The severity or intensity of poverty is defined by the average distance to the poverty line. The poverty headcount ratio and GAP is obtained using the following expression of Foster–Greer–Thorbecke (FGT): $G_i = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{z-y_i}{z}\right)^{\alpha}$

where N is the total population, y_i represents income. z is the poverty line and H is the number of poor (those below the poverty line). For values of $\alpha = 0$ and 1, the index reduces to the headcount ratio and poverty gap index, while $\alpha = 2$ captures the severity of poverty.

We used the poverty line of rural households in Senegal which is 511.96 FCFA per capita per day according to the recent survey by the National Agency for Statistics and Demography (ANSD, 2021).

3.3.2.4 Crop diversification

To capture crop diversification, we use the crop count index for measuring the crop diversification which represents the number of crops grown by farmer. So, a dummy variable is used, which takes on a value of 1, if the farmer cultivates any other crop in addition to the main crop groundnut, and 0 for those who are doing mono-cropping (groundnut only). This method has been applied by other researchers like (Makate *et al.*, 2023).

3.3.2.4 Climate data

To integrate rainfall information in this study, we downloaded secondary data from Climate Hazards Center Infrared Precipitation with Stations (CHIRPS), which is a mixed satellite/station product with a spatial resolution of 0.05 degrees. CHIRPS has demonstrated an interesting performance in Africa compared to other datasets (Dinku *et al.*, 2018). CHIRPS spatial resolution allows it to be used on a fairly small area, such as the Groundnut Basin, with a good degree of precision. Using geo-referenced household data, we accessed household-specific temperature and rainfall data. The Standardized Precipitation Index (SPI) is a drought index first developed by (McKee *et al.*, 1993). The SPI is used for estimating wet or dry conditions based on precipitation variables. The SPI is widely used for defining and monitoring meteorological droughts (Iwata *et al.*, 2012). When the SPI is negative and its value reaches an intensity of -1 or less, a drought occurs, and ends when the SPI becomes positive (wet events).

$$SPI = \frac{X - X_m}{\sigma}$$

X = cumulative precipitation for a year

X_m = Mean precipitation

σ = standard deviation of precipitation in the series

For temperature data, we download it from the Prediction of Worldwide Energy Resources data archive[1] which provides global data at resolution 0.5x0.5 degrees to generate a gridded temperature time series. Regarding the temperature, we computed the monthly average from 1981 to 2018 for each village.

[1] https://power.larc.nasa.gov/data-acces-viewer

The climate information collected extends from 1981 to 2018, since the survey data used was collected in January 2019. For uniformity, the daily data obtained were aggregated to annual measure.

3.4 Study area and descriptive statistics

3.4.1 Study area

The Senegalese Groundnut Basin (displayed in **figure 1**) covers the western and central parts of the country. Thies, Diourbel, Fatick, Kaolack and Kaffrine are the corresponding regions in addition to the departments of Louga, Kébémer and Koumpéntoum. It has a surface area of about 46.367. It covers about a third of the area of Senegal. Groundnut is the main cash crop and constitutes an important income source. Crops cultivated include millet, cowpea sorghum, cassava watermelon and hibiscus (Traore *et al.*, 2021). The Groundnut Basin, for decades, has been the lifeblood of the Senegalese economy. Despite this, from 1970 to 1980, it faced a variety of constraints, which contributed to economic decline in the country.

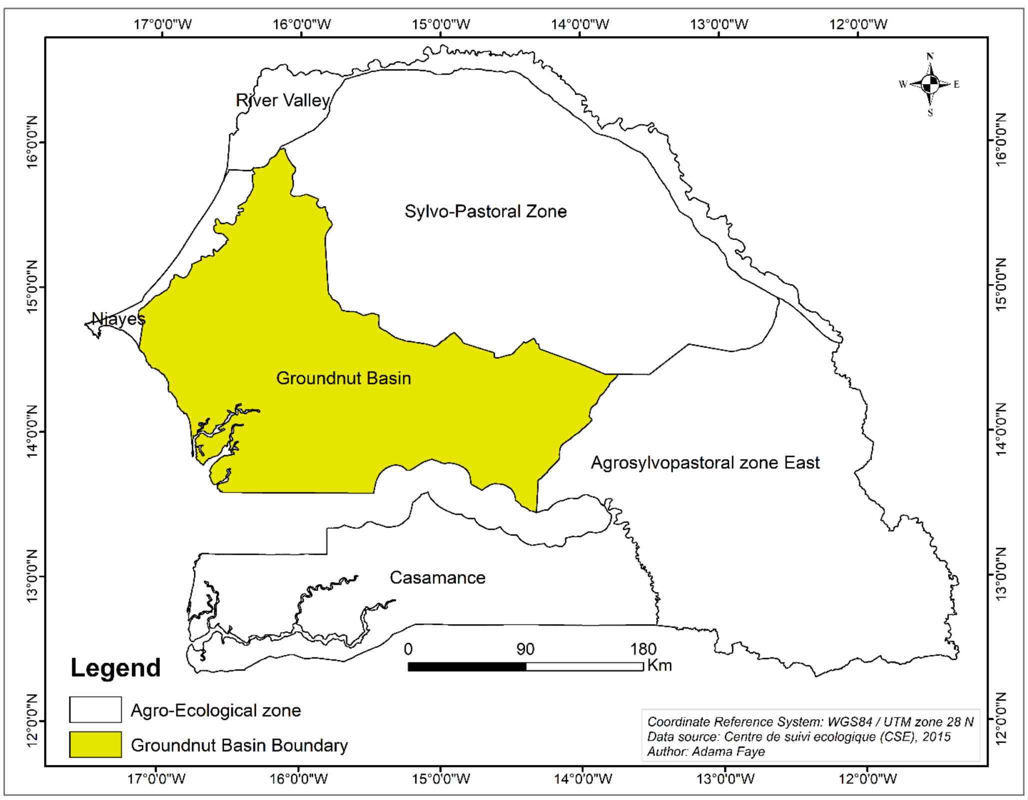


Figure 3- 1: The Agro-Ecological zones of Senegal showing the Groundnut Basin

In the north-central part of the Groundnut basin, rainfall intensity is lower and the rainy season shorter (isohyet between 400 and 600 mm) (Roquet, 2008). The south-central part of the Groundnut Basin is also marked by a decrease in rainfall (isohyet between 600-800 mm). According to Beye, (2015), the Groundnut Basin is the area that has seen the fastest population growth in recent times, the number doubled between 1988 and 2013. Rain-fed agriculture is the main stay among the farm households, fishing and livestock farming, particularly cattle, small ruminants and poultry, play an important role in income generation in the study area. The Groundnut Basin of Senegal is characterized by tropical ferruginous soils, allowing for agricultural production composed essentially of dry cereals (millet) and legumes (groundnuts, cowpeas).

3.4.2 Descriptive statistics

Table 3-1 presents the descriptive analysis of the household survey data. The average HDDS is 8.72, implying that rural households, on average, consume 9 different food categories. These households are, on average, food secure because their HDDS are higher than the base value of 5 groups[2] considered to be diversified. On the other hand, the average household has an rCSI of 7.17, implying that they use several survival strategies to address their level of food insecurity. The poverty headcount index shows that 81% of households live below the poverty line (ANSD, 2021). However, the poverty GAP index shows a 48% gap in relation to the poverty line used. Female-headed households make up only 6% of the sample. The average age of the heads of household is 53 years. In terms of the level of formal education, the majority (43%) have attained primary level, 6% have attained junior high school, 3% senior high school and only 1% university level. The average household size is 12. An average farming household cultivates 1.5 ha. Households are fairly far from the input market (5.4km), and only 10% of households own a motorcycle. The average precipitation anomaly is positive 0.06 with an average temperature of 27.38 degrees Celsius. Concerning shocks, on average 12% of households have experienced idiosyncratic shocks, which are shocks that are unique to an individual or family. The majority (89%) of the sample owns livestock.

[2] Manual harmonized framework, CILSS 2019

Table 3- 1: Descriptive statistics and definition of selected variables

Variables	Variable description	Mean	SD
HDDS	Household dietary diversity score (0-12), 0 represents no diversity in food and 12 represents good food diversity	8.7284	1.6816
rCSI	Reduced Coping Strategies Index (0-56), close to 0 represent a good situation of food security, the higher the score, the more food insecure the household: it has used more negative strategies	7.1761	9.9485
Poverty headcount	1 if a household is living below the poverty line, 0 otherwise	0.8105	0.3919
Poverty GAP	Mean distance of poor household from the poverty line	0.4879	0.2143
Sex head household	1 = female, 0 otherwise	0.0661	0 .2486
Age	Age of the household head in year	53.8238	13.7119
Not educated	1 if not went to school ,0 otherwise	0.4408	0.4966
Primary	1 if primary education, 0 otherwise	0.4394	0.4964
Junior high	1 if junior high school level, 0 otherwise	0.0668	0.2498
Senior high	1 if senior high school level, 0 otherwise	0.0389	0.1936
University	1 if university level, 0 otherwise	0.0139	0.1172
Household size	Size of Household	12.7534	6.2318
Farm Size	Total farm size (Ha)	1.5659	1.2352
Distance to the input market	Distance to the closest input market (km)	5.2434	4.2071
Motorcycle	Number of motorcycles owned by household	0.1044	0.3059
Rainfall anomaly (SPI)	Standardized Precipitation Index	0.0675	1.0098
Mean Temperature	Average of temperature 1981-2018	27.3865	0.8035
Idiosyncratic Shocks	1 if household experienced idiosyncratic Shocks, 0 otherwise	0.1204	0.7014
Livestock ownership	1 if household own livestock, 0 = otherwise	0.8983	0.3023

Note: This table presents a brief description of all the variables used in our estimation.

Sources: ENSANR 2019

Table 3-2 presents the mean difference in characteristics of farmers who adopted or who did not do crop diversification. The results show that 55.92% diversify their crops, compared to

44.08% who did not diversify. We find statistically significant differences in the means for nearly all outcome variables (i.e., HDDS, rCSI and Poverty Gap), with the exception of poverty headcount. Food security indicators such as HDDS and rCSI appear better for those who diversify. In particular, those who diversify their crops have a more diversified diet of 9.02 compared to 8.35 for those who have not diversified; and they also use about 6 compared to 8 survival strategies used by those who grow only groundnut. This may be indicative of the potential role crop diversification plays in food security, which concurs with the findings by Jones (2017) and Nkonde *et al.* (2021), who reported that crop diversification contributes to improving diets and nutrition outcomes in rural households.

Table 3- 2: Descriptive statistics and mean difference between adopters and non-adopters

Variables	**Diversified n=803(55.92%)**	**Non-diversified N=633(44.08%)**	**Mean Diff**
Outcome			
HDDS	9.0249(0.0625)	8.3522(0.0586)	-0.6726***
rCSI	6.4171(0.3386)	8.1390(0.4096)	1.7218***
Poverty headcount	0.8107(0.0138)	0.8104(0.0155)	-0.0002
Poverty GAP	0.4994(0.0083)	0.4734(0.0090)	-0.0260**
Control variables			
Sex	0.0635(0.0086)	0.0695(0.0101)	-0.0059
Age	54.7584(0.4928)	52.6382(0.5286)	-2.1201***
Primary	0.4246(0.0174)	0.4581(0.0198)	-0.0334
Junior high	0.0709(0.0090)	0.0616(0.0095)	0.0093
Senior high	0.0435(0.0072)	0.0331(0.0071)	0.0104
University	0.0174(0.0046)	0.0094(0.0038)	0.0079
Household size	13.523(0.2353)	11.7772(0.2178)	1.7457***
Farm Size	1.9215(0.0547)	1.1148(0.0086)	0.8066***
Rainfall anomalies (SPI)	0.3009(0.0353)	0.0043(0.0389)	-0.2966***
Mean Temperature	27.4022(.0282)	27.3667(0.0321)	-0.0355
Idiosyncratic shocks	0.1357(0.0270)	0.1011(0.0242)	0.0346
livestock ownership	0.8978(0.0106)	0.8988 (0.0119)	-0.0010
Instrumental variables			
Distance to the input market	4.6834(0.1195)	5.9537(0.1976)	1.2703***
Motorcycle	0.1344(0.0120)	0.0663(0.0099)	0.0681***

*Notes: The table presents the mean differences of the variables used in our estimations. For each variable, the table presents the average for the whole sample, for farmers who diversified and those who did not. The main outcome variables are HDDS, rCSI, poverty headcount and Poverty gap; the rest of the variables are the controls and the set of instrumental variables. *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

Sources: ENSANR 2019

On average, farmers who diversify are 2 years older than those who do not diversify, they have generally higher levels of education. Those who diversify have a larger household size, with around 2 more people and a larger field of 0.80 ha than others.

We find a statistically significant difference in the mean for our instrumental variables (distance to the nearest input market and motorcycle). Those who diversify are, on average, 4.7 km away from input markets compared to 5.9 km for those who do not. While about 13% of the farming households who diversified own motorcycles, only about 7 per cent of the non-adopters own motorcycles.

While we observe significant differences between households that diversified and those that did not, it is important to note that potential selection bias due to observed and unobserved factors is not accounted for in those mean differences. Hence, we employ the MTE in the empirical analysis to account for confounding factors, selection bias, and potential heterogeneity.

3.5 Results and Discussion

In this section, we present the results from the MTE estimations. The estimates of the drivers of crop diversification from the first stage selection equation is first presented. This is followed by the estimates of the heterogeneity of the effect of the treatment on the observed characteristics, the unobserved characteristics and finally the results of the robustness of the model, as well as the estimates of the policy simulation analysis (PRTE).

3.5.1 First stage: selection equation results

For the MTE approach to properly work, there should be enough overlap of the characteristics between those who are diversifying and those who are not diversifying. **Figure 3-1** below, shows that, there is sufficient overlap between those who adopt crop diversification and those who do not. So, the first-stage regression produces common support that ranges from 0 to 1. This shows the unconditional common support that is generated by variation in both the instruments and covariates in the second stage.

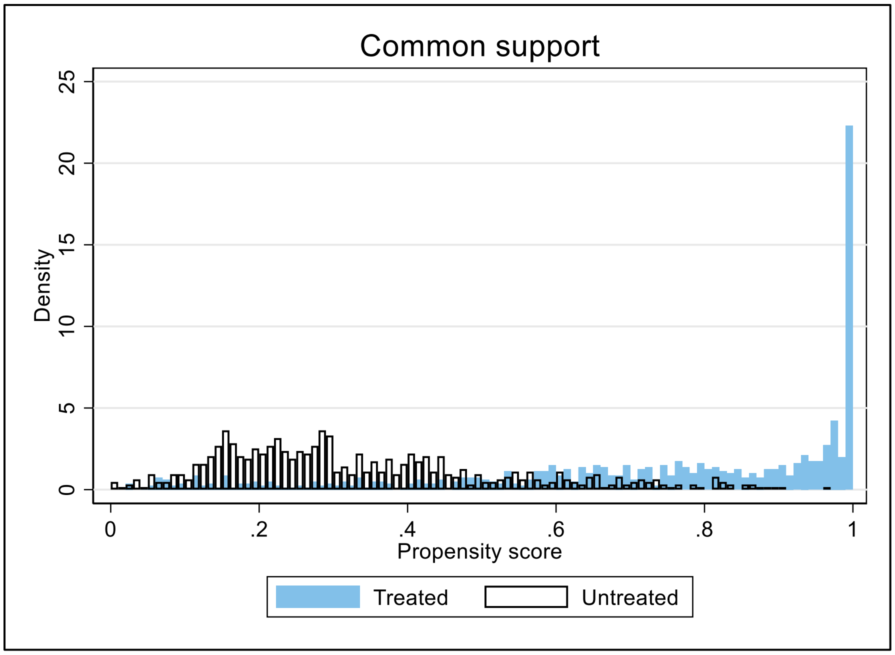


Figure 3- 2: Common support (ENSANR, 2019)

Table 3-3 presents the key factors that significantly influence the decision to diversify from the probit selection equation. First, we check the internal validity of the two instrumental variables using the Wald test for the joint significance. The results show that the instruments have statistically significant influence on crop diversification decision, implying that the instruments are joint drivers of the selection state model. We find negative and statistically significant influence of distance to the nearest input market. Owning a motorcycle, however, has a positive and statistically significant impact on farmer's decision to diversify.

The variable representing the rainfall anomaly (SPI) is positive and statistically significant, implying that higher rainfall shocks tend to raise the probability that farmers will diversify crops which is an adaptation strategy as was found by Shahzad & Abdulai (2020). The Groundnut Basin is dominated by the groundnut crop, which is highly sensitive to both rainfall variability and higher temperatures (USAID, 2017). The higher the climatic shocks households experience in the past, the more they are disposed to diversify crops in order to cope with climatic shocks. As widely documented in the literature, there is substantial heterogeneity across crops in the weather–yield relationship. The marked heterogeneity does suggest that diversification may facilitate the resilience of total production to adverse climate conditions (Auffhammer & Carleton, 2018). This is consistent with the argument by Di Falco *et al.* (2010) that crop diversification leads to better production outcomes during bad rainfall events, suggesting that diversification enhances resilience.

The variable representing farm size is positive and statistically significant, indicating that larger farms are more likely to diversify than smaller ones. This result is in line with (Asfaw *et al.*, 2019) who indicated that the size of the farm is an important factor in crop diversification.

Table 3- 3: Marginal effect of the determinants of crop diversification

Variable	Coefficient	Marginal effect
Sex	0.1202 (0.1563)	0.0369(0.0461)
Age	-0.0023(0.0030)	-0.0007(0.0009)
Primary	-0.2456***(0.0909)	-0.0788***(0.0293)
Junior high	0.0368(0.1583)	0.0115(0.0493)
Senior high	-0.2443(0.2223)	-0.0832 (0.0802)
University	0.1502 (0.3717)	0.0454(0.1061)
Household Size	-0.0173** (0.0082)	-0.0055**(0.0026)
Farm Size	2.4034***(0.1422)	0.7653***(0.0350)
Rainfall anomaly (SPI)	0.1105***(0.0433)	0.0351**(0.0138)
Mean Temperature	0.0101(0.0534)	0.0322(0.0170)
Idiosyncratic Shocks	0.0940(0.6577)	0.0299(0.0209)
Livestock ownship	-0.4318***(0.1397)	-0.1204***(0.0331)
constant	-2.2198(1.5003)	
Instruments		
Distance to the input market	-0.0713***(0.0109)	-0.0227***(0.0035)
Motorcycle	0.3527***(0.13815)	0.1011***(0.0351)
χ^2 test of instruments	47.59***(0.00)	
Pseudo R^2	0.3291	
Observations	1436	

*Notes: The table shows the results for the first stage estimations. The dependent variable=1 if the farmer diversified crop portfolio, 0 otherwise. The first column presents the estimates of the coefficients and the second the marginal effects. We used the χ^2 test for exclusion restriction. *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

Sources: ENSANR 2019

Our results indicate that being educated up to the primary level exerts negative and statistically significant impact on the farmer's decision to adopt crop diversification. On the other hand, famers educated up to junior high and university appear to be more likely to adopt diversification, although the coefficients of these variables did not show by statistically significant effects.

The results also shows that households owning livestock are less likely to adopt crop diversification. These findings are not surprising, given that livestock ownership is a very important economic activity used by most households in mitigating and adapting to shocks. As a result, they tend to have a lower disposition in diversifying their crop portfolio.

The variable representing household size is negative and statistically significant, implying that the larger the household, the less likely farmers are to adopt crop diversification. Large household size does not necessarily suggest the availability of sufficient family labor to carry out different farming operations on time (Matsuura *et al.*, 2023).

3.5.2 Second stage: Heterogeneity in treatment effects on observed characteristics

We report and discuss the results from the second stage estimation of the impact of crop diversification on food security and poverty indicators in **Table 3-4**. The estimates show how the treatment effect varies based on the observed attributes of farmers who diversified $(\beta_1 - \beta_0)$, and those who did not (β_0). We find evidence of heterogeneity in the sample as indicated by the differences in the coefficients of the control variables.

3.5.2.1 Heterogeneity in Treatment Effect on HDDS

The variable representing precipitation anomalies (SPI) is positive and statistically significant (at 1%) in the adoption state compared to the negative and statistically significant coefficient in the non-participation state. These results suggest that when farmers do not diversify their crop portfolio and are exposed to rainfall shocks, their level of HDDS decreases. By contrast, when they adopt crop diversification even under climatic shock conditions, they will gain more on HDDS. This suggests that diversification is still a good option for farmers in terms of food security, even under adverse climatic conditions.

Table 3- 4: Outcome equations results for (ln) HDDS

	Household Dietary Diversity Score (HDDS)			
	Outcome β_0		Outcome $(\beta_1 - \beta_0)$	
	Coef.	St. Err.	Coef.	St. Err.
Sex	0.0134	(0.0648)	-0.0512	(0.0943)
Age	0.0024***	(0.0009)	-0.0022*	(0.0013)
Primary	0.0385	(0.0293)	-0.0252	(0.0395)
Junior high	0.0587	(0.0417)	-0.0837	(0.0649)
Senior high	0.1608***	(0.0563)	-0.1320*	(0.0805)
University	0.0950	(0.991)	- 0.0190	(0.1388)
Household Size	0.0033*	(0.0017)	-0.0039*	(0.0024)
Farm Size	-0.3257***	(0.1038)	0.3323***	(0.1032)
Rainfall anomaly (SPI)	-0.0535) ***	(0.1119)	0.0655***	(0.0170)
Mean Temperature	-0.0366**	(0.0145)	0.3474*	(0205)
Idiosyncratic Shocks	-0.0317*	(0.0188)	0.0223	(0.0254)
Livestock ownership	-0.0782*	(0.0400)	(0.1852) ***	(0.0645)
Constant	3.2637***	(0.1136)	-1.1573*	(0.5914)
χ^2 for excluded instruments		47.57		
p-value for test of excluded instruments		0.0000		
p-values for test of observed heterogeneity		0.0000		
Observations		1,436		

*Note: this table presents the estimates of the crop diversification equation in the non-diversification and diversification states (the difference between diversification and non-diversification), respectively. The p-values for the test of observed and essential (unobserved) heterogeneity as well as the excluded instruments (distance to the input market and ownership of motorcycle) are presented at the bottom of the table. *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

Sources: ENSANR 2019

The age of the household head has positive and statistically significant impact in the non-diversification state, implying that older farm household heads tend to increase their HDDS when they do not diversify. However, in the treatment state (i.e., diversified) they decrease their HDDS. The results also show that, the variable representing the farm size is negative and significant, in the non-diversified state, implying that the larger the farm size, the lower the level of household dietary diversity score. When farmers adopt crop diversification, cultivating larger farm size increases HDDS score. Furthermore, in the non-diversification state, farmers who own livestock gain less in terms of their HDDS compared to those who diversify. Thus, owning livestock in the treatment state (i.e., adopting crop diversification) increases the gains (i.e., HDDS) to farming households. This could be due to farmers using the crop residues as livestock feed, and the manure from the livestock could be used to improve the soil fertility, which results in improved productivity. Thus, crop diversification helps farmers with livestock to gain more in terms of food diversity indicators.

3.5.2.2 Heterogeneity in Treatment Effect on rCSI

Rainfall anomaly (SPI) exerts a positive and significant impact on the non-diversification state, suggesting that the higher the rainfall anomalies, the more likely farmers are to adopt multiple coping strategies against their food insecurity. Our results from temperature anomalies show similar effect signs as the SPI variable. However, when they diversify, even under worse climatic conditions, farmers are likely to improve their food security status.

Possession of livestock allows farmers to reduce their survival strategies for both diversifying and non-diversifying states but is only significant for those who are diversifying their crops.

Table 3- 5: Outcome equations results for (ln) rCSI

	Reduced Coping Strategy Index (rCSI)			
	Outcome β_0		Outcome $(\beta_1 - \beta_0)$	
	Coef.	St. Err.	Coef.	St. Err.
Sex	0.0097	(0.2492)	0.0929	(0.4005)
Age	-0.0056	(0.0049)	0.0011	(0.0070)
Primary	-0.3448***	(0.1273)	0.4166**	(0.1867)
Junior high	-0.1836	(0.2906)	-0.0845	(0.4572)
Senior high	-1.3229***	(0.3403)	1.1057**	(0.4758)
University	-0.6213	(0.5532)	-0.0102	(0.7205)
Household Size	0.0010	(0.0135)	-0.0190	(0.0169)
Farm Size	1.5313***	(0.5359)	-1.5510***	(0.5459)
Rainfall anomaly (SPI)	0.1024*	(0.0606)	-0.3330***	(0.0880)
Mean Temperature	0.2137***	(0.8176)	-0.0200	(0.1090)
Idiosyncratic Shocks	0.3000*	(0.1699)	-0.1225	(0.1971)
Livestock ownership	-0.0946	(0.2243)	-0.7971**	(0.3948)
Constant	-4.6919**	(2.2968)	2.05556	(2.9804)
χ^2 for excluded instruments		47.57		
p-value for test of excluded instruments		0.0000		
p-values for test of observed heterogeneity		0.0000		
Observations		1436		

*Note: *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

Sources: ENSANR 2019

However, the household head's education level (Primary, senior high school) is negative and significantly related to rCSI in the non-diversifying state. This means that human capital has a positive influence on reducing survival strategies in the non-diversifying state, with the inverse effect on diversifying states.

At the non-diversification state, the positive and significant sign of the coefficient for the variable representing farm size shows that households with large farms are more likely to develop food survival strategies by about 2 points than those who diversify their production. As a result, those who diversify and have large fields have a better rCSI than those who do not diversify.

3.5.2.3 Heterogeneity in Treatment Effect on poverty headcount ratio

The results in **Table 3-6** reveal a positive and statistically significant effect of rainfall anomalies on the poverty headcount in the non-treated state, implying that when farmers experience higher rainfall anomalies and do not diversify, they tend to be poorer. In the treatment state, however, even when farmers experience rainfall anomalies, our results show a negative and statistically significant effect, suggesting that crop diversification can help to reduce the incidence of poverty even under adverse rainfall anomalies.

Table 3- 6: Outcome equations result for poverty headcount

	Poverty headcount			
	Outcome β_0		Outcome $(\beta_1 - \beta_0)$	
	Coef.	St. Err.	Coef.	St. Err.
Sex	0.0954	(0.1159)	-0.2888	(0.1871)
Age	-0.0007	(0.0017)	-0 .0005	(0.0025)
Primary	-0.0039	(0.0421)	-0.0591	(0.0661)
Junior high	0.1159	(0.0755)	-0.2118	(0.1224)
Senior high	-0.1984	(0.1598)	0.0047	(0.2411)
University	-0.4468	(0.3070)	0.2949	(0.4113)
Household Size	0.0210***	(0.0062)	-0.0052	(0.0080)
Farm Size	0.4323***	(0.1617)	-0.4565***	(0.1629)
Rainfall anomaly (SPI)	0.1105***	(0.0213)	-0.1408***	(0.0284)
Mean Temperature	0.0202	(0.0304)	0.0072	(0.0529)
Idiosyncratic Shocks	0.0529	(0.0411)	-0.0900	(0.0648)
Livestock ownership	0.0164	(0.0801)	-0.0214	(0.1280)
Constant	-0.2928	(0.8576)	0.3117**	(1.4693)
χ^2 for excluded instruments		47.57		
p-value for test of excluded instruments		0.0000		
p-values for test of observed heterogeneity		0.0000		
Observations		1436		

*Note: *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels.*

Source: ENSANR 2019

The empirical results further show that the variable representing farm size is positive and significant in the non-diversification state indicating the larger the farm size, the higher the incidence of poverty. Interestingly, the results show a negative and statistically significant effect in the treated state for households who farm on larger farm sizes. Household size exerts positive and statistically significant effect at the non-adoption stage, suggesting that farm households with larger farm sizes will be poorer when they do not diversify their crop production. However, when farmers diversify, a positive but statistically insignificant effect is observed.

3.5.2.4 Heterogeneity in Treatment Effect on Poverty GAP

Household size and farm size are positive and significant at non-diversifying states. These results reveal that the poverty gap will be higher for households with a large number of family members and bigger farm sizes when they are not diversifying their crops (**table 3-7**). However, the poverty gap is negative and significant at crop diversification level suggesting that crop diversification can lead to a reduction in the poverty gap. The estimates for the SPI show that in the non-diversification state, the poverty gap tends to increase. However, it decreases in the diversification state. Therefore, farmers will be more vulnerable to climate issues and subsequently increase their poverty level when they do not diversify their crops.

Table 3- 7: Outcome equations results for poverty GAP

	Poverty GAP			
	Outcome β_0		Outcome $(\beta_1 - \beta_0)$	
	Coef.	St. Err.	Coef.	St. Err.
Sex	-0.0917	(0.0567)	0.0743	(0.1061)
Age	-0.0017*	(0.0010)	0.0011	(0.0015)
Primary	-0.0412	(0.0253)	0.0159	(0.0375)
Junior high	0.0057	(0.0559)	-0.0123	(0.0935)
Senior high	0.0026	(0 .0886)	-0.0769	(0.1455)
University	-0.2473	(0.2529)	0.1190	(0.3403)
Household Size	0.0182 ***	(0.0021)	-0.0083***	(0.0028)
Farm Size	0.2108**	(0.0921)	-0.2307**	(0.0946)
Rainfall anomaly (SPI)	0.0488***	(0.0135)	-0.0547***	(0.0202)
Mean Temperature	0.0192	(0.015)	-0.0025	(0.0253)
Idiosyncratic Shocks	-0.0165	(0.0274)	0.0437	(0.0369)
Livestock ownership	-0.0253	(0.0597)	-0.0001	(0.0921)
Constant	-0.2999	(0.4301)	0.2979	(0.6886)
χ^2 for excluded instruments		47.57		
p-value for test of excluded instruments		0.0000		
p-values for test of observed heterogeneity		0.0083		
Observations		1436		

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

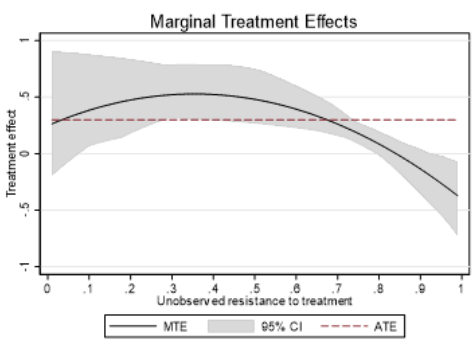
Sources: ENSANR 2019

3.5.3 Heterogeneity in treatment effects on unobserved characteristics

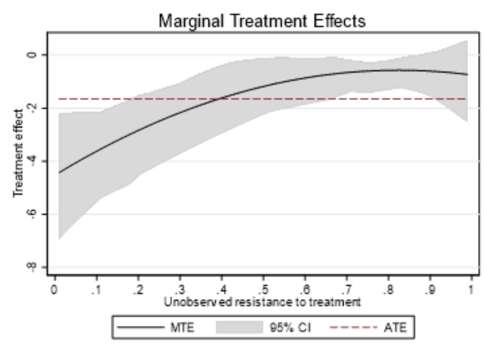
Figure 3-3 presents the graphs for the MTE on the unobserved resistance of a farmer adopting crop diversification. The curve for HDDS clearly reveals that the gain from crop diversification increases when unobserved resistance is lower, suggesting that households who have better unobserved attributes to improve their adoption decision are likely to benefit the most in terms of their food and nutrition security. These findings corroborate previous studies that report that crop diversification enhances the food quality of households (Kabir *et al.*, 2022; Kissoly *et al.*, 2020). Diversification of crop production allows the consumption of diversified foodstuffs produced farmers, which helps in improving the household's food and nutrition security. The marketable surplus allows farmers to generate additional income, which they use to purchase other foodstuffs that are not produced by the household, and thus ensuring diversified foods (Sauer *et al.*, 2018).

We observe an inverse curve for the "MTE curve rCSI" which increases, suggesting that farmers who are more likely to diversify their production are more likely to reduce the use of food survival strategies after crop diversification. Knowing that coping strategies are detrimental to the household food situation, this result is rather positive, since households that reduce coping strategies will have a better level of food security. In fact, according to Mango *et al.*, 2018, households that have relatively higher number of crop species grown per season are less likely to adopt more desperate food insecurity coping strategies.

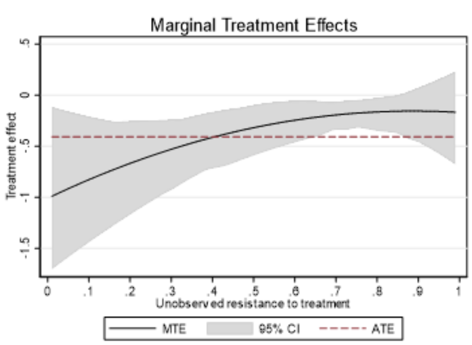
The MTE curve for poverty headcount is similar to the rCSI curve, with the same upward trend. However, farmers with high unobserved resistance to diversification have higher levels of poverty and derive less benefit from diversification, hence likely to remain in poverty. On the other hand, the greater the inclination to diversify crops, the greater the gain and the lower the poverty rate. It can therefore be inferred that the poverty rate grows up with resistance to crop diversification. Crop diversification could be pursued as a strategy to assist farm households escape poverty (Nga & Lantican, 2011).



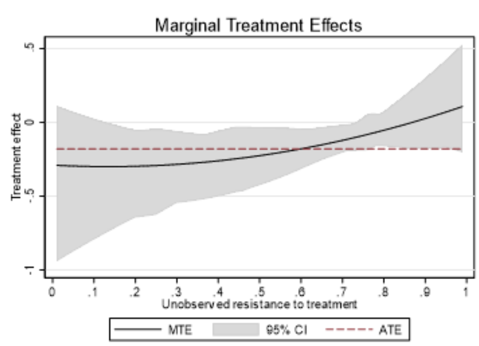
A: MTE curve for HDDS



B: MTE curve for rCSI



C. MTE curve for poverty headcount



D. MTE curve for poverty GAP

Figure 3- 3: MTE curves for the outcome variables (ENSANR, 2019)

*Notes: This Figure shows the estimated MTEs of the outcome equations (HDDS, rCSI, poverty headcount and poverty gap) estimated at the mean values of the observed covariates (**X**). The dashed lines are ATEs and the 95% confidence interval (95% CI) is based on bootstrapped standard errors with 50 replications.*

Sources: ENSANR 2019

The "MTE curve poverty gap" figure is also ascending, indicating that the less resistance there is to crop diversification, the more the gain increases and consequently the poverty gap will decline. In other words, crop diversification has a positive effect on the poverty gap, since it is reduced as farmers are more inclined to diversify their crops.

In all, with variable heterogeneities, we can see a pattern of positive selection on the unobserved gains from crop diversification for all the results analyzed. In effect, given the unobserved characteristics, farm households who are most likely to diversify their crops, appear to have better food security and poverty status.

3.5.4 Causal effects of the adoption of crop diversification on food security and poverty

Table 3-8 reports the average gains of crop diversification on food and nutrition security (HDDS and rCSI) and poverty of farmers. The ATE, which indicates the impact of crop diversification on a randomly sampled farmer, increases the HDDS by 30% on average, reduces his coping strategies by about 165%, and reduces his poverty rate by 40% and his poverty gap by 18%. However, the magnitude of the impacts is much better, if we randomly select farmers who diversify their crops (ATT): dietary diversity is improved by 49%, survival strategies are reduced by more than double by (274%), and the poverty rate and poverty gap are reduced by 69 and 31% respectively. The effects of the treatment on the untreated (ATU), although not statistically significant, are less than those of ATE and ATT. Therefore, ATT is far superior to ATE and ATUT, confirming the positive selection of unobserved gains. Thus, it can be said that the different treatment effects parameters suggest the gain from crop diversification for adopters is higher than for the randomly selected farmer, or for non-adopters, ATT >ATE >ATUT, implying positive selection on the gains from adopting crop diversification as shown by the MTE curve.

Table 3- 8: Impact of crop diversification on food security and poverty

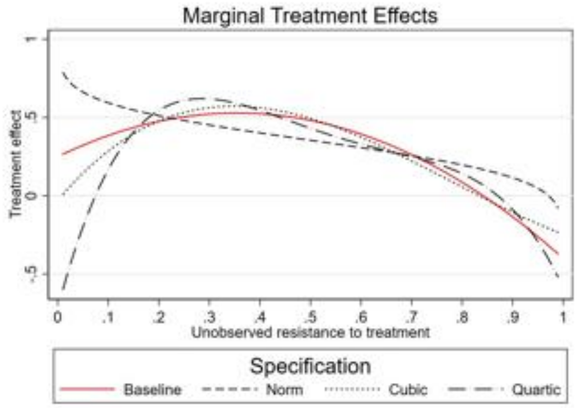
Parameters	HDDS	rCSI	FGT	Poverty GAP
ATE	0.2991***	-1.6547***	-0.4069***	-0.1800**
	(0.0952)	(0.4794)	(0.1191)	(0.0797)
ATT	0.4971***	-2.7485***	-0.6973***	-0.3195**
	(0 .1565)	(0.8337)	(0.2114)	(0.1364)
ATUT	0.0423	-0.2361	-0.0302	-0.0008
	(0 .0350)	(0.2007)	(0.0606)	(0.0428)

*Note: The table presents ATE (average treatment effect), ATT (average treatment on treated) and ATU (average treatment on untreated) effect of crop diversification. *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels*

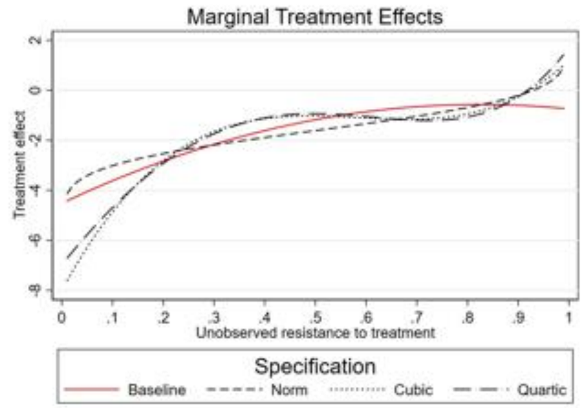
Sources: ENSANR 2019

3.5.5 Robustness checks

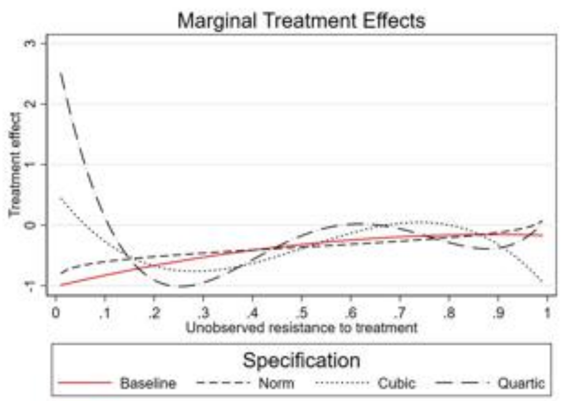
To test the sensitivity of the baseline estimates, we perform robustness checks that include the use of different functional forms such as the linear specification, which assumes returns to crop diversification decrease monotonically cubic, and quartic of the propensity score in the equation. The graph of the different functional forms reveals similar patterns to the baseline specification and does not vary by using linear and higher-order specifications. This reveals that our choice of the quadratic functional form of the propensity score is appropriate.



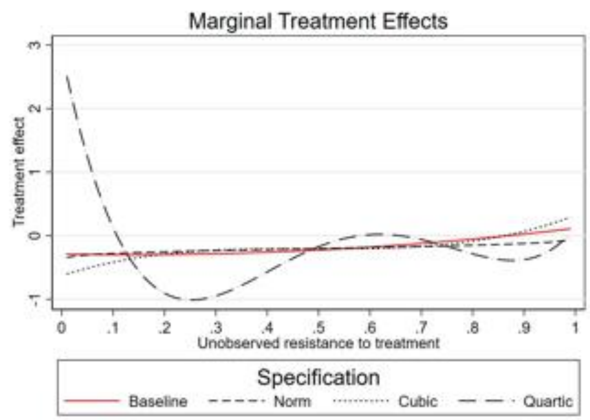
A: Robustness check HDDS



B: Robustness check rCSI



C: Robustness check poverty headcount



D: Robustness check poverty GAP

Figure 3- 4: Robustness check (ENSANR, 2019)

Notes: figure 3-4: show the marginal treatment effects (MTE) functional form robustness checks, evaluated at average values of the covariates. The MTE curves A represent the HDDS, the B shows the MTE curve for the rCSI, the C is the MTE curve for poverty headcount, while the D is the MTE curve for poverty GAP.

Sources: ENSANR 2019

3.5.6 Policy-relevant treatment effect

The results indicate the important role of crop diversification on food security and poverty through the instrument used, i.e. distance to the input market. Thus, insofar as the farmers least likely to diversify their crops see their food security and poverty indicators reduced, they should be encouraged to start diversifying, since the results of our work have shown us the gains that these farmers would have if they adopted crop diversification. So policies that seek to overcome structural problems and encourage people to adopt can be very rewarding. This suggests that appropriate policy changes could induce (change propensity scores) adoption. Thus, using PRTE, we show the effect of a policy change that reduces the distance from the household to the input market by half. The distance policy attempts to improve accessibility to the input market, which offers many possibilities for households to purchase agricultural and consumer products, but also to seed their farm produce.

The estimates, therefore, indicate that reducing the distance to the input market by half will improve food and nutrition status and reduce poverty. By improving food diversity by 43%, survival strategies will be reduced by 237%. With regard to poverty indicators, even if they are not significant, this will make it possible to reduce the level of poverty by 30% and the intensity of poverty by 13%.

Table 3- 9: Policy-relevant treatment equations (PRTE)

Outcome variable	**Distance to the input market (50% reduction)**		
	Propensity scores		**Policy effect**
	Baseline	**Policy**	**PRTE**
HDDS (ln)	0.564	0.578	0.4399*** (0.1193)
rCSI (ln)	0.564	0.578	-2.3715*** (0.6856)
Poverty headcount	0.564	0.578	-0.3076 (0.2280)
Poverty GAP	0.564	0.578	-0.1363 (0.1098)

*Notes: table 9 presents the estimate of the simulation of the policy impact of 50% reduction in the distance to the input market. *, ** and *** are respectively show statistical significance at 10%, 5% and 1% levels*

Sources: ENSANR 2019

3.6 Conclusion and policy implications

Crop diversification has widely been identified as a meaningful strategy in combating food insecurity and reducing poverty in low-income countries. In particular, there is increasing evidence that crop diversification could be leveraged by smallholder farmers in their climate adaptation strategies to stabilize farm households' incomes (e.g., Adam & Abdulai, 2024; Asfaw *et al.*, 2019). In this study, we examine the drivers and heterogeneous impacts of crop diversification on household welfare measures such as food and nutrition security as well as incidence and severity of poverty. In particular, we employ the Marginal treatment effect (MTE) analytical framework to account for potential endogeneity arising from observed and unobserved attributes, using farm level data from rural households in Senegal.

Our empirical results show substantial heterogeneity in the benefits that households derive from crop diversification. We also find that crop diversification is essential to improving the food and nutrition status of rural households in Senegal by improving the dietary diversity score and reducing the number of coping strategies against food insecurity (rCSI) (Zanello *et al.*, 2019). Crop diversification is an adaptation strategy for farmers to mitigate climate-related risks and decrease vulnerability. This strategy improves welfare even under climate-related shocks by improving food security indicators and poverty status. Observable characteristics also show that even under adverse weather conditions, households will earn more if they diversify crops. We find a positive selection pattern on the unobserved gains from crop diversification. Indeed, according to the results, households who diversify their crops benefit from improved food and nutrition, as well as lower poverty levels. Thus, poor households can derive significant benefits from adopting crop diversification strategies.

The policy-relevant treatment analysis shows that reducing the distance to the input market by increasing the number of marketplaces could encourage people to diversify. This could reduce the production cost of transport for the purchase of inputs needed for production and for the sale of harvested products. Thus, the option of facilitating access by reducing the distance to the input market could produce additional gains in terms of nutrition and poverty levels. As a result, policymakers could expand the effectiveness of interventions to promote crop diversification by improving market access infrastructure, and supporting investment in input and output markets to stimulate crop diversification to improve the well-being of rural households by improving food security and poverty indicators.

The findings imply that investing in basic infrastructure such as rural roads and markets, and facilitating equipment access could be fundamental for agricultural development and crop diversification, and income generation for farmers. Crop diversification has proven to be a critical strategy for mitigating climate-related risks and improving welfare in the Senegalese Groundnut Basin, offering a pathway toward greater resilience and food security. Building on this foundation, the next topic will explore the heterogeneous impact of household resilience on food insecurity, shedding light on how varying levels of resilience influence the ability of households to cope with and adapt to challenges in the region. This analysis will provide deeper insights into the dynamics of food security and resilience within the Senegalese Groundnut Basin.

CHAPTER 4: ANALYSIS OF HOUSEHOLD RESILIENCE TO FOOD INSECURITY WITHIN A GENDER PERSPECTIVE IN THE SENEGALESE GROUNDNUT BASIN

Abstract

This chapter investigates the heterogeneous impact of household resilience on food and nutrition security, using household level data from Senegal. We use the Resilience Index Measurement Analysis (RIMA II) to capture household resilience capacity. We employ Two-Stage Least Squares (2SLS) method to account for potential endogeneity and Dose Response Function approach to analyze the impact of resilience on key food security indicators such as Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS), disaggregating the analysis according to gender. The RIMAII reveals that pillars access to basic services, assets and adaptive capacity are all significant predictors of resilience. Our empirical results reveal also that higher resilience leads to better food and nutrition security outcomes. However, the dose response function analysis highlights general heterogeneous positive impact of the dose (RCI) across both male and female-headed households. Female-headed households are found to benefit substantially more from increased RCI in terms of food security outcomes, but show a higher potential adverse effects for them when they are non-treated. The estimates suggest that policy measures could tailor resilience-building programs to address the distinct needs and responses of different gender groups, ensuring equitable and effective distribution of benefits.

Keywords: resilience capacity index, food insecurity, household, gender

4.1 Introduction

Sustainable Development Goal 2 aims at putting an end to all forms of hunger and malnutrition by 2030 by ensuring that all people, particularly, children and the most vulnerable, have access to sufficient food of good quality throughout the year (United Nations, 2019). Despite this Sustainable Development Goals, in 2021, one human being in ten (828 million people) went a whole day or more without eating for lack of food (FAO, FIDA, 2022). Globally, the percentage of women experiencing moderate-to-severe food insecurity climbed to 31.9% in 2021, while the percentage for men was 27.6% (FAO, FIDA, 2022). In sub-Saharan Africa, recurrent climate shocks, socio-political instability, and economic disruptions are exacerbating household vulnerability to food insecurity (D'Errico *et al.*, 2018). Climate-related hazards such as droughts, irregular rainfall, floods, and desertification, combined with community conflicts and market volatility, contribute to the erosion of household resilience capacity and further entrench chronic food and nutritional insecurity (Brück & Pietrelli, 2019; Fan *et al.*, 2014).

In Senegal, agriculture plays a vital role in the economy and livelihoods, rural areas are especially vulnerable. The rainfed crop yields in some African countries could be reduced by more than 50% (IPCC, 2022). This fact is already perceptible in Senegal; agriculture plays a vital role in the economy and livelihoods, and rural areas are especially vulnerable. Among these, the Groundnut Basin, known for its significant contribution to domestic consumption and export revenues, faces numerous threats that jeopardize food security. These include climatic variations, market fluctuations, and socio-economic constraints (Ibrahim, 2023). The rural Groundnut Basin's dependence on agriculture makes it highly vulnerable to climatic variations such as droughts and irregular rainfall patterns, which have become increasingly common due to climate change adversely affecting agricultural productivity (IPCC, 2014). These climatic shocks can lead to crop failures, reduced agricultural productivity, and subsequent food shortages. Additionally, market fluctuations, including price volatility and limited market access, further exacerbate the food security situation (Jeder *et al.*, 2020). Faced with the adverse effects of climate change and growing fears about the ability of agriculture to meet food needs, food insecurity remains a constant concern for many Senegalese households, particularly in rural areas. Food insecurity remains a pressing issue in Senegal's Groundnut Basin. According to the 2019 National Food Security, Nutrition, and Resilience Survey, the national average rate of food insecurity stands at approximately 8%. However, in the Groundnut Basin, food insecurity rates are significantly higher, with estimates ranging between 20% and 35%, indicating the region's heightened vulnerability compared to the national average (SE/CNSA, 2019). The legacy of farmers' strategies in the Groundnut Basin is an important dimension that should not be ignored, as they help build resilient livelihoods among rural dwellers. Henceforth, agricultural and non-agricultural strategies interplay to reduce food insecurity and improve welfare in the area.

To effectively tackle food insecurity and build resilience among these vulnerable populations, it is essential to understand the factors that contribute to or hinder their ability to withstand and recover from adverse conditions. A comprehensive assessment of resilience can provide valuable insights into the strengths and weaknesses of households, guiding the development of targeted policies and interventions. Resilience has emerged as a crucial cornerstone in tackling poverty and vulnerability among populations facing various shocks (Egamberdiev *et al.*, 2024). One of the advanced tools for assessing resilience is the Resilience Index Measurement and Analysis II (RIMA-II). Developed by the Food and Agriculture Organization (FAO), RIMA-II offers a comprehensive framework for quantifying resilience through four dimensions such as access to basic services, assets, social safety nets and adaptive capacity. RIMAII were built using the following definition: "Resilience is the capacity of a household to bounce back to a previous level of well-being (for instance, food security) after a shock" (Alinovi *et al.*, 2008). Alinovi *et al.* (2008) were pioneers in defining and quantifying household resilience to food insecurity. In their model, the household served as the primary unit of analysis. This focus was due to the household's role as the decision-making entity where crucial choices are made regarding risk management, both before and after risks occur, especially those impacting food security.

Measuring the impact of resilience on food insecurity can present endogeneity challenges. Previous studies (Ansah *et al.*, 2019; Brück & Pietrelli, 2019; Smith & Frankenberger, 2018) have noted an endogeneity relationship between resilience and food insecurity. Firstly, there is the potential for reverse causality, as more food-resilient households are better able to develop strategies to maintain their resilience when facing shocks (Ansah *et al.*, 2019). Secondly, omitted variable bias may arise from excluding factors that influence both resilience and food insecurity, such as household capabilities and skills (d'Errico & Pietrelli, 2017). Lastly, measurement error in assessing resilience can occur due to the simplification process involved (d'Errico & Pietrelli, 2017). Despite recognizing potential endogeneity in studies on resilience and food insecurity, few researchers have adequately addressed this in their estimations (Ansah *et al.*, 2019).

To establish a causal relationship between resilience and household food security, various econometric methods have been employed. The estimation method employed in this study is the simultaneous equation model using Two-Stage Least Squares (2SLS) to address potential endogeneity issues and Dose-Response Function (DRF) to account for the heterogeneity in the impacts of resilience on food insecurity. Too little attention has been paid to in-depth gender inequality analysis in household resilience to food insecurity. However, these studies do not examine the impact of varying levels of resilience capacity on food and nutrition security, providing a detailed understanding of how incremental changes in resilience influence outcomes.

By examining the relationship between resilience and food security outcomes, this chapter makes several significant contributions to the existing literature. Employing the dose-response function (DRF) approach to evaluate the heterogeneity in the impact of the resilience index on food and nutrition security is a novelty, as it disaggregates the causal effect of different resilience capacity levels instead of a single average causal effect. In that light, considering the heterogeneity nature of the target group and the context in which they operate, the study emphasis targets gender inequalities in resilience capacity comparing the average Resilience Capacity Index (RCI) of male-headed households (MHH) to that of female-headed households (FHH) (FAO, 2016b; FAO, 2017; FAO, 2019a; D'Errico & Di Giuseppe, 2018). Indeed, our analysis pays special attention to gender issues, assuming that resilience capacity impacts male-headed and female-headed households differently. This gender-sensitive approach is crucial for designing effective policies that enhance food security for all demographics. Addressing these gaps will provide a more comprehensive understanding of the relationship between resilience and food insecurity and help in designing more effective interventions to enhance food security.

Our findings show that, based on the 4 pillars of resilience, the more resilient the household, the better the food and nutrition security indicators (FCS and HDDS). Given the heterogeneity of the target group, the resilience outcomes show a differential between men and women, all things being equal. Under the same context, food security status for female-headed households is revealed to be more fragile than that of male-headed households.

4.2 Literature review

The concept of resilience has been increasingly applied to development contexts, particularly in rural development, sustainable livelihoods, well-being, and food security (Beauchamp *et al.*, 2021; Fan *et al.*, 2014; Quandt, 2018; Salvia & Quaranta, 2017). In the context of food security, resilience is understood as a household's ability to withstand, adapt to, and recover from socio-economic and environmental shocks (Alinovi *et al.*, 2008; D'Errico *et al.*, 2018). This capacity is multidimensional and includes various aspects of household livelihoods (Crookston *et al.*, 2018). Resilience acts as a buffer between shocks and food security outcomes. Shocks can be exogenous (covariate shocks such as droughts and floods) or endogenous (idiosyncratic shocks such as illness or death) (Ansah *et al.*, 2019). Household resilience plays a key role in determining food security by influencing both immediate coping mechanisms and long-term adaptation strategies (D'Errico & Di Giuseppe, 2016). Empirical studies quantify resilience using latent indices, highlighting its critical role in mitigating food insecurity (Alinovi *et al.*, 2010). However, previous studies have largely focused on estimating an average causal effect of resilience on food security without fully exploring how different levels of resilience influence food security outcomes.

The relationship between resilience and food security has been widely studied through the Resilience Index Measurement and Analysis (RIMA) framework. The RIMA-II model considers resilience as a distinct capacity separate from food security and shocks, allowing for more precise analysis (FAO, 2016). Studies have shown that resilience capacity significantly impacts food security outcomes (Brück & Pietrelli, 2019; Chiwaula *et al.*, 2022; Haile *et al.*, 2022). Using an instrumental variables (IV) approach, d'Errico & Pietrelli (2017) found that higher resilience reduces child malnutrition and enhances household food security stability. Despite these findings, limited attention has been paid to analyzing the heterogeneous effects of resilience on food security. By employing a dose-response function (DRF), this study provides a more nuanced understanding of how incremental changes in resilience capacity influence food security outcomes. Household resilience is reflected in the ability to implement effective coping strategies in response to shocks. These strategies include crop diversification (Bullock *et al.*, 2017), contract farming, and agricultural intensification (Azumah *et al.*, 2017; Ellis, 1998). The ability to sustain food security through these mechanisms underscores the importance of resilience in household adaptive capacity (Pingali *et al.*, 2005). A resilient food system retains its core functions even in times of crisis, ensuring food availability and access. However, existing studies often overlook gender disparities in resilience capacity, particularly the differential impacts of resilience on food security among male-headed and female-headed households.

Resilience has gained prominence as a framework for addressing food insecurity and poverty. Strengthening household resilience is seen as a key strategy for achieving long-term food and nutrition security (Barrett & Constas, 2014). Resilient households can better manage shocks, thereby reducing chronic vulnerability and promoting sustainable development (USAID, 2012). Programs aimed at enhancing resilience capacities can significantly contribute to food security in regions prone to recurrent shocks (Frankenberger *et al.*, 2012). This study seeks to address critical gaps in the literature by examining how resilience capacities vary across genders and how different levels of resilience affect food security outcomes. A gender-sensitive approach is essential for designing effective policies that promote equitable food security solutions.

The resilience approach has become integral to food security studies, emphasizing the importance of household adaptive capacities in mitigating food insecurity risks. Empirical evidence supports the role of resilience in buffering shocks and sustaining food security. However, significant gaps remain in understanding the heterogeneity of resilience effects and gender disparities in resilience capacity. This study aims to contribute by employing advanced econometric methods to better capture these complexities, particularly in the Senegalese Groundnut Basin.

4.3 Methodology

4.3.1 Analytical Framework

4.3.1.1 RIMA II method

The RIMA II approach analyzes resilience of households to food insecurity by accounting for all types of shocks (idiosyncratic or covariant) RIMA-II uses a variety of econometric techniques to show how households deal with shock variations. The approach is based on a two stage procedure, including factor analysis (FA) to construct pillars and multiple indicators and multiple causes (MIMIC)[3] model to estimate resilience capacity index (RCI) from pillars for the

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[3] *The MIMIC model is a latent variable structural equation model initiated by Jöreskog and Goldberger in 1975. The model is based on behavioral hypotheses linked to an unobservable variable. The main underlying idea is to use observable variables (causal variables) to determine the form and magnitude of an unobservable variable of an unobservable variable (latent variable).*

relationship between RCI and food security outcomes (FAO, 2016). RCI is derived from a combination of several directly observable household characteristics to capture the household's resilience to food insecurity. The resilience structure illustrates the relationship between each pillar and resilience capacity to indicate the extent to which each pillar contributes to overall resilience. It also shows the connection between each observed variable and its respective pillar, highlighting how much each variable influences the pillar. A direct measure of resilience describes both resilience capacity and resilience structure. Resilience capacity is quantified by the RCI. Resilience structure is defined by the weightings assigned to each pillar in determining resilience capacity and to each variable in determining the respective pillar. To estimate the RCI, a factor analysis is carried out to construct the four pillars of resilience: access to basic services (ABS), assets (AST), social safety nets (SSN) and adaptive capacity (AC). To avoid the risk of multicollinearity, we used the weighted sum method proposed by Barlett (1937), which produces relative unbiased estimation. The pillars are used to construct a composite index (Resilience Capacity Index), representing the resilience of a household. The **Table 4-1** presents the list of the underlying variables used to construct the four pillars.

Table 4- 1: Resilience pillars definition

Pillars of resilience	Definition	Number of variables used	Variables used
Access to basic services (ABS)	ABS reflects a household's ability to meet its basic needs through effective use of basic services	6	-Main source of drinking water source -Toilet facility -Solid waste -Main source of energy for lighting -Sludge removal mode -Health service distance
Asset (AST)	Assets are categorized into productive and non-productive. Productive assets are the main elements that enable households to ensure their subsistence by producing consumable and marketable goods. Non-productive assets relate to the characteristics of the home and the household's capital goods.	3	- Wealth index per capita[4] -Agricultural index per capita -TLU[5]
Social Safety Net (SSN)	The social security pillar measures a household's ability to receive prompt and reliable assistance from relatives and friends, as well as from international organizations, aid agencies and NGOs.	5	-Food voucher -Cash assistance -Food assistance -Sickness cover -Association membership
Adaptive Capacity (AC)	This is the household's ability to recover from a shock and develop new strategies.	5	-Education level of head household -Dependence ratio[6] -Coping strategy -Salary -Income sources diversity

Note: This table presents a brief description of all the different pillars of resilience used in our estimation.

The RCI of a household is a function of the pillars ABS, AST, SSN and AC, as shown in equation (13).

$$RCI = f(ABS, AST, SSN, AC) \quad (13)$$

Min-Max scaling transformation was applied to generate a standardized index. Following Errico et al., 2018; Lascano Galarza, 2020 we standardize RCI index as presented in equation (14).

[4] Dummy variables taking on the value of one if a HH has specific non-productive assets e.g., telephone, furniture, TV, radio, solar, buildings, vehicle, motorbike, bicycle. The index is created thru **FA**. It is a proxy for the richness of a HH. It assumes higher values for HHs with a higher non-productive asset position.

[5] TLU is a weighted sum of the number of different livestock owned by the HH. The conversion weight is 1 camel; 0.7 cattle; 0.55 donkey/mule/horse; 0.1 sheep/goat; 0.01 chickens (poultry).

[6] It is given by: (([Population ages 0-14] + [Population ages 65-plus]) ÷ [Population ages 15-64]) × 100). The lower, the better.

$$RCI = \frac{RCI - RCI\,\mathrm{m}in}{RCI\,\mathrm{m}ax - RCI\,\mathrm{m}in} * 100 \tag{14}$$

The descriptive analysis is then followed by a causal analysis. To do this, the model considers two indicator variables which are the resultant of the latent variable. In this study, the causal variables are the pillars of resilience and the two indicator variables are food security indicators: the food consumption score (FCS) and the household dietary diversity score (HDDS). Several model validation tests are carried out before estimating a regression model to determine the effects of household socio-demographic characteristics and shocks on resilience.

The MIMIC model comprises of two key components. The first is the measurement equation (15), which accounts for the fact that observed indicators of food security are imperfect measures of resilience capacity. The second is the structural equation (16), which links the estimated attributes to resilience capacity. The main factors used in the structural model used in the MIMIC modelling process are: access to basic services (ABS), assets (AST), social safety nets (SSN) and adaptive capacity (AC).

The two food security indicators are modelled in the measurement part of the Structural Equation Model (SEM) as:

$$\begin{bmatrix} FCS \\ HDDS \end{bmatrix} = \left[\Delta_1, \Delta_2\right] \times \left[RCI\right] + \left[\varepsilon_1, \varepsilon_2\right] \tag{15}$$

$$[RCI] = [\beta_1, \beta_2, \beta_3, \beta_4] \times \begin{bmatrix} ABS \\ AST \\ SSN \\ AC \end{bmatrix} + \left[\varepsilon_3\right] \tag{16}$$

In the formative model, it is hypothesized that the resilience capacity index (RCI) is influenced by the four pillars as in equation (16). These formative indicators are assumed to be correlated and directly measured. In the reflective component, the model accounts for correlated errors (ε) in the reflective indicators, which include measurement errors. The MIMIC model thus enables the simultaneous estimation of the measurement model while incorporating causal variables into the structural model for the latent variable. This latent variable is linearly determined by formative indicators or pillars (with some random errors, ε_3), and in turn, Res influences the observed reflective indicators (with random errors, ε_1 and ε_2).

The estimated RCI is not inherently tied to a specific measurement scale. To establish a scale, the coefficient for food consumption score loading ($\Lambda 1$) is set to 1. This means that a one-unit standard deviation increase in the RCI corresponds to a one-unit standard deviation increase in the food consumption score. This approach also sets the unit of measurement for the other outcome indicator ($\Lambda 2$) and defines the variance for the two food security indicators.

4.3.1.2 Identification strategy

As explained in detail in the introductory chapter of this study, endogeneity arises in the analysis of household resilience and food insecurity due to potential reverse causality, omitted variable bias and measurement error. If not properly addressed, this can lead to biased and inconsistent estimates. To address endogeneity issues, we estimate the first stage of the 2SLS of the endogenous variable (RCI) on a set of independent variables and instrumental variables (d*istance to the mosque/church and number of religious brotherhood groups in the community).* Social capital has been observed to increase resilience (Neagu, 2024; Ögtem-Young, 2018), and religion is used as a measure of social capital (Maselko et al., 2011; Radu et al., 2019). Some authors have shown that spirituality and religious faith are important factors in promoting resilience (Howard-Snyder & McKaughan, 2022; Neagu, 2024; Ögtem-Young, 2018) through emotional and psychological support, social support networks, a sense of purpose, and spiritual practices. Social learning strengthens faith/religion; in fact closeness to religious entities enhances social learning by providing regular exposure to religious practices and values and facilitates social interaction within the community, easy access to religious education and reinforces religious norms and values. The higher the number of religious groups, the higher the faith of individuals through social learning due to the inter-religious exchanges which can enrich their understanding and practice of religion. However, Poppendieck, J. (1999) argues that systemic food insecurity issues are rooted in economic and policy domains rather than proximity to religious services. Spirituality and religious engagements do not address the broader economic and structural causes of food insecurity. In fact, any impact on food security would be indirect, such as through improved social networks and support systems that might help members find food during emergencies, but not in a consistent or direct manner.

Thus, we used distance from the household to the nearest mosque/church and the number of religious brotherhood groups as identifying instruments. We argue that it is likely to influence the resilience capacity of households but not the food security indicators directly, it can only influence food security through resilience. Regarding the exclusion restriction, some studies have highlighted the relationship between geographic distance and resilience, using distance as a reliable proxy for resilience (e.g., Sadri et al., 2018). The relationship is estimated using instrumental variables (IV) through two-stage least squares (2SLS). Food security is expressed as function of resilience and other exogenous shifters as shown in the specification in equation (17) below:

$$Y_i = \alpha_0 + \alpha_1 X_i + RCI + \varepsilon_{1i} \tag{17}$$

Where, Y_i the outcomes variables are FCS and HDDS, α_0 the control variables include gender, sex, shocks and others, α_1 the parameters to be estimated and the exogenous variable are specified by X_i. RCI is endogenous variable and the model includes the ε_{1i} Error terms.

Given that resilience is endogenous, we used the 2SLS instead of OLS. The first-stage is shown in equation (18) which is a reduced form equation where the endogenous variable (RCI) is expressed as a function of independent variables including the instruments.

$$RCI = \alpha_0 + \alpha_1 X_i + \alpha_2 Z_i + \varepsilon_{2i} \tag{18}$$

Z_i Instrumental variable

The second-stage estimates the structural equations using first-stage predictions as instruments, as shown in equation (19)

$$Y_i = \alpha_0 + \alpha_1 X_i + R\hat{C}I + \varepsilon_{1i} \tag{19}$$

where $R\hat{C}I$ represents predicted values of the endogenous variable

To check for endogeneity, we applied Wu Haussman test to assess the strength of our instruments. The results of this test indicate that the chosen variable is a valid instrument.

4.3.1.3 Dose-response function

We utilize the Generalized Propensity Score (GPS) method for continuous treatments, as proposed by (Hirano, K. & Imbens, 2004), to assess the impact of RCI on household food security in a continuous framework, moving beyond the discrete analyses discussed earlier. Our focus is on estimating the Average Dose-Response Function (DRF), which links the potential food security outcome $Yi\ (t)$ for household i to varying levels of adoption intensity t.

The variable $D_{it}(T_i)$ which denotes receiving treatment t for farmer i can be expressed as:

$$D_{it}(T_i) = \begin{cases} 1, \text{ if } \mathrm{T}_i = t \\ 0, \text{ otherwise} \end{cases} \tag{20}$$

The observed outcome Y_i can be expressed as a function of the treatment indicator D_{it} and potential outcome Y_{it} as: $Y_i = \sum_{t=0}^{\varphi} D_{it}(T_i)Y_{it}$ (21)

The generalized propensity score (GPS) is defined as the conditional on probability of a household belonging to a particular intensity level of RCI given the pretreatment covariates X_i

$$r(t,x) = \Pr\left[T_i = t \mid X_i - x\right] - E\left[D_{it}(T_i) \mid X_i - x\right], \forall t \in \Lambda \tag{22}$$

Where $r(t,x)$ is the generalized propensity score.

Pr is the probability of treatment conditional on the pretreatment covariate minus the expectation of the (extent) intensity of the level of treatment also conditional of the pretreatment covariate ∀ for all t that are members of Λ

The conditional expectation of each outcome is modelled as a function of two treatments (T_i), and the GPS.

$$E\left[Y_i \mid T_i = t, \hat{R}_i = r\right] = \partial_0 + \partial_1 T_i + \partial_2 T_i^2 + \partial_3 \hat{R}_i + \partial_4 \hat{R}_i^2 + \partial_5 T_i \hat{R}_i \tag{24}$$

Expectation of the outcome is conditional on the treatment status and the GPS is expressed as the linear combination of the treatment (T_i), the GPS ($\hat{R}_i$), their squares ($\hat{R}_i^2$) and their products.

The approach leverages the continuous nature of the treatment (i.e., Resilience Capacity Index) without requiring the full normality assumption. It considers both treated (i.e., resilient) and non-treated (i.e., non-resilient) units to identify dose-response functions and average treatment effects, thereby utilizing the complete information in the dataset. Additionally, it estimates other key causal parameters, including the average treatment effect (ATE), the average treatment effect on the treated (ATET), and the average treatment effect on the untreated (ATENT).

4. 3.2 Data description

The data utilized in this study originates from the National Food Security, Nutrition, and Resilience Survey (ENSANR 2019), carried out by the Executive Secretariat of the National

Council for Food Security (SE_CNSA). Data collection occurred from January to February 2019 through a multistage sampling method to gather quantitative data on households.
For the specific analysis of household resilience to food insecurity in the Senegalese Groundnut Basin, data was extracted from 19 departments within the basin, resulting in a sample of 3,100 households composed of 2442 MHH and 568 FHH. Detailed information was gathered on household characteristics, living conditions, farming practices, food consumption, income and expenditure, and responses to shocks. To analyze food security information from the survey data, two food access indicators are used: the Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS).

4.3.2.1 Food consumption score (FCS)

The Food Consumption Score (FCS) is a composite indicator, calculated on the basis of frequency, diversity and nutritional importance of the food groups consumed by the household during the seven (07) days preceding the interviewer's visit. With the FCS, households are classified into three consumption groups: poor, borderline and acceptable.

$$FCS = \sum_{i=1}^{8} x_i$$

$$X_i = W_i F_i$$

where i represents one food item, a total of eight groups of food. W represents the weight of food and F is the frequency of consumption (seven days' worth).

4.3.2.2 Household Dietary Diversity Score (HDDS)

The food utilization dimension and micronutrient intake are measured using HDDS (Mulwa & Visser, 2020). It is a qualitative measure of food consumption that reflects a household's access to a variety of foods. The number of foods or food groups that households consumed on the last day before the survey is represented by the HDDS. Twelve food groups were created from the items: cereals, tubers, vegetables, fruits, eggs, meat, fish, legumes, milk, oil, sugar, and other foods (condiments). Higher scores are associated with increased diversity and indicate enhanced food and nutrition security, whereas lower scores indicate fewer diversified sources (Amolegbe *et al.*, 2021). The HDDS formula is:

$$\text{HDDS} = \sum P_i$$

where P_i =1 if the food group is consumed and 0 otherwise

4.3.2.3 Climate data

We obtain secondary data from Climate Hazards Center Infrared Precipitation with Stations (CHIRPS), a mixed satellite/station product with a spatial resolution of 0.05 degrees, in order to incorporate rainfall information into this study. In comparison to other datasets, CHIRPS has shown an intriguing performance in Africa (Dinku *et al.*, 2018). Because of CHIRPS's spatial resolution, it may be employed with good precision on a relatively limited area, like the Groundnut Basin. We obtained rainfall data particular to each family by using geo-referenced household data. First created by (McKee *et al.*, 1993), the Standardized Precipitation Index (SPI) is a drought indicator. Based on variables related to precipitation, the SPI is used to estimate wet or dry conditions, and it is a common tool for identifying and tracking meteorological droughts is the SPI (Iwata *et al.*, 2012). The SPI is measured as:

$$SPI = \frac{X - X_m}{\sigma}$$

Where X is a cumulative precipitation for a year, X_m is mean precipitation, and σ is the standard deviation of precipitation in the series.

4.4 Study area and descriptive statistics

4.4.1 Study area

The region is bordered to the north by Saint Louis, to the south by The Gambia, to the west by Dakar region and the Atlantic Ocean, and to the east by the Tambacounda region. It spans roughly one-third of Senegal’s territory and hosts nearly half of the national population. Agriculture, trade, crafts, and animal husbandry are the dominant activities, with main crops including millet, peanuts, cowpeas, sorghum, cassava, watermelon, and hibiscus. Groundnuts are the principal cash crop, providing a significant portion of farmers' income, though other crops such as cowpeas and cassava also contribute. Secondary activities such as vegetable production, livestock, poultry farming, and forest product exploitation are increasingly being adopted as farmers diversify their income sources. However, anthropogenic pressure and climate change have accelerated ecosystem degradation, leading to significant shifts in agricultural production systems.

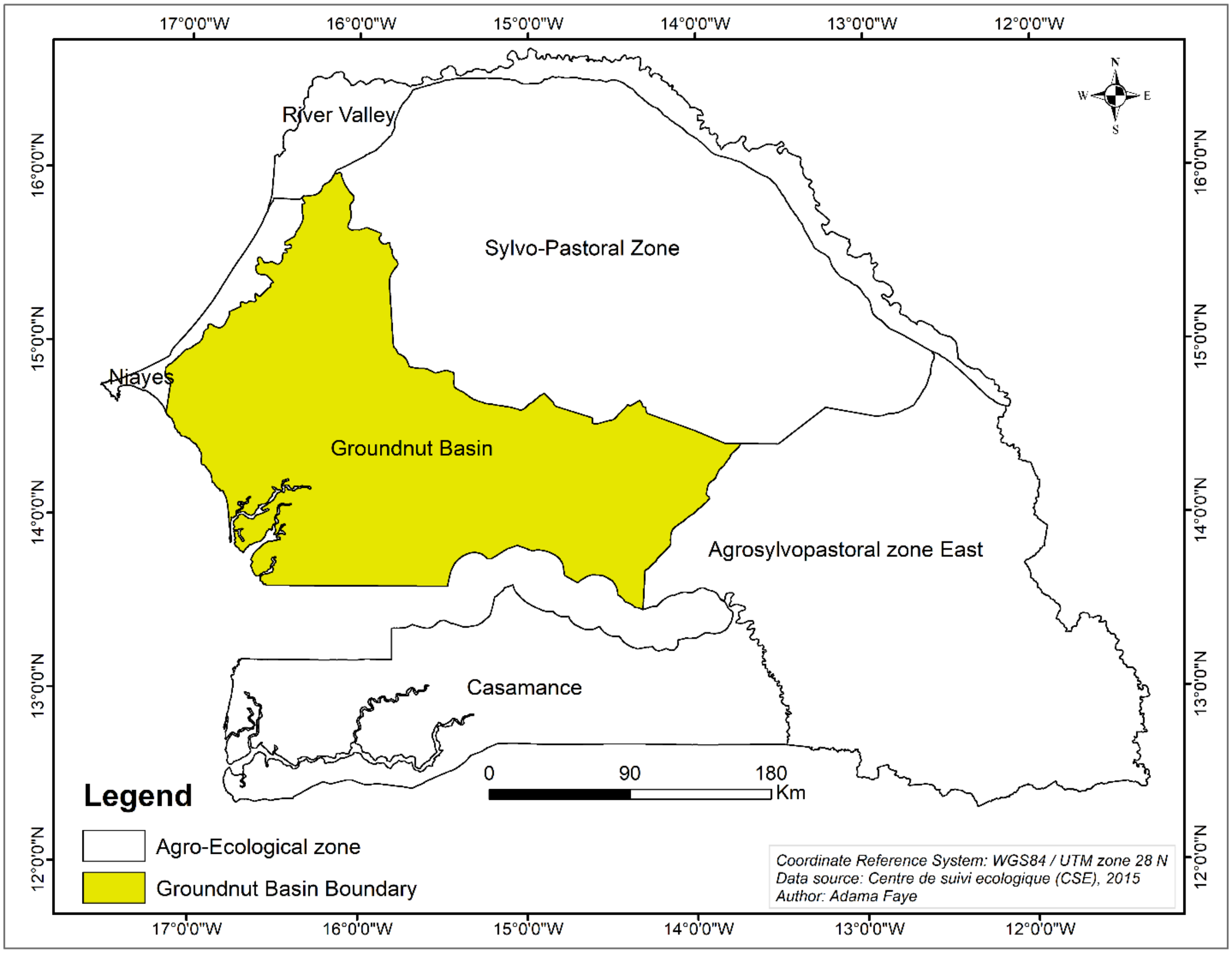


Figure 4- 1: The Agro-Ecological zones of Senegal showing the Groundnut Basin

4.4.2 Descriptive statistics

Table 4-2 presents the descriptive analysis of the included variables to create the resilience pillars. The latent variables representing each pillar of resilience, such as access to basic services, assets, social safety nets, and adaptive capacity, are assessed using observed variables from the questionnaire through factor analysis, and most of the variables are dummies. Having ABS, such as water source, evacuation mode, solid waste, lighting source, sludge removal mode, and health service distance, is a fundamental aspect of resilience. The table illustrates that, on average, 85% of households have access to water sources and 56% to electricity. On the other hand, less than 30% of households have access to evacuation mode, solid waste and sludge removal mode. Productive assets are crucial for livelihood, enabling households to produce consumable or tradable goods. Indicators for this include (the wealth index, agricultural wealth index and TLU).

Access to transfers, whether cash or in-kind, is a significant source of poverty alleviation in many developing countries, encompassing formal and informal transfers. We used food vouchers, cash assistance, food aid, sickness cover, and association participation to assess the social safety net. The descriptive statistics show that SSN is very low, with less than 3% of the households with all variables used. Adaptive capacity refers to the ability to adapt to a new situation and develop new sources of livelihood. Observable variables for adaptive capacity include (education level, dependence ratio, coping strategy, salary, and diversity of incomes). On average, 84% of the household heads went to school. On average, 96% of the households use coping strategies to address their level of food insecurity.

Table 4- 2: Descriptive statistics of the variables

Pillars	Variables	Mean	Standard Deviation
ABS	Water source	0.8538	0.3533
	Evacuation mode	0.0634	0.2438
	Solid waste	0.2906	0.4541
	Lighting source	0.5890	0.4920
	Sludge removal mode	0.2774	0.4477
	Health service distance	0.0600	0.1010
AST	Wealth index per capita	0.00711	0.0847
	Agricultural wealth index per capita	0.0080	0.1417
	TLU	1.2720	4.2670
SSN	Food voucher	0.0009	0.0315
	Cash assistance	0.1328	0.3395
	Food aid	0.0272	0.1628
	Sickness cover	0.0056	0.0749
	Association participation	0.3820	0.7935
AC	Education level	0.8458	1.0297
	Dependence ratio	7.5741	3.9818
	Coping strategy	0.9658106	0.8815907
	salary	370,110.7	1,608,635
	diversity of income sources	1.5534	0.7305

Note: This table presents a brief descriptive statistics of the variables used in our estimation.

Source: ENSANR 2019

4.4.2.1 Resilience Structure Weighting Variables

Figure 4-1 shows the simple correlation between the pillars of resilience and RCI measured by the Pearson correlation coefficient. It can be observed that, the most correlated pillars with the RCI are respectively access to basic services, adaptive capacity, assets and social safety nets. Therefore, any increase in these pillars leads to an increase in the RCI.

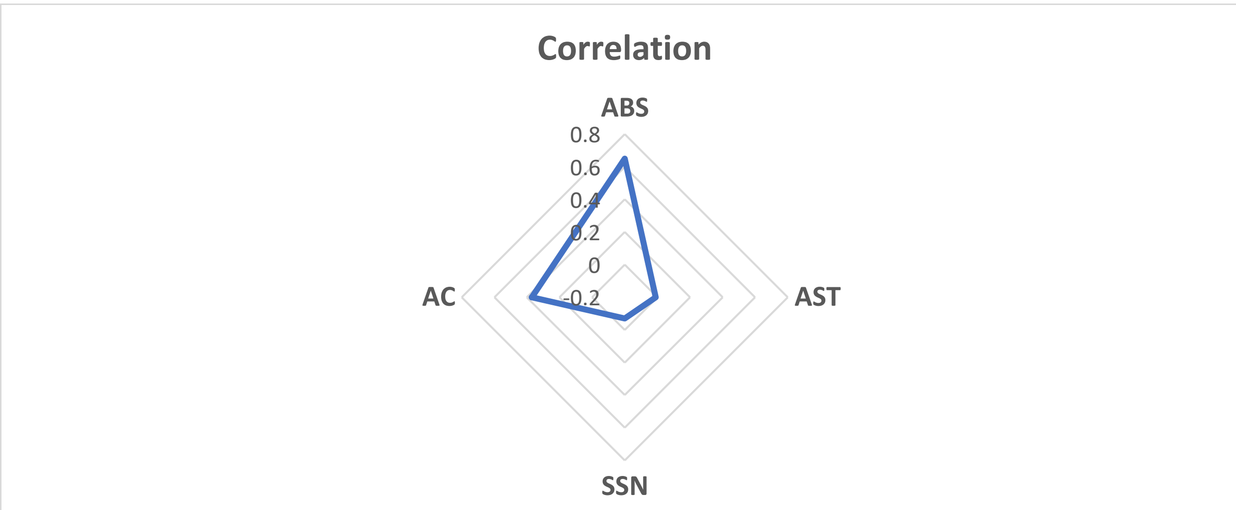


Figure 4- 2: Resilience structure- Correlation of pillars with RCI (ENSANR, 2019)

In figure 4-3, we present the weighting and correlation of variables as the pillars. The Figure reveals that the access to basic services (ABS) pillar, access to draining system, solid waste and electricity are the most correlated variables in this pillar. In fact, these variables, which strongly contribute to access to basic social services, are essential predictors of resilience, because they enable households to meet their basic needs to better cope with shocks. In terms of assets (AST), the agricultural index plays an important role in creating the asset pillar. The level of equipment and the number of livestock are equally important. Assets are crucial predictors of resilience, providing households with a buffer against shocks and the means to generate income or facilitate exchange. With regard to social safety nets (SSN), food assistance (cash, vouchers, food) are more correlated and contribute more to this pillar. Programs or mechanisms that assist vulnerable households during crises through cash transfers, vouchers and food distribution play an essential role in improving household resilience. For the adaptive capacity (AC) pillar, salary, level of education and coping strategies are the most important factors. Adaptive capacity is strongly influenced by education, skills and knowledge.

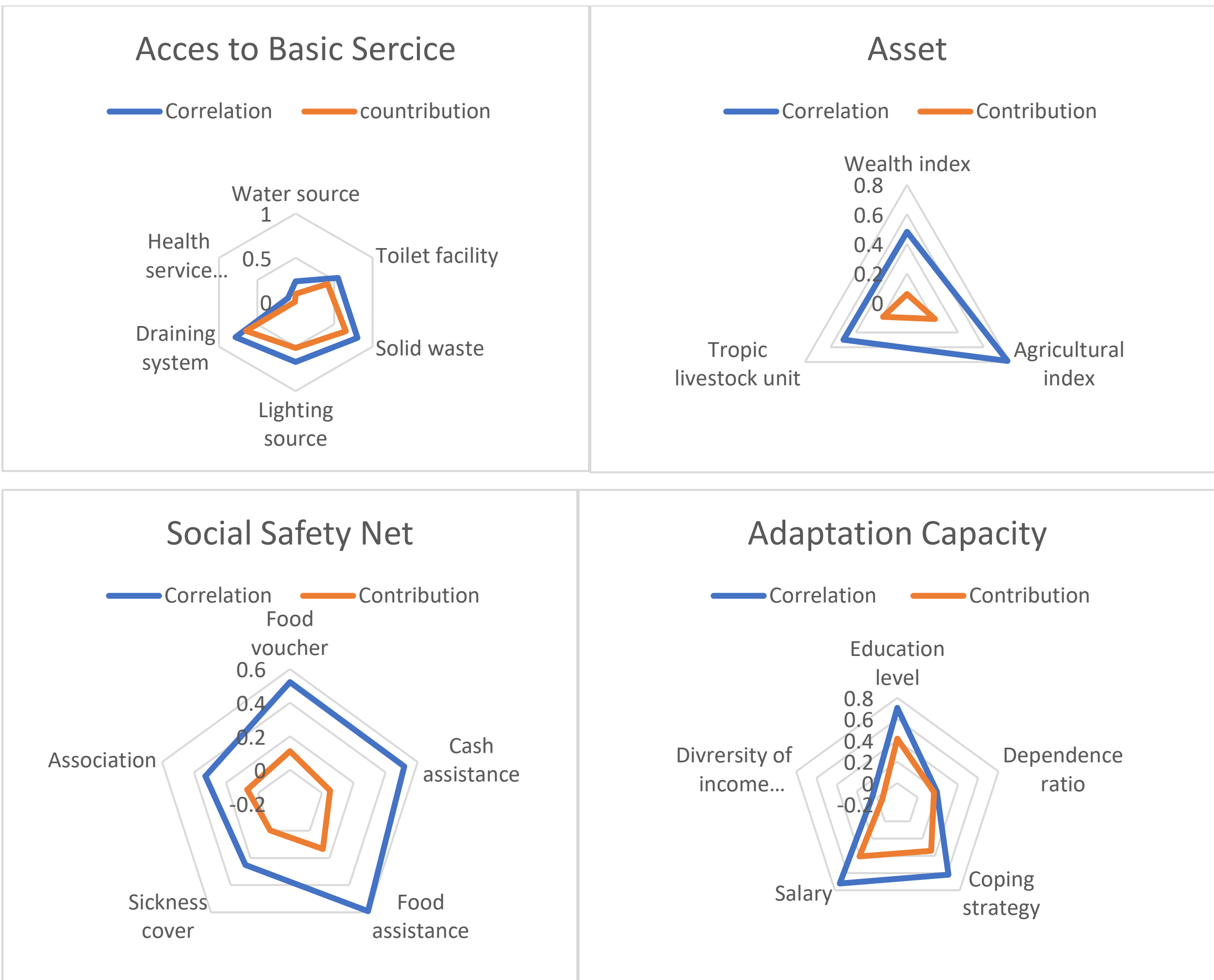


Figure 4- 3: Resilience structure-weighting and correlation of variables in the pillars (ENSANR, 2019)

4.5 Results and discussion

In this section, we present the results from the RCI estimations. The estimates of the drivers of resilience from MIMIC is first presented. This is followed by the estimates of the first and second stage of the 2SLS to account for the potential endogeneity and finally the results of the dose resposne fonction to account for the heterogeneity in the impacts of resilience on food insecurity in general and by gender.

4.5.1 Effect of pillar factors on RCI

In this section, we analyze the correlations between the RCI and the variables used to estimate the different pillars, in order to gain a better understanding of the main factors determining household resilience. For the pillar 'Access to basic services' , analysis of the results shows that better access to draining system, evacuation mode and electricity improves household resilience. Distance to the health services has a negative influence on resilience. However, for the AST, wealth index and TLU have a positive and significant impact on resilience, in opposite, agricultural index per-capita has negative impact on resilience. This unexpected result may be due to the fact that farming is more common in rural areas. In relation to the 'social safety nets' pillar, the variables relating to food assistance (voucher, cash, nature) are negatively correlated with resilience. However, the variables of health cover and association are positively correlated with resilience. Analysis of the model results shows that, in relation to the 'adaptive capacity' (AC) pillar, the variables used have almost all a positive effect on resilience. However, the diversity of income sources has a negative and none significant effect on resilience.

Table 4- 3: Effect of pillar factors on household's resilience

variables	RCI
ABS	
Drainging system	9.1217***(0.6465)
Evacuation mode	8.7813***(1.0352)
Lighting source	7.2266***(0.5464)
Solid waste	7.3346***(0.6332)
Principal water source	4.3657***(0.6538)
Health service distance	-14.4040***(2.2811)
AST	
Wealth index per capita	13.9161***(3.0186)
TLU	0.02690*** (0.0546)
Agricultural index per capita	-4.7191***(1.7827)
SSN	
Sickness cover	4.2477(3,0597)
Cash assistance	-4.2695***(0.6895)
Food aid	-.0123*(1.4137)
Food voucher	-1.7649 (7.2765)
Association	2.1876***(0.2939)
AC	
Education level	0.0878(0.2396)
Dependence ratio	0.0830 (0.0585)
CSI	1.7552***(0.2830)
Salary	9.26e-07***(1.51e-07)
Diversity of income sources	-0.2786 (0.3255)
Constant	32.8086***(0.9541)
Observations	3010
R-squared	0.4907

***Note**: * p < 0,1, ** p < 0,05, *** p < 0,01*

4.5 2 Resilience by Gender

In the sample, 81% of households are headed by a man, while 19% are headed by a woman. FHH register an average RCI of 58 while MHH score an average of 52. Analyzing resilience by gender shows that FHH is, on average, more resilient than MHH. This is in line with previous findings in the FAO resilience report for Senegal in 2005 and 2011 (FAO, 2017; FAO, 2018). This result could be linked with the localization of households; in fact, the majority of female-headed households are located in urban areas, where RCI is generally higher than in rural areas. According to the 2023 general population census, 78% of FHH in Senegal live in urban areas, which are better off in terms of resilience. In addition, FHH are less affected by poverty in Senegal. In 2021, 21.8% of people living in FHH were poor, compared to 42.7% of people living in MHH (ANSD, 2021).

4.5.3 Multiple Indicators Multiple Causes model results

The MIMIC model was estimated using the maximum likelihood (ML) method. The goal is to understand the relationship between a latent variable (RCI), observed exogenous variables (4 resilience pillars) and observed outcome indicators (FCS and HDDS). Table 2 below presents estimates of the MIMIC model for the resilience capacity index. The statistical section presents the results of the robustness test to the different methods. The Chi-square statistic is 23.565 with a p-value of 0.000, indicating a good fit of the model. The RMSEA, is 0.048, which is below the threshold of 0.05, suggesting a good fit, the probability of RMSEA is 0.542, providing additional support for a good fit (Brown, 1993). Also presented in the table are the TLI (0.984) and CFI (0.995) indices. The TLI measures the proportion of the variance explained by the model compared with the base model, while CFI compares the model with the base model. The two indices source specified indicate an excellent fit (values closer to 1 represent better fit). The results of the robustness test show that the model is validated.

Table 4- 4: *Results of the estimated Multiple Indicators Multiple Causes model for estimating household resilience index*

Covariates	ML
ABS	0.3495*** (0.0176)
AST	0.0902*** (0.0176)
SSN	0.0282 (0.0173)
AC	0.1645 *** (0.0187)
MEASUREMENT MODEL	ML
FCS	0.8622*** (0.0121)
HDDS	0.0946*** (0.0124)
STATISTICS	ML
OBSERVATION	3010
Chi-square	23.565
(P-value)	0.000
RMSEA	0.048
Probability RMSA<0.05	0.542
CFI	0.995
TLI	0.984

Note: Standard errors in parentheses, * p < 0,1, ** p < 0,05, *** p < 0,01

Source: ENSANR 2019

The variables representing resilience (ABS, AST, AC and SSN) are all positive, suggesting that an increase in these variables increases the resilience of households. However, the variable representing SSN, although positive, is not statistically significant. The results show that of all the pillars, ABS is the most contributory to resilience, followed respectively by AC, AST and SSN. In particular, a one standard deviation unit in the ABS pillar increases the resilience capacity index by 0.34 standard deviation units. The adaptive capacity and asset pillars also contribute significantly to the resilience of households in the Groundnut Basin. Thus, a one standard deviation increase in adaptive capacity and assets leads to an increase in the magnitude of the RCI of 0.16 and 0.09 standard deviations respectively. Concerning SSN which show any significance, the result is also in line with previous studies analyzing resilience in Senegal which find any significance for this pillar (FAO, 2016; SECNSA, 2017). These results are also in line with previous studies such as Ado et al., (2019) and Pietrelli (2018), who argue that ABS, AST and AC pillars exert significant influence on household resilience. Our empirical results further reveal a positive and statistically significant effect of resilience capacity index on food outcomes. Resilience serves as a mediating variable significantly influencing both FCS and HDDS in the study area. This suggests that households with higher resilience levels are more likely to have better food consumption patterns. Furthermore, these results suggest that households with a high level of ABS, AST and AC are more likely to be resilient to food insecurity in the study area, findings that are in line with research on household resilience by Bezabih (2021), who found similar results.

4.5.4 Household resilience capacity and food security

In this section, we present the estimates from the 2SLS regression analysis in Table 3. The results provide valuable insights into the factors influencing Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS) in the context of resilience measurement. The first-stage regression reveals a statistically significant relation between the RCI and the set of instruments (i.e.), fulfilling the instrumental variable relevance assumption. Religious faith is a key factor in fostering resilience (Greeff & van der Merwe, 2004). The number of religious brotherhood groups shows a highly significant and positive relationship, indicating that an increase in these groups is associated with a higher RCI. In contrast, the coefficient for distance to mosques or churches is statistically significant and negative, suggesting that being closer to places of worship is also associated with higher RCI. The results also show that female-headed households' resilience capacity index is higher by 7.16, compared to male-headed household's resilience capacity index. Older household heads tend to be more resilient. In particular, an increase in age by one year, increases the RCI by 0.14 units. Being older is associated with increased experience in earning income and managing shocks. These findings are consistent with the findings from research by d'Errico & Pietrelli (2017). However, households that experience shocks (theft or death of livestock) tend to be less resilient.

The second-stage regression results from the 2SLS show a positive relationship between resilience capacity and food consumption and household dietary diversity score, implying that, higher RCI increases the outcome indicators on average by 0.01 in food consumption and 0.03 in dietary diversity. This suggests that improved resilience capacity significantly enhances the food consumption score and dietary diversity score, implying better food security as resilience increases. These results reinforce previous empirical research, demonstrating that increased household resilience leads to a reduction in food insecurity levels (D'Errico et al., 2018). The relationship between shocks and food security outcomes appears to be rather complex. The rainfall anomaly, represented in Table 3 by SPI, is negative and significant. In particular, a unit increase in SPI reduces the FCS and the HDDS by 0.005 and 0.019, respectively. The coefficients of the variables representing shocks from livestock theft are negative and statistically significant, suggesting that when livestock get stolen, the food consumption tends to decrease by 0.05, while the HDDS falls by 0.14. These results indicate that higher climatic or economic shocks tend to exacerbate the household food and nutrition insecurity status. Gender of the household head does not appear to have any significant impact on FCS. However, the results show that households led by women have higher dietary diversity scores, probably because women tend to have more information on nutrition aspects.

Table 4- 5: Two-Stage Least Squares models of food security outcomes

		FCS	**HDDS**
	First stage	**Second stage**	**Second stage**
RCI		0.0109*** (0.0011)	0.0341 *** (0.0038)
Occupation status	-0.1142 (0.6607)	0.0024 (0.0095)	0.0287 0.0319
Female-headed HHS	7.1605*** (0.7850)	-0.0229 (0.0149)	0.0876* 0.0496
Age	0.1432*** (0.0224)	0.0002 (0.0003)	-0.0013 (0.0012)
Rainfall anomaly (SPI)	0.1401 (0.2263)	-0.0054* (0.0032)	-0.0194* (0.0109)
Theft livestock	-2.3784* (1.4132)	-0.0552*** (0.0206)	-0.1416** (0.0686)
Death livestock	-3.4557** (1.3798)	-0.0374* (0.0204)	-0.0646 (0.0679)
Instruments			
Number of religious groups	1.2561*** (0.3057)		
Distance to the mosque/church	-1.9332*** (0.1690)		
cons	40.7856*** 3.4648	3.6802*** 0.0669	4.6846*** 0.2227
R-squarred	0.1013	0.5293	0.4690
Wu-Hausman		17.2367***	7.701***
Observations		3010	

Note: Standard errors in parentheses, * $p < 0,1$, ** $p < 0,05$, *** $p < 0,01$

Source: ENSANR 2019

The instrumental variable test statistic (Wu-Hausman) is significantly different from zero, supporting the validity of the instruments.

4.5.5 Impact of RCI on food security indicators

A significant motivation of this study is to assess whether households are resilient to food insecurity and how this effect varies based on their resilience capacity. To achieve this, we present the estimation results of key treatment effect parameters in **Table 4-6** for the FCS and the HDDS, respectively, and we also illustrate the estimated dose-response functions in **Figure 4-4**. The RCI has a statistically significant positive impact on both FCS and HDDS, as indicated by the positive average treatment effect (ATE) values. This means that, on average, a percentage increase in RCI intensity in a randomly selected household increases the FCS and HDDS by 4% and 16%, respectively. Concerning the average treatment effect on treated (ATET), among households with positive RCI value, a percentage increase in RCI intensity increases the FCS and HDDS by 8% and 26%, respectively. The average treatment effect on non-treated (ATET) values is higher than the ATE values for both FCS and HDDS, indicating that the resilience capacity is particularly effective for those with higher resilience. However, if the household had no positive RCI value (ATENT), a percentage increase in RCI intensity decreases the FCS and HDDS by 152% and 336% respectively. This highlights the importance of resilience capacity in maintaining food security and dietary diversity, as the lack of resilience is associated with substantial negative outcomes. The results imply that increasing resilience capacity generally improves food security indicators for the overall population and particularly for those who are already resilient. The estimates reveal that ATET >ATE >ATENT, implying a positive selection effect, where those with higher resilience capacity benefit more from increases in RCI.

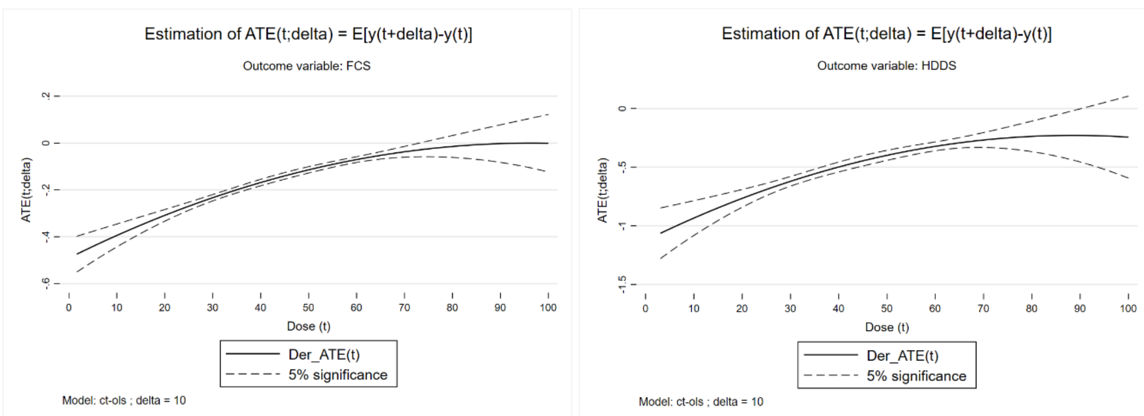
Table 4- 6: Estimates of Treatment Effects Parameters

Parameters	FCS	HDDS
ATE	0.0464*** (0.0096)	0.1640*** (0.0322)
ATET	0.0824*** (0.0131)	0.2677*** (0.0390)
ATENT	-1.5200*** (0.0815)	-3.3655*** (0.2716)
Number of observations	3010	

Note: This table displays the estimates for various treatment effect parameters: ATE (average treatment effect), ATET (average treatment effect on the treated), and ATENT (average treatment effect on the untreated). Standard errors for ATET and ATENT, shown in parentheses, are derived from 200 bootstrap simulations. Significance levels are indicated as follows: *p < 0.1, **p < 0.05, ***p < 0.01.

Source: ENSANR 2019

The results above show evidence of heterogeneity in the effects of RCI on FCS and HDDS. To shed more light on this relationship, we present in Figure 4-5 the estimated dose-response functions of FCS and HDDS at each resilience level, together with the 95% confidence interval bounds. The outcomes demonstrate a positive relationship between RCI and intensity of FCS and HDDS. Figures 4-4 A and B particularly show non-linear relationships, where the outcomes first increase with increasing RCI, until a maximum and then decline slightly.



A. Curve for FCS *B. Curve for HDDS*

Figure 4- 4: Estimated dose-response functions (ENSANR, 2019)

4.5.6 Impact of RCI on food security indicators by gender

The comparative analysis of dose-response function results for resilience capacity index (RCI) on food security indicators (FCS and HDDS) across genders (female and male-headed households) and the aggregated data reveals several interesting insights. The ATE shows a significant positive effect of resilience on both food consumption and dietary diversity for randomly selected male-headed and female-headed households. However, the effect on dietary diversity (HDDS) is more pronounced for female-headed, compared to male-headed households. This suggests that increased resilience capacity generally improves dietary diversity for both male and female-headed households, with a stronger effect observed in female-headed households. Similarly, the estimated ATET is significantly positive for all food security indicators for both genders, with female-headed households showing larger impacts. This indicates that resilience effectively enhances food consumption scores among those who receive the treatment (RCI). In terms of dietary diversity, treated female-headed households show a much stronger positive impact than treated male-headed households, indicating that resilience interventions are particularly effective in improving dietary diversity among female-headed households. Regardless of the gender of the household head, ATENT is negative and statistically significant, implying that non-treated households would experience substantial adverse impacts of RCI on food security indicators, with females showing a larger negative effect. In terms of HDDS, significant negative effect for female-headed households, although larger in magnitude, indicating substantial potential adverse impact for non-treated female-headed households.

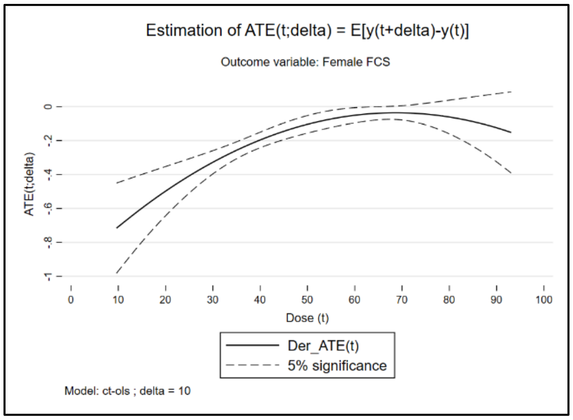
Table 4- 7: Estimates of Treatment Effects Parameters by Gender

	Female		**Male**	
Parameters	Ln_FCS	HDDS	Ln_FCS	HDDS
ATE	0.0406* (0.0234)	0.2186*** (0.0820)	0.0490*** (0.0114)	0.1577*** (0.0358)
ATET	0.0914*** (0.0318)	0.3909*** (0.1046)	0.0831*** (0.0144)	0.2582*** (0.0444)
ATENT	-2.4347*** (0.3143)	-5.8082*** (1.0799)	-1.4395*** (0.0808)	-3.1912*** (0.2971)
Number of observations	568		2442	

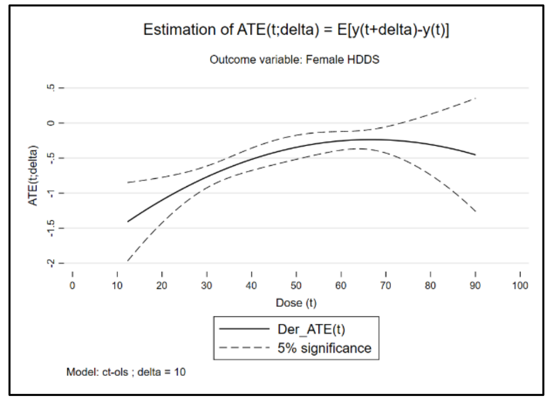
*Note: This table displays the estimates for various treatment effect parameters: ATE (average treatment effect), ATET (average treatment effect on the treated), and ATENT (average treatment effect on the untreated). Standard errors for ATET and ATENT, shown in parentheses, are derived from 200 bootstrap simulations. Significance levels are indicated as follows: *p < 0.1, **p < 0.05, ***p < 0.01.*

Source: ENSANR 2019

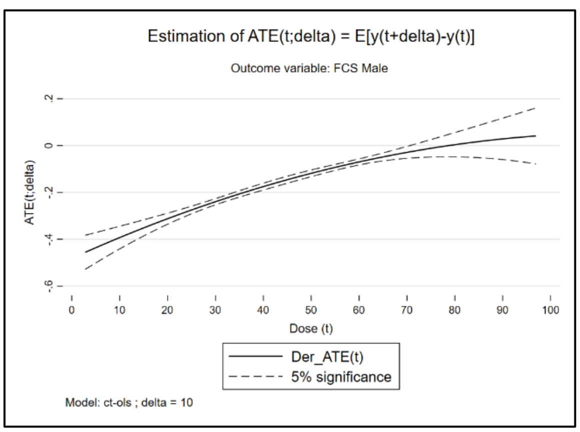
RCI has a positive and significant impact on both FCS and HDDS, with a particularly strong effect on HDDS. Female-headed households appear to benefit substantially from increased resilience capacity in terms of dietary diversity. RCI also has a positive and significant impact on both FCS and HDDS for Male-headed households. The effects are significant, but slightly less pronounced compared to Female-headed households. Treated individuals (both female- and male-headed households) experience greater increases in food consumption and dietary diversity, with increased resilience capacity. The positive ATET values highlight the effectiveness of resilience capacity in improving food security and dietary diversity among those who have higher resilience. Non-treated households (both female- and male-headed households) suffer substantial declines in food consumption and dietary diversity. The negative ATENT values underscore the critical need for resilience-building interventions to prevent significant negative outcomes.



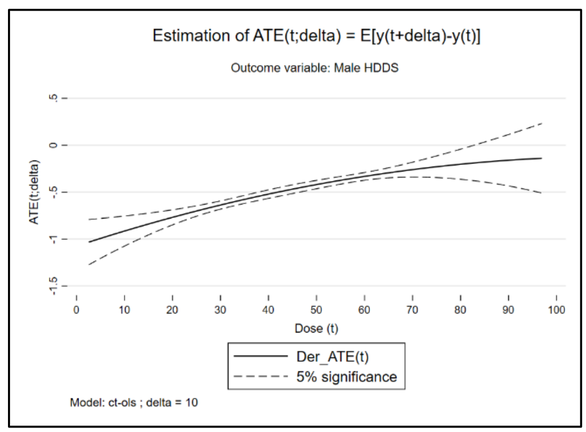
A.Curve for female FCS



B. Curve for female HDDS



C. Curve for male FCS



D. curve for male HDDS

Figure 4- 5: Estimated dose-response functions by gender of household head (ENSANR, 2019)

The ATE increases with the dose initially, indicating that as the RCI increases, the Female FCS and HDDS improves. After reaching a certain point, the ATE starts to plateau and then slightly decreases, suggesting diminishing returns or possible negative effects at very high doses. The optimum women resilience is between 60 and 70, with any other dose likely to have negative effects on FCS and HDDS. The results suggest that while resilience is generally beneficial for female-headed households, there are limits to its effectiveness, and other factors, may need to be considered to further improve food security beyond a specific level. However, for male-headed households, the curves show that the higher the dose (RCI), higher the ATE of the food security indicators (FCS and HDDS). This curve shows also the heterogeneity of RCI on food security indicators across gender.

4.6 Conclusion and Policy Implications

The study examines the heterogeneous impact of resilience on food and nutrition security by gender. This study applies the RIMA II analytical framework, the two stage least square (2SLS) that analyze the impact of the Resilience Capacity Index (RCI) on food security indicators by addressing potential endogeneity and the dose response analysis to understand the relationship between the "dose" (the level of the Resilience Capacity Index, RCI) and the "response" (FCS and HDDS) . In particular, we use household-level data from Senegal to analyze the causal relationship between household resilience and food security. Our empirical results show that ABS, AST and AC affect positively and significantly households' resilience to food insecurity. FHH are more resilient than male-headed ones. The results from the 2SLS underscore the importance of resilience in improving food security outcomes. Higher RCI positively influences food and nutrition security indicators (FCS and HDDS). In contrast the finding underscore that the rainfall anomaly (SPI) and theft or death of livestock have a negative and significant effect on households' resilience capacity and on food and nutrition security indicators (FCS and HDDS). The dose response analysis reveals substantial heterogeneity in the impact of resilience capacity index on food and nutrition security of households by gender headed. While the impact is generally positive across both genders, female-headed households benefit substantially more from increased RCI in terms of food security outcomes, but show a higher potential adverse effects for them when they are non-treated. Continuous monitoring and evaluation are essential to adapt and refine interventions, considering the significant heterogeneity in treatment effects.

By understanding and leveraging the distinct impacts on females and males, programs can be more effectively designed to improve food security outcomes and build resilient communities. Policymakers should focus on strengthening resilience through targeted interventions, addressing the specific needs of vulnerable groups, enhancing gender-sensitive policies, mitigating the impact of shocks and scaling successful initiatives. By adopting these comprehensive and targeted measures, policymakers can enhance the resilience of households and communities, ultimately leading to improved food security and well-being.

CHAPTER 5: GENERAL CONCLUSION AND POLICY IMPLICATIONS

5.1 Introduction

The impacts of climate-related shocks on agriculture and the implications for food and nutrition security are already severe. They are expected to worsen over time, if nothing is done, with varying effects across different regions, especially in the Sahel region. Additionally, the degradation of arable land and declining agro-ecosystem conditions further reduces food production. These persistent challenges threaten agriculture’s capacity to meet the needs of a rapidly growing global population, hindering progress toward achieving the Sustainable Development Goals (SDGs) of eradicating hunger, undernutrition, and poverty by 2030. This thesis investigates the resilience of rural households to food insecurity in Senegal's Groundnut Basin, a region affected by climate variability and shocks. The research focuses on the impacts of erratic rainfall, droughts, and rising temperatures on agricultural productivity, household food security, and resilience. It explores how rural households respond to these climate-induced challenges through adaptive strategies, such as crop and livelihood diversification, and examines the role of community-based approaches. By doing so, it aims to identify key drivers that strengthen resilience against food insecurity and provide insights into the policy frameworks required to support rural farmers in mitigating climate risks. The specific objectives of this research were threefold: (i) to conduct an analysis of climate-related risks and agriculture yield assessment in the Senegalese Groundnut Basin; (ii) to analyze the impact of crop diversification in mitigating climate-related risk and improving welfare in the Senegalese Groundnut Basin, and (iii) To measure the resilience of these households in coping with food insecurity under climate variability.

To address these objectives, three main research questions were formulated: (i) what are the major climate-related risks affecting agricultural yield to which the rural populations in the Senegalese Groundnut Basin are exposed? (ii) how does crop diversification help in mitigating climate-related risks and improving welfare in the Senegalese Groundnut Basin? (iii) what is the level of resilience to food insecurity of households in the Senegalese Groundnut Basin? This research aims to analyze the resilience to food insecurity of rural households in the Senegalese Groundnut Basin in relation to climate-related risks.

Using a sample of 3,100 households, the research applied various data analysis techniques to answer these questions. Each chapter of the thesis (chapters 2 through 4) focused on a specific aspect of these questions, presenting detailed empirical evidence. This concluding discussion explores the findings within a broader context, showing how they contribute to the existing literature on climate variability and resilience to food insecurity. The research also highlights potential avenues for future studies and offers significant policy implications.

Ultimately, this research contributes to a better understanding of how rural households in Senegal can enhance their resilience to climate-induced food insecurity. By identifying key adaptation strategies, such as crop diversification, and emphasizing the role of targeted policies, it provides a pathway for developing more resilient agricultural systems that can better withstand the adverse effects of climate change. The findings are relevant for Senegal and have broader implications for other regions facing similar challenges.

5.2 Links between topics covered

Understanding the intricate relationship between climate-related risks, agricultural yield, crop diversification, and household resilience is essential for developing sustainable strategies to enhance food security and rural welfare in the Senegalese Groundnut Basin. These three elements are deeply interwoven, forming a complex system where each component influences and is influenced by the others. Climate variability and extreme weather events pose significant threats to agricultural production, particularly in rainfed agricultural systems. These climatic shocks directly impact agricultural yield, which in turn affects household food security and overall welfare. As a response, farmers adopt risk-mitigating strategies such as crop diversification, which serves as a crucial adaptation mechanism to climate risks and an avenue for enhancing resilience.

The increasing frequency and intensity of climate-related risks such as droughts, erratic rainfall, temperature fluctuations, and soil degradation pose a severe threat to agricultural productivity in Senegal's Groundnut Basin. Given the region's dependence on rainfed agriculture, any disruption in climate patterns can lead to significant yield losses, affecting staple crops like groundnut, millet, and maize. These climatic shocks exacerbate food insecurity by limiting production volumes, reducing household incomes, and increasing the volatility of local food supply. Furthermore, climate-induced variability in yield creates economic uncertainty, compelling households to adopt alternative strategies to safeguard their food security and livelihoods.

In response to climate-related risks, crop diversification emerges as a crucial adaptation strategy that enhances agricultural resilience and stabilizes food production. By cultivating multiple crops with different climatic requirements and growth cycles, farmers can reduce their dependence on any single crop, thereby mitigating the risk of complete yield failure due to adverse weather conditions. Crop diversification not only contributes to food security but also plays a vital role in improving household nutrition by increasing dietary diversity. Moreover, the economic benefits of diversification extend beyond direct food consumption; diversified farming systems create opportunities for market engagement, enhancing rural incomes and economic stability. Additionally, access to agricultural inputs, such as improved seeds, fertilizers, and climate-smart technologies, further strengthens the effectiveness of diversification in mitigating climate risks.

While crop diversification enhances the adaptive capacity of households, resilience to food insecurity is shaped by multiple factors, including access to basic services, assets, social safety nets, and adaptive capacity. The ability of rural households to withstand and recover from climate shocks depends on their overall resilience capacity, which determines their long-term food security and welfare outcomes. Resilience is not merely the capacity to cope with shocks but also the ability to transform and improve household livelihoods despite recurring environmental and economic challenges. Social and economic factors, such as market access, infrastructure, institutional support, and gender dynamics, play a crucial role in shaping resilience outcomes.

The interconnected nature of climate risks, agricultural productivity, crop diversification, and household resilience highlights the need for an integrated policy framework that addresses these challenges holistically. By fostering climate adaptation, promoting diversified farming systems, and enhancing resilience-building mechanisms, Senegal can move towards a more sustainable and food-secure agricultural landscape in the face of ongoing and future climate challenges.

5.3 Summary of research findings

Research Question 1: what are the major climate-related risks affecting agricultural yield to which the rural populations in the Senegalese Groundnut Basin are exposed?

Chapter 2 analyses climate change and variability, which pose significant threats to agricultural production, particularly in regions heavily dependent on rainfed agriculture like Senegal. The problem being addressed in this chapter revolves around the impact of climate-related risks on agricultural yields in the Senegalese Groundnut Basin, a key agricultural region. Daily rainfall, temperatures, and yield over 1991-2020 are used. The study finds that overall seasonal precipitation is increasing in the Groundnut Basin, though at a slower rate in the south. The northern zone has a more consistent and predictable growing season, while the southern zone shows higher variability. Both regions are experiencing a warming trend, with the south seeing a greater increase in maximum temperatures compared to the north. Regression analysis reveals that total seasonal precipitation and maximum temperature positively affect yields of groundnut, millet, and maize in both zones, though other weather factors vary in their influence. These findings emphasize the diverse climatic conditions across the study area and the significant impact of climate on crop yield variability.

Research Question 2: How does crop diversification help in mitigating climate-related risks and improving welfare in the Senegalese Groundnut Basin?

To contribute to the existing literature, Chapter 3 utilizes the Marginal Treatment Effects (MTE) approach to examine the heterogeneous treatment effects of crop diversification on food and nutrition security and poverty among rural households, using farmer-level data from Senegal. This approach accounts for treatment effect heterogeneity arising from both observed and unobserved characteristics. It estimates a range of treatment effects across the entire distribution of farmers' unobserved resistance to adoption. Additionally, it reveals patterns of selection and enables the estimation of several key economic parameters: the average treatment effect (ATE), the average treatment effect on the treated (TT), and the average treatment effect on the untreated (TUT). The results show that farmers with a higher propensity to adopt crop diversification gain more in terms of their food security status and poverty reduction status, even under climatic shocks, compared to their lower propensity counterparts. The policy-relevant treatment effect (PRTE) shows the effects of reducing distance to the input market on food security and poverty indicators.

Research Question 3: what is the level of resilience to food insecurity of households in the Senegalese Groundnut Basin?

Chapter 4 investigates the heterogeneous impact of household resilience on food and nutrition security, using household-level data from Senegal and RIMA tools developed by FAO. It addresses potential endogeneity between RCI and food security outcomes, ensuring the consistency of the estimates through 2SLS estimation. This method enables the estimation of a causal relationship between the outcome variables and different levels of the applied dose (i.e., RCI). Additionally, it allows for the calculation of other important causal parameters, including the average treatment effect (ATE), the average treatment effect on the treated (ATET), and the average treatment effect on the untreated (ATENT). The RIMAII reveal that access to basic services, assets and adaptive capacity pillars are all significant predictors of resilience. Female-headed households are more resilient than men-headed ones. The results reveal also that higher resilience capacity leads to better food security outcomes. However, the results highlight the general heterogeneous positive impact of the dose (RCI) across both genders. Female-headed households benefit substantially more from increased RCI in terms of food security outcomes but show bigger potential adverse effects for them when they are non-treated.

5.4 Theoretical and empirical contribution and avenues for future research

This research makes significant contributions to both the theoretical and empirical understanding of climate variability, crop diversification, resilience to food insecurity and rural household welfare, particularly in the Senegalese Groundnut Basin.

5.4.1Theoretical Contribution:

The study integrates the concept of resilience into the climate change-food security discourse by providing a theoretical model that connects climate variability with household welfare through crop diversification. This framework contributes to existing resilience theory by showing how both covariate and idiosyncratic shocks can affect food security, and how diversification strategies can act as a buffer. The research highlights the critical role of distance to input markets in shaping farmers' capacity to adopt resilient agricultural practices, such as crop diversification. Access to agricultural inputs, including seeds, fertilizers, and climate information, is shown to be a key factor influencing the success of resilience-building strategies, particularly in regions affected by climate variability like Senegal’s Groundnut Basin. This insight underscores the importance of market infrastructure in determining the adaptive capacities of rural households, as proximity to input markets enhances the ability of farmers to adjust their agricultural practices in response to climate shocks. This perspective extends the understanding of how improving market access can play a central role in strengthening resilience and promoting sustainable agricultural development under climatic stress. By focusing on market accessibility, the study offers a practical pathway for policymakers to enhance agricultural productivity and household welfare by prioritizing investments in rural market infrastructure and reducing geographic barriers to essential agricultural resources.

Another major theoretical contribution of this thesis is the adoption of a multi-dimensional approach, incorporating climate shocks, crop diversification, market accessibility, and household adaptability to better understand how rural households cope with and recover from food insecurity. This study contributes to resilience theory by framing food insecurity as a dynamic process influenced by both idiosyncratic (household-specific) and covariate (community-wide) shocks, providing a more nuanced understanding of vulnerability. The analysis shows that resilience is not just about immediate recovery from food insecurity but about the ability to adapt and build long-term capacity to withstand future shocks. By incorporating pillars like access to basic services, asset, social safety net and adaptive capacity, the research broadens the traditional scope of resilience theory.

Furthermore, the study highlights the importance of gender dynamics in resilience, showing that female-headed households, often considered more vulnerable, may exhibit higher levels of resilience under certain conditions. This gendered dimension of resilience offers a new theoretical angle that can inform future research and policy frameworks aimed at enhancing food security in vulnerable regions.

5.4.2 Empirical Contribution:

The study adds to the empirical literature on food security and resilience by providing extensive household-level data from the Groundnut Basin, a region that has not been extensively studied in climate resilience research. The analysis of 3100 households offers robust evidence of how climate variability influences crop yields, poverty, and food security.

The study's findings aim to inform policy processes and help reorient farming systems to better support the shift towards crop diversification, improving the livelihoods of low-income farm households and strengthening the resilience of agrifood systems, particularly in the context of climate change. Senegal has made strides in integrating climate-smart agriculture into its national development plans, agricultural policies, and initiatives through the National Climate Change Policy (NCCP). The country has also aligned its policies with sub-regional climate initiatives such as the Climate Change, Agriculture, and Food Security (CCAFS) program. These coordinated efforts address barriers to the adoption of climate-smart technologies. Notably, Senegal's Nationally Determined Contributions (NDCs) include specific sections on mitigation and adaptation in the agriculture sector, which are critical for building the resilience of smallholder farmers, reducing emissions, and creating synergies with other sustainable development goals, such as ending hunger and reducing poverty. This dissertation provides microeconomic evidence on the benefits of crop diversification, offering insights to improve policy formulation and guide project implementation.

Crop diversification can significantly improve household welfare, suggesting that policies and programs must continuously integrate crop diversification as an essential component and facilitate its adoption by providing low-income farm households with incentives through improved access to seeds and fertilizers, weather information and extension services. Furthermore, this research employs an innovative PRTE approach, which allows policymakers to understand the effect of crop diversification under increasing access to markets. It demonstrates the importance of geographically-targeted interventions to enhance resilience. The study breaks new ground by providing a gendered analysis of resilience to food insecurity. It reveals that female-headed households, although more resilient, face different challenges compared to male-headed ones, underscoring the need for gender-sensitive policies in climate adaptation. In addition, this work is a valuable contribution to Senegal's second Sustainable Development Goal (SDG): "Eradicate hunger, ensure food security, improve nutrition and promote sustainable agriculture". Indeed, this work could help improve the monitoring and evaluation tools of Senegal's National Strategy for Food Security and Resilience (SNSAR), which aims to "Ensure sustainable food security and greater resilience to shocks for Senegalese populations by 2035". This study will help to better inform the decisions of governments and their development partners in designing food security and climate change policies.

5.4.3 Avenues for Future Research

While this study provides a cross-sectional snapshot of resilience to climate change and food security, future research could explore:

-Longitudinal data to better understand the dynamic nature of resilience over time. This would allow for a deeper analysis of how households' resilience to food insecurity evolves in response to repeated climatic shocks.

-Beyond crop diversification, future studies should investigate the role of other adaptive strategies, such as the adoption of climate-smart agricultural technologies or changes in livestock practices, in enhancing household resilience.

-There is need for comparative research that examines how the findings from Senegal's Groundnut Basin compares to findings in other regions of sub-Saharan Africa. A regional comparative study could highlight the role of different climatic conditions, agricultural practices, and policy environments in shaping resilience to climate shocks.

-Future research could delve deeper into the role of climate information services in enhancing resilience, particularly examining how real-time access to weather forecasts and agricultural advice influences decision-making at the farm level.

-Research could explore the intersection of indigenous knowledge and modern technological interventions, assessing how traditional farming knowledge interacts with innovations like precision agriculture to enhance resilience.

5.5 Implications and Recommendations for Policy and Farmers

The findings of this study offer significant implications for both policymakers and farmers, particularly in addressing the challenges posed by climate change in the Senegalese Groundnut Basin. First, understanding the influence of climate variability on crop diversification is essential for formulating targeted agricultural policies and adaptation strategies that mitigate risks and promote sustainable productivity. The results suggest that crop diversification can serve as an effective coping mechanism, helping farmers enhance food security and reduce poverty in the face of changing climatic conditions. Policymakers should prioritize support for crop diversification, enabling it to serve as a cornerstone for climate-resilient agricultural systems, provide access to diverse seed varieties, training, and financial incentives for crop diversification can be effective.

A key policy recommendation is the provision of improved access to climate information services. By equipping farmers with timely and accurate data on weather patterns and climate risks, they will be better positioned to make informed decisions, adjust farming practices, and adopt strategies that ensure stable yields. These services should be tailored to the needs of smallholder farmers in rural regions and integrated into broader agricultural development initiatives.

In addition, the study highlights the importance of strengthening market infrastructure to enable farmers to efficiently market their diversified crops. Investments in rural infrastructure, such as roads and transportation networks, will facilitate easier access to markets, enabling farmers to purchase inputs and sell their produce more effectively. This will help increase household income and food security. By establishing resilient value chains, governments can ensure that diversified crops reach broader markets, further encouraging farmers to adopt climate-smart practices.

Gender-sensitive policies are also critical. The study shows that resilience-building programs must address the distinct needs and capacities of both men and women. Tailoring programs to gender differences will help ensure the equitable distribution of resources and benefits, amplifying the positive impact on resilience and minimizing adverse effects on households that are not reached by these initiatives.

Lastly, investments in agricultural financing and climate insurance mechanisms for smallholder farmers, especially women and youth, should be prioritized to further enhance resilience and foster long-term food security. Such programs should align with national frameworks like the Plan Senegal Emergent (PSE) and National Strategy for Food Security and Resilience (SNSAR) to ensure holistic agricultural development and climate adaptation.

By implementing these strategies, Senegal can improve the resilience of its agricultural sector, helping to safeguard food and nutrition security even under adverse climate conditions.

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APPENDICES

Appendice 1

Metadata from the ENSANR survey

Summary

The Government of Senegal conducted the Integrated Food Security, Nutrition and Resilience Survey (ENSANR) between January and February 2019. This nationwide survey followed the SMART model and was organized in close collaboration with the Ministry of Health and Social Action (MSAS). ENSANR was designed as a stratified two-stage sample survey. The sample sizes were calculated using the ENSANR ENA software, version of July 2015. The Agence Nationale de la Statistique et de la Démographie (ANSD) drew the sample using the 2013 RGPHAE sampling frame. Random draws of enumeration areas (RDs) and households were carried out systematically. All children aged 0 to 59 months within each selected household were included in the sample. Data collection was conducted using tablets and the SapMobil application. The data were transmitted daily to a central platform to assess the quality and completeness, with feedback provided to field supervisors and team leaders. The ENSANR survey is scheduled to be repeated every five years.

Data and geographical coverage

The survey collected data from the sampled households, the households being the units of analysis. Several aspects were covered, including household characteristics, living conditions, food consumption, income and expenditure, shocks and coping strategies, as well as anthropometric measurements for women and children. Additional focus areas included infant and young child feeding practices and the iodization of salt. The geographical coverage of the ENSANR survey extended across the 14 regions and 45 departments of Senegal. The geographical unit of analysis was the department, and the universe included all ordinary rural and urban households within the surveyed areas. Three main questionnaires were used for the survey: a household questionnaire, a child questionnaire for children aged 0 to 59 months, and an anthropometry questionnaire for women aged 15 to 49 years.

Producers and sponsors

The principal investigator of the survey was the SE-CNSA, supported by the Maternal and Child Health Department. Funding was provided by several organizations and partners, including WFP, FAO, UNICEF, DRIAS, P2RS, USAID, the Canadian government, Nutrition International, ACF, the Government of Senegal, and Helen Keller International.

Sampling method and response rate

The survey employed a two-stage systematic random cluster sampling method. In the first stage, RDs were selected through systematic random draws with a probability proportional to the population size of the primary sampling units, stratified independently for each stratum. The second stage involved selecting households within the sampled districts using a systematic random approach and a specified sampling step (P). The final sample consisted of 16 strata, 515 census districts (CDs), 7,847 households, 11,684 children under the age of five, and 12,783 women aged 15 to 49 years.

There were minor deviations from the planned sample design. Specifically, 0.2 percent of Dakar's RDs were not visited, and 5.2 percent of the planned households were not surveyed. However, full coverage was achieved in the Diourbel, Fatick, Kaffrine, and Kolda regions. The response rate was 99.8 percent for RDs and 94.8 percent for households. Weighting adjustments were made, with weighting factors referred to as Weight_DR.

Data collection

Data collection took place from January 28 to February 20, 2019, across 25 survey cycles. The fieldwork was carried out by 32 teams, each composed of four agents: two interviewers and two anthropometric measurers. Two pairs of interviewers worked independently within each stratum, with one interviewer in each pair trained in the use of tablets and the other specializing in anthropometric measurement. The questionnaires were digitized and deployed on tablets using the SapMobil version 1.6v application, developed in WLanguage and JAVA. In addition to the electronic version, a paper version of the anthropometry questionnaire was used in all households. The data collected via SapMobil were sent to a server managed by the SE-CNSA, decoded, and exported to Excel for further reconciliation and analysis.

The anthropometric equipment provided to each team included SECA scales for measuring weight, graduated height boards for measuring height, and MUAC (mid-upper arm circumference) tapes. Interviewers were selected and trained by the SE-CNSA.

The coordination of the survey was managed by the SE-CNSA in collaboration with the DSME through the Food and Nutrition Division (DAN). A steering committee was established to define and discuss the objectives of the integrated survey, with consultants providing technical support. Several planning challenges emerged during the coordination phase, notably the underestimation of the required sample size for departmental-level representativeness and the complexity of the questionnaire. This resulted in the recalculation of the sample, leading to delays and budget overruns. As a result, the objectives were adjusted, and the representativeness of nutrition indicators was limited to the regional level.

On an organizational level, technical coordination was provided by the nutrition and food security consultants. However, a key recommendation from SMART regarding daily plausibility checks of data was not fully implemented. The first data sets were only received five days after data collection began, limiting the ability to address quality issues promptly. For future integrated surveys, it was recommended that the nutrition consultant have daily access to the data to monitor and improve data quality continuously. Additionally, some regional SA office heads were responsible for reproducing data collection tools, but shortages were reported at the start of the survey, which further hampered operations.

Discussion of Database Limitations

While the ENSANR 2019 database provides rich and valuable information on food security, nutrition, and resilience in Senegal, several limitations must be acknowledged:

1. **Limited Representativeness at the Departmental Level**: Due to planning and budget constraints, the survey design only ensured representativeness of nutrition indicators at the regional level. Departmental-level analyses, particularly for nutritional outcomes, may suffer from insufficient sample sizes, limiting the reliability of disaggregated findings.
2. **Non-response and Coverage Gaps**: Although the response rates were high (99.8% for RDs and 94.8% for households), two enumeration areas in Dakar were not visited, and 5.2% of planned households were not surveyed. This may introduce some bias, particularly in Dakar or other regions with partial coverage.
3. **Delayed Quality Control**: The SMART methodology recommends daily plausibility checks for anthropometric data. However, the first data were received after five days of

fieldwork, potentially delaying corrective measures in the early stages of data collection. This could affect the precision of the anthropometric indicators.

4. **Questionnaire Length and Complexity**: The survey's comprehensive scope led to a lengthy questionnaire, which may have contributed to respondent fatigue and interviewer errors, especially in multi-module sections (e.g., shocks and coping strategies combined with nutrition modules).
5. **Potential Measurement Errors**: While the use of trained teams and standardized equipment mitigated this risk, anthropometric measurements are always subject to measurement error due to inter-observer variability or logistical constraints in field conditions.
6. **Data Entry and Technology Challenges**: Although tablets were used to enhance data quality, some teams faced technical difficulties related to the SapMobil application and data transmission, particularly in remote areas with limited network coverage.

Despite these limitations, the ENSANR 2019 database remains a vital source for analyzing the intersection of food security, nutrition, and resilience in Senegal.

République du Sénégal
Un Peuple - Un But - Une Foi
PRIMATURE
Cabinet du Premier Ministre

AND SOCIAL ACTION

National Food Security, Nutrition and Resilience Survey (ENSANR, 2019)

January 2019

INFORMATION NOTE

My name is [Interviewer's first and last name]. I am with my (my) colleague [First name and Surname of the investigator].

We work for the Executive Secretariat of the National Food Security Council (SECNSA) and the Department of Mother and Child Health (DSME). These two institutions are conducting a Household Food Security, Nutrition and Resilience Survey nationwide.

The survey complied with all laws in the country relating to surveys and the protection of personal data. The administrative, customary and religious authorities are informed of the holding of this survey, the results of which will make it possible to better guide public policies in terms of food security, nutrition and resilience.

Your household has been randomly selected to participate in this survey. We are going to ask you some questions about your household. We will also ask questions to female caregivers of children under 5 years old. We will take measurements of the height, weight and upper arm circumference of women of childbearing age and children under 5 years old. We will take a small amount of the cooking salt that the household uses

The information collected is strictly confidential and will be carefully protected. They will only be used for purely statistical purposes. Under no circumstances will this information be used for the purposes of criminal or tax prosecution or repression of any kind whatsoever.

Your household is not exposed to any sanction if you refuse to participate in the survey. However, the participation of your household is strongly desired because it will allow the collection of very useful data for the fight against malnutrition, food insecurity and for strengthening the resilience of Senegalese populations.

We ask you to sign us the document of consent to participate in the survey.

MODULE 1: CHARACTERISTICS OF THE HOUSEHOLD

Q100	**Region**	Q101	**Department**
Q102	**Commune**	Q103	**Name of village or neighborhood**
Q104	**District**census	Q105	**Environment**of residence *Dakar...1* *Other urban...2* *Rural...3*
Q106	**latitude** **longitude**	Q107	District
Q108	**Health post**	Q109	**cluster number**
Q110	Team number	Q111	**Household number**
Q112	Respondent's first name Last name	Q113	**Respondent Status** *Head of household ...1* *Wife of the CM ....2* *Child of CM ...3* *Other member....4*
Q114	**First and last name of head of household**	Q115	**Household telephone**
Q116	**investigator**	Q117	**supervisor**

Q118	**Gender of head of household** *Male...1* *Female...2*	**Q119**	**Age of head of household** ***If Don't Know: put zero***
Q120	**Nationality** *Senegalese...1* *West African...2* *Other African...3* *Other nationality...4*	Q121	**Ethnicity of the head of household:** *Wolof/Lebou ...1* *Serer ...2* *Fulani...3* *Toucolour...4* *Diola...5* *Mandingo/Soci...6* *Bambara...7* *Sarakolé/soninké...8* *Mandiac...9* *Other to be specified...10*
Q122	**Marital status of head of household** *Married monogamous...1* *Married polygamist ...2* *Divorced/widowed ...3* *Single...4* *Other to be specified...5*	Q123	**Highest level of education of head of household** *None...0* *Elementary...1* *Middle/Secondary...2* *Superior...3* *Literate in local language...4* *Quranic only...5*
Q124	**Highest degree** *None...0* *Elementary School Certificate...1* *Certificate of completion of middle studies...2* *Bachelor...3* *License ...4* *Master 1...5* *Masters 2...6* *Doctorate (PHD)...7*	Q125	**Does the head of household suffer from a chronic illness?** *No chronic disease...0* *Diabetes...1* *Hyper/hypotension...2* *Sickle cell disease...3* *Tuberculosis...4* *Cancer...5* *Kidney failure ...6* *Other to be specified...7*

Q126	**Does the head of household have a disability?** *No disability...0* *Limb paralysis/amputation...1* *Blindness...2* *Deafness...3* *Difficulty speaking...4* *Mental disability...5* *Other to be specified...6*	Q127	**Head of household religion** *Muslim-Khadre* *Muslim-Layene* *Muslim-Muride* *Muslim-Tidiane* *Muslim without brotherhood* *Christian-Catholics* *Christian-Protestants* *Other Christians (Lutherans, Jehovah's Witnesses, etc.)* *Other religions (Jews, Buddhists, Animists, etc.)* *Animists* *Without religion (atheists, agnostics, etc.)*
Q128	**Socio-professional category of the head of household** *Agricultural independent* *Non-agricultural self-employed* *Formal sector employer* *Informal sector employer* *public employee* *Private employee* *other specify*		
Q129	**Household size**		

	Number of persons	0-5 months	6-59 months	5 years and over
1	**Male**			
2	**Feminine**			

3	Pregnant women	
4	Breastfeeding women	
5	Women of reproductive age (15 – 49 years old)	
6	Physically handicapped	
7	Mentally handicapped	

MODULE 2: HOUSEHOLD LIVING CONDITIONS

Q200	**Type of housing in the residential area of the household** *not subdivided* *partially subdivided* *fully endowed*	Q201	**Housing occupancy status of the household** *Owner* *Tenant* *Roommate* *Hosted* *Loaned housing* *Squatted housing*
Q202	**Number of rooms in household accommodation**	Q203	**Type of habitat** *Building* *Permanent villa* *mud house* *shack* *Hut/hut*

Q204	**Main soil component of household habitats** *Cement* *Floor tile* *Clay/sand* *Wood/Plank* *Bamboo/Palm* *Other specify*	Q205	**Type of toilet used by the household?** *latrine* *the TRtraditional pit ines* *Soulimproved with ventilated pit (VIP)* *open sky (no walls)* *None / bush, stream* *Other to specific*
Q206	**Roof covering** Concrete Tile/ Slate Zinc Thatch/Straw Other (s) to be specified		
Q207	**Main source of energy for cooking** *Firewood* *Coal* *Gas* *Electricity* *cow dunge* *Other specify*	Q208	**Main light source** *SENELEC Electricity* *Generator* *Solar panel* *Gas* *Kerosene lamp/ Oil lamp* *Torch (batteries)* *Other specify*
Q209	**Main source of drinking water** Tap, running water in SDE houses …….1 Public tap…….2 Improved (protected) well……..3 Traditional well (unprotected)…..4 Drilling…….5 Surface water (backwater, river, stream, Séane)…..6 Rainwater (directly or from a reserve)……..7 Mineral/filtered water (bottled/bag)…..8 Tap in concession……..9 Faucet in another dealership……..10 standpipe……..11 Other	Q210	**Main method of solid waste disposal 210** *None* *Collection truck/cart* *Deposit allowed* *wild deposit* *landfill* *Incineration* *Other: specify)*
Q211	**Main mode of sewage disposal** *concession yard* *Street, road, nature* *Ditch* *Single sump/Lash-sump* *Public pipelines* *Other specify……………….*	Q212	**Main mode of disposal of faecal sludge** *Emptying truck* *Hole* *Sewer connection* *Other specify*

Q213 Functional household goods

No.	GOODS	NUMBER	No.	GOODS	NUMBER
1	Radio		13	Car	
2	TV		14	Motorcycle	
3	Computer		15	Bicycle	
4	Internet (Live box)		16	Tractor	
5	TV channel decoder		17	Cart	
6	Air conditioner		18	Plow	
7	Washing machine		19	seeder	
8	Sewing machine		20	Canoe	
9	Fridge Freezer		21	Fish net	

10	Jambar stove		22	motor pump	
11	Phone		23	Home	
12	Cellphone		24	Housing plots	
25	Fan		26	Hoe	

Q214 **Did the household practice agriculture in the strict sense during the 2017/2018 campaign?**

No
Yes

Q215 **If not why ?**

Lack of land
Lack of seeds
Lack of manpower
Lack of tools, equipment
Health problems
Not concerned (never practice)dd
Other (s) to be specified

Q216 **If yes, what is the main mode of access to land?**

Property
Lease
Sharecropping
loan

Q217 **Crops grown during the 2017/2018 campaign**

No.	Crops	Area sown in ha	Total production in tons
1	Cereals		
2	cowpea		
3	Peanut		
4	Cotton		
5	Horticultural products		
6	Ornamental trees and plants		
7	Other (s) to be specified)		

Q218 **Main mode of acquisition of inputs**

No.	**Crops**	**Capture mode**
1	Cereals	
2	Peanut	
3	Cotton	
4	Vegetables	
5	Ornamental trees and plants	

Cash purchase
Purchase on credit
Government subsidy
Donation from organizations/NGOs
old stock
Loan
Work for input
Other

Q219 **Do you know agricultural insurance?**

	No *Yes*
Q220	**If yes, will a member of the household take out agricultural insurance?** *No* *Yes*
Q221	**If not why ?** *very expensive font* *Lack of confidence* *Other specify*
Q222	**If yes, has any member of the household ever received a payment from an insurance company?** *No* *Yes*
Q223	**What is the amount received?**

Q224	**Does the household practice animal husbandry?** *No* *Yes*						
Q225	**If yes, specify the number of species raised**						
Cash possessed	**Cattle** (oxen, cows)	**Sheep**(sheep, ewes)	**goats**(goats, goats)	**Poultry** (roosters, hens, ducks, turkey geese, guinea fowl)	**Equine**(horses, mares)	**Assins**(donkeys)	**Pigs**(pigs, sows)
Total number of animals owned							
Number of breeding females							

Q226 Does the household practice fishing? *No* *Yes*			
Q227 If not, why? *Lack of canoe* *Lack of fishing equipment* *Lack of manpower* *Health problems* *Not concerned (never practices)* *Other (s) to be specified*			
Q228 If yes, specify the types of fishing practiced			
Types of fishing	**Convenient** *No*	**Production in the last 30 days**	**Total amount reported**

	Yes		
sea fishing			
Inland fishing			
Aquaculture			

Q229 Does the household exploit forest resources? *No* *Yes*			
Q230 If not, why? *Administrative measures* *Lack of manpower* *Health problems* *Not concerned (never practices)* *Other (s) to be specified*			
Q231: If yes, specify the resources exploited			
Resource Types	**Convenient** *No* *Yes*	**Production in the last 30 days**	**Total amount reported**
Wood, coal			
Picked products			
Game			

Q232 **In the past 12 months, has the household received food assistance?**

Type of support	**Aggregate amount/aggregate quantity**
Cash transfer	
Food vouchers	
rice	
oil	
sugar	
but	
lens	
millet	
cowpea	
Family Safety Scholarships	
Universal health coverage	
Other specify	

MODULE 3: FOOD CONSUMPTION

Q300: In the past 12 months:	
1	**have you or other household members been worried about not having enough to eat because you did not have enough money or other means of obtaining food?** *0=No* *1=Yes* *98=DK* *99=Refused*
2	**Have you or other members of your household been in a situation where you could not eat nutritious and healthy foods because you did not have enough money or other means?** *0=No* *1=Yes* *98=DK* *99=Refused*
3	**Have you or other members of your household found yourself in a situation where you almost always ate the same thing, because you did not have enough money or other means to obtain food?** *0=No* *1=Yes* *98=DK* *99=Refused*
4	**Have you or other members of your household had to skip a meal because you did not have enough money or other means to get food?** *0=No* *1=Yes* *98=DK* *99=Refused*
5	**Have you or other members of your household been in a situation where you have not eaten as much as you should have, due to lack of money or other means of obtaining food?** *0=No* *1=Yes* *98=DK* *99=Refused*
6	**Have you or other members of your household found yourself in a situation where there was nothing left to eat at home because there was not enough money or other means of get food?** *0=No* *1=Yes* *98=DK* *99=Refused*
7	**Have you or other members of your household been in a situation where you were hungry but did not eat because there was not enough money or other means to get food? food ?** *0=No* *1=Yes* *98=DK* *99=Refused*
8	**Have you or other members of your household found yourself in a situation where you had not eaten anything for a whole day, due to lack of money or other resources?** *0=No* *1=Yes* *98=DK* *99=Refused*

Q301	How many children in the household eat at a school canteen?

Q302	If there is no child who eats at a school canteen, why? *No canteen needed* *The school does not have a school canteen* *Expensive contribution* *Poor quality of meals* *Other specify*

Q303**Does the household currently have food stocks for each of the following cereals**		
	No *Yes*	**Quantity (kg)**
Rice		
Mil		
Sorghum		
But		
peanut shell		
Shelled peanut		
cowpea		
Fonio		
Other specify		

Q304: How many days during the last 7 days, the members of your household consumed the following foods and how these foods were acquired?
(Use the codes on the right, write 0 for products not consumed in the last 7 days and if necessary note the source of food)

	Foodstuffs	**Q304.1 Number of days of Consumption during the 7 last days ?** **(0 to 7)**	**Q304.3 Main source of food consumed?**(Enter the corresponding code) **<u>Source code</u>** *own production* *Fishing/Hunting* *Collection/Pickup* *Loan / purchase on credit* *Cash purchase* *Barter* *work for food* *Don* *Food aid (State, humanitarian)* *Other (s) to be specified*
1.	Rice		
2.	Pasta, bread/cake and/or donuts, bread		
3.	**Roots, tubers**: potato,yam, cassava, sweet potato and/or other tubers		
4.	**Other Cereals**: sorghum, millet, maize		
5.	**Legumes/nuts**: beans, cowpeas, peanuts, lentils, soybeans, and/or other nuts		

	Foodstuffs	Q304.1 Number of days of Consumption during the 7 last days ? (0 to 7)	Q304.3 Main source of food consumed?(Enter the corresponding code) Source code *own production* *Fishing/Hunting* *Collection/Pickup* *Loan / purchase on credit* *Cash purchase* *Barter* *work for food* *Don* *Food aid (State, humanitarian)* *Other (s) to be specified*
6.	**orange vegetables**(vegetables rich in vitamin A): (carrot, red pepper, pumpkin, orange sweet potato, etc.)		
7.	**Green leafy vegetables (**spinach, broccoli, amaranth and/or other dark green leaves, cassava leaves etc.)		
8.	**Other vegetables**(onions, tomatoes, cucumber, radish, green beans, peas, lettuce, etc.)		
9.	**orange fruit**(fruits rich in vitamin A): mango, papaya, apricot, peach etc.)		
10.	**Other fruits**(banana, apple, lemon, tangerine)		
11.	**Meat/offal/poultry**(meat in large quantities and not as a condiment)		
12.	**Fish/Seafood (in large quantities)**		
13.	**Eggs**		
14.	**Fresh or curdled milk**		
15.	**Other dairy products**(yogurt, cheese, other dairy EXCEPT margarine/butter or small amounts of milk for tea/coffee)		
16.	**Oil/fat/butter:**oilvegetable, palm, shea butter, margarine, other fats/oil		
17.	**Sugar or sweet products:**sugar, honey, jam, donuts, sweets, cookies, pastries, cakes and other		

	Foodstuffs	Q304.1 Number of days of Consumption during the 7 last days ? (0 to 7)	Q304.3 Main source of food consumed?(Enter the corresponding code) Source code *own production* *Fishing/Hunting* *Collection/Pickup* *Loan / purchase on credit* *Cash purchase* *Barter* *work for food* *Don* *Food aid (State, humanitarian)* *Other (s) to be specified*
	sweet products, (sweet drinks),		
18.	**Condiments/Spices:** tea, coffee/cocoa, salt, garlic, spices, yeast/baking powder, tomato/hot sauce, meat or fish as condiments, other condiments		

Q305.Dietary diversity questionnaire at household level (recall of the last 7 days)

- Interview only the person in charge of preparing household food for the SDAM, the children for the SDAIE and pregnant and lactating women for the SDAIF.
- Ask everyone what they ate and drank yesterday (meals and snacks), whether during the day or at night, at home or away for the SDAIE and the SDAIF.
- Start with the first food or drink consumed in the morning. Note all foods and beverages mentioned.
- If a cooked dish is mentioned, ask the person responsible for preparing the food for the list of ingredients.
- When the person has finished, check with them that they have not missed any meals or snacks.

	Breakfast	Lunch	Dinner
Day 1			
Day 2			

Day 3			
Day 4			
Day 5			
Day 6			
Day 7			

When the respondent's summary is complete, fill in the food groups according to the information given above.

MODULE 4: INCOME AND EXPENSES

4.1 Household income

Q400	**Main source of household income** *Agriculture* *Breeding* *Fishing* *Trade* *Salary* *Transfers* *Transportation* *Annuity* *Other specify………………………………………………..*	**Q401**	**Who was the main provider of household resources in 2017?** head of household Father/Mother of the CM Spouse of CM CM Siblings Other CM relatives Boss Friends Marabout Myself Other*(to specify)*
Q402	**What is the socio-professional category of the main household provider?** *Agricultural independent* *Non-agricultural self-employed* *Formal sector employer* *Informal sector employer* *public employee* *Private employee*	**Q403**	**In the past 30 days, what is the total amount of household income**

Q404	In the last 30 days, how much was received from each source of income

Income description	Amount
Breeding	
Fishing	
Trade	
Salary	
Business	
Transfers	
Donations	
Legacy	
Other	

Household expenses

Q405:In the past 30 days, how much did the household spend on the following foods?

Type of expenses	*Amount (put 0 if there is none)*
Cereals	
tubers	
Vegetables	
Pulses, oilseeds	
Meat	
Milk	
Fish	
Oil	
Sugar	
Other food products	

Q406:During the last 30 days, how much did the household spend on the following items?

	Amount (put 0 if there is none)
Tuition fees (registration, monthly payments)	
Supplies (books, notebooks, pens, etc.)	
Student transportation	
Uniforms, outfits	
Various expenses	

Q407:During the last 30 days, how much did the household spend on the following items?

Type of expenses	*Total amount at (put 0 if there is none)*
Consulting fees	
Traditional and modern medicines	
Examinations and care	
Transport for health reasons	
Other miscellaneous expenses (glasses, prostheses, equipment, etc.)	

Q408:In the last 30 days, how much did the household spend on the following items

Type of expenses	Amount
electricity	
Gas	
Charcoal	
Firewood	
Fuel	
Cigarettes/tobacco	
Phone credit	
Public transport	
Water	
TV packages	
Phone	
Soap	
Rent	
Cosmetic products	
Hairdressing, pedicure, manicure	
Land rental	
Housing construction and maintenance	
Clothes	
Ceremonies (baptisms, weddings, etc.)	
Celebrations (Korité, Tabaski, First Communion, etc.)	
Equipment and furniture (radio, car, TV, fridge, cupboards, beds, etc.)	
Other expenses	

MODULE 5: SHOCKS AND COPING STRATEGIES

5.1 Shocks

Q500During the last 30 days, has the household faced one or more shocks?

	Type of Shock	**Q500.1** **In the past 30 days, has the household experienced shock (*number*)**	**Q500.2** **What was done to deal with the shock***(quote main action)* Sell assets Apply for family support Rely on the support of the community network Incur a debt (bank, individual, etc.) Be helped by the friendly network Use savings Migrate
1	Drought		
2	Flood		
3	Thunderstorm		
4	Bad harvests		
5	loss of land		
6	Damage to stored productions		
7	Loss of fishing gear		
8	bad fishing season		
9	Plant pathologies		
10	Significant fodder deficit		
11	Livestock death		
12	Cattle theft		
13	Livestock outbreak		
14	Fire		
15	Bushfire		
16	severe water shortage		
17	business bankruptcy		
18	Rising food prices		
19	Rise in agricultural input prices		
20	Accident		
21	Serious illness		
22	Death of the main breadwinner		
23	Job loss / no pay		
24	Inability to repay a loan		
25	Involuntary displacement		
26	Community/political crisis		
27	Conflict		
28	Other shocks to be specified		

Q501	**In the past 12 months, has a household member had a health problem?***(if there are several cases, take the most serious)* *No* *Yes*
Q502	**If yes, specify the most serious health problem** *Organ ailments (head, throat, ear, legs, arms, stomach, etc.)* *Diarrhea* *Vomiting* *Fever* *Loss of consciousness* *injuries* *Parasites* *skin problems* *Other (s) to be specified*
Q503	**Did this member go to consult?** *No* *Yes*
Q504	**If not why ?** *Far distance* *High cost* *Quality of care / resources* *Cultural choice* *Other reasons (specify)*
Q505	**If so, what is the location?** *Marabout Healer* *Private doctor* *Pharmacist* *Neighborhood doctor/nurse* *public hospital* *Health center* *Dispensary/public health post* *Health hut* *Private Christian/NGO* *company doctor* *company doctor* *Private clinic* *other*
Q506	**How far is the place of treatment?** Less than 1km Between 1 and 2 km Between 3 and 5 km Between 6 and 10 km Between 11 and 50 km More than 50km
Q507	**How long does it take to get to this place on foot?** (in minutes)
Q508	**Is the health problem solved?** *No, I am still on treatment* *No, but I abandoned the treatment* *Yes*
Q509	**Is one of the household members a member of an association?**

	No *Yes*

Q510	**association type**	**Q510.1 Membership** *No* *Yes*	**Q510.2 Can the household rely on this association if necessary?** *No* *Yes*
1	Economic interest group (GIE)		
2	Women's Promotion Group (GPF)		
3	Sports and Cultural Association (ASC)		
4	Development Association		
5	religious association		
6	Customary association		

5.2 Coping Strategies

Q511	**During the last 7 days, has the household had to resort to one of the following strategies because of food difficulties: (list the strategies one by one. If the strategy is not adopted, enter 0 in the number of days).**	**Frequency (0 to 7)**
1	Consuming less popular, less expensive foods	
2	Borrowing food or relying on help from relatives (friends, neighbours, colleagues, relatives, etc.)	
3	Decrease the amount of food taken during meals	
4	Reduce the amount of meals taken by adults for the benefit of children	
5	Reduce the number of meals taken per day	

Q512: In the past 30 days, has the household had to resort to any of the following strategies because of food difficulties

	Strategies	***1. Yes*** ***2. No, it is not necessary*** ***3. No, I have already used this strategy without success***
1	Sell more animals than usual on a sustainable basis	
2	Reduce spending on health and/or education	
3	Reduce support expenditure for agro-sylvo-pastoral and fisheries production	
4	Borrow money to buy food	
5	Unsustainably sell livestock (high level of sale, unusual sale of young breeding females)	

6	Sell productive goods or household assets (plows, seeders, transport vehicle, etc.)	
7	Remove children from school	
8	Sell all livestock	
9	Sell farmland	
10	Migrate the entire household	
11	Consuming seeds for the next crop year	
12	Harvesting immature crops/hunting/gathering wild fruits	
13	Send one or more members of the begging household	

atmosphere

MDPI

Article

Climate-Related Risks and Agricultural Yield Assessment in the Senegalese Groundnut Basin

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