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RETURN MIGRATION, COPING STRATEGIES AND FOOD SECURITY STATUS OF AGRICULTURAL HOUSEHOLDS IN TIMES OF FLOODING IN RIVERS STATE, NIGERIA

BY
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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF DOCTOR OF PHILOSOPHY IN APPLIED AGRICULTURAL ECONOMICS AND POLICY

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DECLARATION

This thesis is the result of research work undertaken by Umechukwu Jacinta Nmutaka in the Department of Agricultural Economics & Agribusiness, University of Ghana, under the supervision of Prof. Daniel Bruce Sarpong, Prof. Akwasi Mensah-Bonsu, Dr. Ama A. Ahene-Codjoe and Prof. Taeyoon Kim. In whole or in part, it has never been presented for a degree at this university or any other. All citations to the work of others have been properly recognised.

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ABSTRACT

This study assessed the dynamics of return migration, coping strategies and food security status of agricultural households in the context of escalating flooding in Rivers State, Nigeria. Data were collected from 440 respondents (246 for treatment/migrants and 194 for control/non-migrants groups) on the episodes that occurred between 2011-2022 to estimate the trend and coping strategies of the migrating farmers in the study area. Data on 2022 crop production activities specifically were also collected to estimate the technical efficiency (TE) of the farms. This was used in estimating the effect of migration on farm's TE. The farmers Household Food Insecurity Access Scale (HFIAS), farm revenue and Daily Per Capita Dietary Energy Supply were also computed and used to estimate the effect of migration on the farmers' food security. Endogenous treatment effect models were estimated to identify the average treatment effect of migration on farm's TE, famers' HFIAS, farm income and food availability. A robustness check was also undertaken on these analyses using Propensity Score Matching approach. The results obtained showed that flooding episodes occurred yearly. On the average, 8 persons migrated from each household and 7 persons returned home after the floods. The average household size is 8 and this number that migrated represents the average household size, thus all household members migrate each episode. The results showed that 97.2% of the farmers have crop damage as their primary concern while 2.8% stated infrastructural damage. Early planting and harvesting are the coping strategies identified. The Translog stochastic frontier analysis revealed that migration significantly contributes to technical inefficiency, with migrants operating at 71.17% efficiency compared to 74.63% for non-migrants. Both groups have room to improve. Results from the endogenous treatment model showed a significant average treatment effect on the treated (ATT)/migrants of negative 3.85%, and a significant average treatment effect on the untreated (ATU)/non-migrants of positive 2.01%. This indicates that migration, as shown in the technical inefficiency model, negatively impacts TE, reducing it by 3.85%. Without flooding-induced migration, migrants' TE is expected to rise by 2.01%. The result showed that migrants' average HFIAS was 13.5 while that of the non-migrants was 2.2 depicting that migrants are more food insecure when compared with the non-migrants. The ATT result showed a significant mean difference of 9.17. This means that flooding problems and conversely migration, increases food insecurity. The result on average farm revenue showed the migrant's mean farm revenue per head was ₦54509.34 while that of non-migrants was ₦183153.6 (USD 128.90 and USD 433 respectively). The ATT result showed an insignificant mean difference of negative ₦290.45 (USD 0.69). The ATU had a mean difference of positive ₦114439.5 (USD 270.54) which is significant. This means that if the migrants are not faced with flooding issues and eventual migration, their expected farm revenue will increase by ₦114439.5 per head. The result of food availability showed the migrants are only able to supply 39% of their daily energy requirement while non-migrants supply 56%. The ATT had a mean difference of 38.31% which is significant indicating that, on average, households that migrated due to flooding had higher caloric availability than they would have had if they remained in flood-prone areas. However, this improvement in caloric supply did not translate into broader food security benefits as HFIAS and farm revenue suggested otherwise. It is recommended that the government and all other stakeholders initiate and execute projects meant to curb flooding in these communities. Embarkments can be built around the river banks to stop the overflow. Also, the government can give these farmers grants and credits to assist with coping after flooding episodes. The Federal Ministry of Agriculture and Food Security should educate farmers on farm management, crop combinations, and optimal use of fertilizer and labour for better productivity. Non-farm income generating activities is also advised for income diversification. With improved income, farmers will access more food and HFIAS will equally improve.

DEDICATION

This thesis is dedicated to God Almighty, who blesses without measure. This is another blessing of his and may his name be praised forever, Amen.

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TABLE OF CONTENTS

CONTENT PAGE

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS AND ACRONYMS

ADER	Average Dietary Energy Requirement
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
CSA	Climate Smart Agriculture
DES	Dietary Energy Supply
ESR	Endogenous Switching Regression
FAO	Food and Agricultural Organisation
FCS	Food Consumption Score
FIML	Full Information Maximum Likelihood
FS	Food Security
GAR	Global Assessment Report
GLSS	Ghana Living Standards Survey
HDDS	Household Dietary Diversity Score
HFIAS	Household Food Insecurity Access Scale
HLPE	High Level Panel of Experts on Food Security and Nutrition
ICEM	International Centre for Environmental Management
IDPs	Internally Displaced Peoples' camps
IITA	International Institute of Tropical Agriculture
IMRs	Inverse Mills Ratios
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental Variable
LGA	Local Government Area
NASRDA	National Space Research and Development Agency

NEMA	National Emergency Management Agency
NIMET	Nigerian Meteorological Agency
PSM	Propensity Score Matching
SAS	Statistical Analysis System
TE	Technical Efficiency
UN	United Nations
UNDP	United Nations Development Programme
UNICEF	United Nations Children's Fund
UNISDR	United Nations Office of Disaster Risk Reduction

CHAPTER ONE

INTRODUCTION

1.1 Background

Migration refers to the movement of people within or across national borders and may be voluntary or forced, temporary or permanent (International Organization for Migration (IOM), 2022; FAO, 2018). This broad concept encompasses economic migrants, individuals displaced by conflict or environmental shocks, internally displaced persons (IDPs), refugees, asylum seekers, returnees, and persons relocating for education or family reasons. Return migration specifically describes the process by which individuals or households move back to their place of origin or a previous residence after spending a period away (UN, 2020; FAO, 2018).

Globally, migration has continued to increase, reflecting growing economic integration, environmental pressures, and political instability. The International Organization for Migration (IOM, 2024) estimates that the number of international migrants reached approximately 281 million by 2020 and surpassed 280 million by 2023, accounting for over 3.6% of the world's population. Migrant workers constitute a substantial share of this population, with over 169 million migrant workers globally, representing about 4.9% of the global labour force (ILO, 2021). Migration therefore remains a defining feature of contemporary demographic and economic change.

Migration patterns also reveal important demographic and spatial characteristics. A significant proportion of migrants are young people between the ages of 15 and 34, nearly half are women, and a large share originates from rural areas (UN, 2017). Rural communities receive close to 40% of international remittances, highlighting the strong rural–urban and rural–international linkages embedded in migration processes (UN, 2017). Internal migration is even more extensive than international migration, with an estimated 763 million internal migrants worldwide (FAO, 2018). In many developing countries, particularly in Africa, more than half of rural households report having at least one internal migrant, underscoring the centrality of migration as a livelihood strategy (FAO, 2018).

While migration can contribute positively to development when it is safe, orderly, and well-managed, large-scale and unregulated migration often poses serious challenges. Conflict, persecution, natural disasters, poverty, food insecurity, limited economic opportunities, environmental degradation, and climate change are major drivers of forced displacement (IOM, 2024; FAO, 2023; Intergovernmental Panel on Climate Change (IPCC), 2022). Millions of forcibly displaced individuals reside either in camps or host communities, frequently with limited humanitarian assistance and restricted access to livelihood opportunities. Supporting displaced populations in rebuilding livelihoods is therefore critical, not only for economic survival but also for restoring social stability and psychological well-being. In response, organisations such as UNHCR and FAO have implemented livelihood support programmes since the late 1990s to enhance self-reliance among displaced populations (FAO, 2018; 2023).

Migration is not a uniform phenomenon. Studies distinguish between non-migration, temporary migration, and permanent migration, each with distinct implications for households and economies (Revathy, 2020; IOM, 2022). Evidence from empirical studies, including Australian data, shows that temporary migration may function as a precursor, complement, or alternative to permanent migration, with differing economic and social outcomes. In agricultural contexts, migration has long served as a subsistence and risk-coping strategy in both developed and developing countries. Different migration strategies can therefore produce different selection effects and livelihood outcomes for farming households that initiate migration.

In Nigeria, migration is strongly linked to recurrent environmental shocks, particularly flooding. Seasonal floods displace households from agricultural communities to Internally Displaced Persons' (IDP) camps, relatives' homes, and government shelters, especially in flood-prone regions (Adebayo & Oruonye, 2022; Okonkwo *et al*., 2021; Nkwunonwo, 2016). These movements are largely temporary, with households returning once floodwaters recede. Rivers State, located in southern Nigeria, exemplifies this challenge. Despite its rich natural resources and economic importance, the state experiences persistent flooding due to its tropical climate, low-lying terrain, and network of rivers (Ede & Edokpayi, 2021; Ikechukwu, 2015).

Agriculture remains central to livelihoods in Rivers State, supporting crop farming, fishing, and related activities. Fertile floodplain soils sustain crops such as cassava, rice, maize, and yams, while proximity to the Gulf of Guinea supports fishing-based livelihoods (Ede & Edokpayi, 2021). However, recurrent flooding repeatedly submerges farmlands and residential areas, forcing farming households to abandon their communities for weeks or months at a time. These disruptions undermine agricultural production, income generation, and household food security, with long-term implications for rural welfare and resilience.

Against this backdrop, this study examines the nexus between temporary migration, return migration, and coping strategies among agricultural households affected by flooding in Rivers State, Nigeria, and the implications for household food security, particularly food access and availability. By focusing on return migrants in flood-prone agricultural communities, the study seeks to deepen understanding of how households respond to environmental shocks and how migration-related decisions shape livelihood outcomes. The findings aim to contribute to academic discourse and inform policies and interventions targeted at enhancing resilience and food security in environmentally vulnerable regions.

1.2 Problem statement

The agricultural landscape in Rivers State, Nigeria, is increasingly threatened by the dual challenges of escalating flooding events and return migration. Historically, flooding in the region has shifted from isolated incidents to a persistent and widespread hazard, significantly disrupting agricultural livelihoods and rural stability. This shift is attributed to accelerated urbanisation, climate change, and alterations in land use patterns (Adebayo & Oruonye, 2022; Okonkwo *et al*., 2021; Nkwunonwo, 2016; Ede & Edokpayi, 2021; Ikechukwu, 2015). These factors, now driving the escalating challenge of flooding, necessitate comprehensive understanding for the development of effective strategies to mitigate its consequences.

Rivers State was not spared the devastation caused by the floods in Nigeria in 2022. The Federal Government's data indicates that the flood brought about the relocation of more than 1.4 million people, loss of lives of over 603 individuals, with more than 2,400 people injured. Furthermore, about 82,035 homes and 332,327 hectares of land were damaged (Nwiyii *et al*., 2022; OCHA, 2022). Nigeria experiences frequent flooding, but the most recent flood of 2022 is the worst since the floods of 2012 (Nwiyii *et al*., 2022; OCHA, 2022).

Amidst this escalating challenge, return migration has become a notable phenomenon. The motivations, and patterns of this return migration are complex and require thorough exploration to unravel the dynamics shaping the socioeconomic landscape (Tezcan, 2019; King, 2015).

Previous research on the recurring flood events in Rivers State (Nwiyii *et al*., 2022; Nkwunonwo, 2016; Ikechukwu, 2015), primarily addressed the causes, impact, panacea and strategies for risk reduction. None explored how the farmers cope each year, given the yearly migratory movements, and how it affects their food security.

Although the effects of flooding on agriculture are widely recognized, a considerable gap still exists in comprehending the complex interplay of return migration and the strategies of coping employed by agricultural households amid escalating flooding and their effects on households' food security status. This study seeks to fill this gap by analyzing the intricate relationships among flooding, return migration, coping mechanisms and food security status, in Rivers State.

Central to this context is the need to investigate how agricultural households cope with environmental vulnerability due to persistent flooding. From immediate responses to the inundation of fields to long-term adaptations in the face of altered soil conditions, understanding the coping mechanisms is crucial. This involves a comprehensive examination of both conventional and innovative strategies employed by farm families. These all affect farm productive output and at the long-run also affects the status of food security of these farm families.

The conceptual framework in Figure 1.1, provides a structured lens through which the research will systematically explore the interplay of environmental vulnerability, return migration patterns, coping strategies, socio-economic characteristics, rural-urban migration dynamics, food accessibility and availability (food security status), and resilience within the context of escalating flooding in Rivers State.

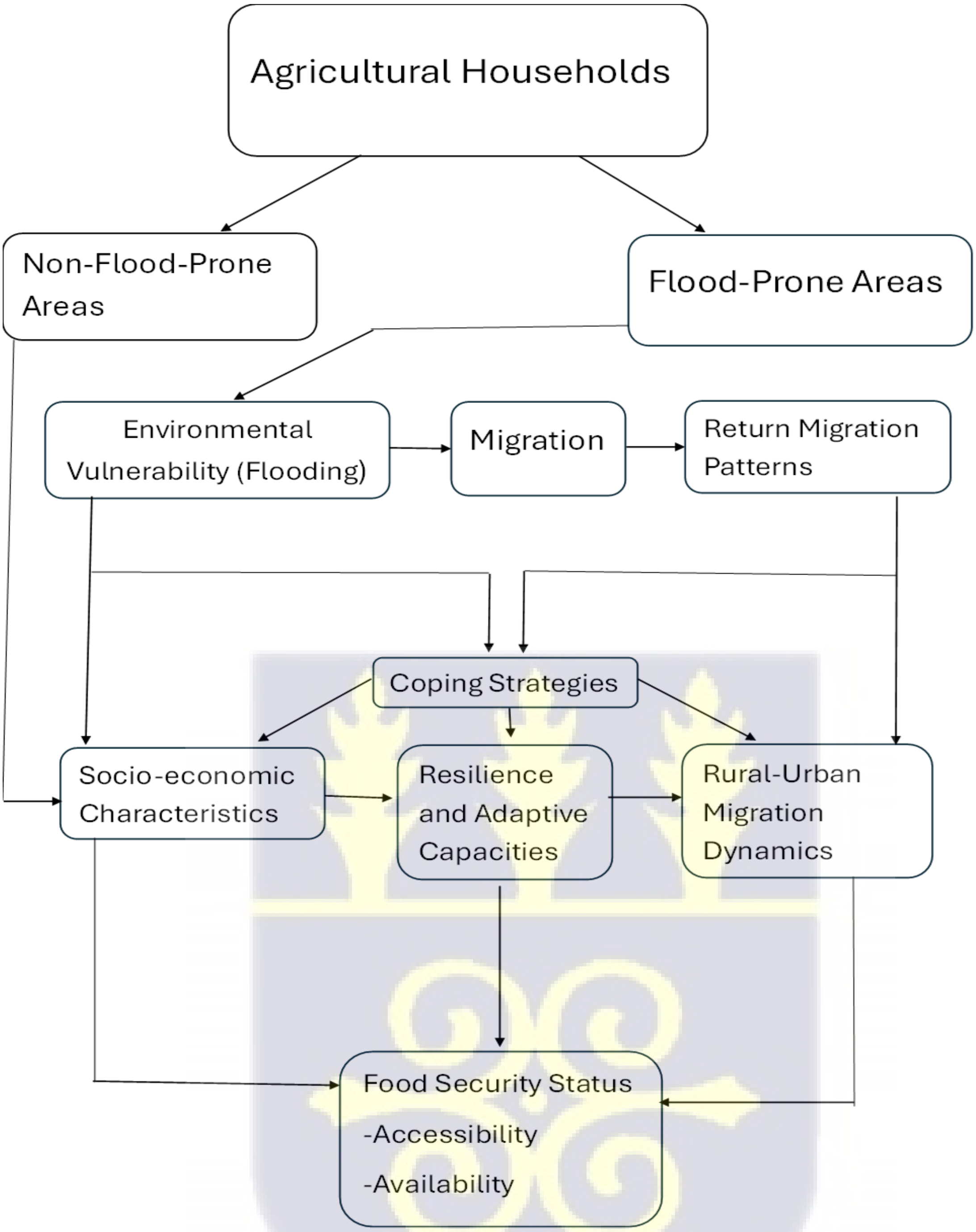

Figure 1.1: Conceptual Framework

Source: Author (2024)

Figure 1.1 illustrates the pathways through which agricultural households, differentiated by their exposure to flooding, experience and respond to food security challenges in the context of environmental stress.

At the top of the framework is the broader category of agricultural households within the study area, which includes all households under investigation. These are then categorized into two distinct groups based on their geographical location and exposure to environmental vulnerability.

On the right side, households residing in flood-prone areas are subject to environmental vulnerability, particularly seasonal flooding. These households typically experience displacement through migration, recurrently. Migration, in turn, gives rise to return migration patterns, as displaced households eventually return to their communities once the flood subsides. Upon return, these households adopt various coping strategies aimed at restoring livelihoods and rebuilding agricultural productivity. These strategies feed into their overall resilience and adaptive capacities, which determine how well they are able to absorb and recover from shock. Ultimately, this influences their food security status, particularly in terms of accessibility and availability of food.

On the left side, the framework depicts households in non-flood-prone areas who are not directly affected by environmental vulnerability. These non-migrant households do not face displacement but still experience socio-economic conditions that influence their food security. Their socio-economic characteristics such as income, education, asset ownership, and farm size, interact with their resilience and adaptive capacities, shaping their ability to withstand market or environmental shocks. Like their migrant counterparts, these households also arrive at the food security outcome, albeit through a different pathway.

By distinguishing between flood-affected and non-affected households, this framework supports a comparative analysis of how exposure to flooding and migration shapes coping strategies and food security outcomes. It also highlights the critical role of resilience as a central mechanism in determining food system stability under conditions of climate stress.

The interplay of environmental factors, migration patterns, and coping strategies creates a complex framework that shapes the lived realities of agricultural households. Understanding how these elements intersect is crucial for developing a holistic comprehension of the experiences of agricultural households facing the challenges of escalating flooding. Consequently, this interrelationship substantiate the rationale for conducting this study, guiding the formulation of the research questions that follow:

1. What are the trends in flooding episodes, migration and return migration of farming households in the study area between 2011-2022?
2. What coping mechanisms are utilized by these farmers in addressing their flooding challenges?
3. To what extent does migration and return, prompted by flooding, affect the output and conversely technical efficiency of farming households in Rivers State?
4. How does migration influence the food security status of farming households in Rivers State, and what differences in effects are observed between migrant and non-migrant households following flooding?

1.3 Objectives of the study

The main objective of this study was to assess the dynamics of return migration, coping strategies and food security status of agricultural households in the context of escalating flooding in Rivers State, Nigeria. The specific objectives are to:

1. Describe the trend in flooding episodes, migration and return migration of farming households in the study area between 2011-2022,

2. Identify and analyse the coping strategies adopted by farming households in Rivers State, in mitigating the impacts of flooding,
3. Examine the effect of flooding-induced migration and return on farm productivity (technical efficiency),
4. Estimate the effects of migration on the food security status of farming households following flooding.

1.4 Hypotheses

The following hypotheses were tested:

I. Flooding episodes have no influence on the livelihood of farming households in the study area.

II. The farmers' coping strategies are not characterized by crop diversification, community support networks, adaptive capacities and government interventions.

III. Flooding-induced migration and return has no effect on the productivity (technical efficiency) of farms in the study area.

IV. Migration has no effect on the food security status of migrant households in the flooding-prone study area.

1.5 Relevance of the study

The research on return migration and coping strategies among agricultural households in the context of escalating flooding in Rivers State is of paramount importance, due to its multifaceted relevance, both to academic literature and policy-makers.

The study contributes to the literature by addressing specific research gaps within the unique setting of Rivers State. It seeks to refine and apply established theoretical frameworks, adapting them to the region's distinctive circumstances. This adds to available literature on how environmentally vulnerable communities navigate migration, return migration and resilience through context-specific coping strategies.

The lessons garnered from this study have significant effects for policy formulation and community development. Policymakers can leverage the understanding of the interplay between migration, return migration and coping strategies for flooding to craft targeted interventions. These interventions will enhance the resilience of agricultural communities, ensuring that formulated policies address the particular demands and difficulties associated with escalating flooding.

This study actively engages with local communities. By amplifying their voices, the research aims to empower these communities and ensure their perspectives are reflected in the discourse. The findings are intended to inform community-based initiatives, fostering a sense of ownership, relevance, and practical applicability within the research process. The ultimate goal is not just to add to literature and assist in policy formulation, but also the initiation of positive change through collaborative, community-driven endeavours.

1.6 Proposed organization of thesis

The thesis is structured into five chapters, beginning with the general introduction as the first chapter. This chapter provides the background, motivation and aims of the research. Chapter two presents a literature review on flooding, return migration, coping strategies employed by agricultural households in times of flooding and food security. Chapter three will encompass the methodology of the thesis. The theoretical framework and empirical estimation methodologies are delineated for each thesis objective. This third chapter also provides the data source and sampling methodology. Chapter four presents the findings emanating from the analysis of the objectives and discussions on these results. Chapter five then presents the general conclusion of the entire study, comprising summary, conclusions and policy recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews relevant literature related to return migration, coping strategies during flooding and food security. The chapter is organised into four distinct sections. Section one considers literatures on return migration and coping strategies in times of environmental vulnerabilities. Section two gives an overview of empirical studies on flooding and coping strategies adopted by farmers around the world. It also has information on the Rivers State situation and the role of government over the years. The third section delves into the measurement of food security and linkage with migration and finally section four considers empirical studies on the impact of migration on farm output, some impact studies on food security and also looks at the analytical review of production frontier estimation.

2.2 Return migration in the context of flooding

Return migration refers to the process where the farming households move back to their place of origin or a previous residence after spending a period away. It takes on particular significance amidst the recurring challenges posed by flooding. The intricate phenomenon of return migration in the aftermath of flooding unveils a tapestry of motivations, intricately woven with socio-economic factors, exhibiting a complexity that varies across flooding-prone communities (Manandhar *et al.,* 2023; King, 2015). Understanding the driving forces behind the decision to return is essential for grasping the nuanced dynamics that influence the choices made by farming households in the wake of devastating flooding events. There are several motivations for this move and these are discussed extensively.

Motivations for Return Migration

Environmental Considerations: The threat of flooding, especially during the rainy season, serves as a compelling factor for individuals who have migrated to other regions or urban centres during flooding, to return back to their homelands once flooding is over. Environmental risks and vulnerabilities drive a reconsideration of residence, particularly when faced with the cyclical nature of flooding (Mashi *et al.,* 2020; Joarder and Miller, 2013).

Cultural and Social Ties: Return migration is often intertwined with cultural and social connections. Individuals may return to their ancestral homes or communities, driven by a sense of belonging, family ties, and the desire to contribute to rebuilding their communities after environmental challenges (King, 2015; Carling and Erdal, 2014).

Socio-Economic Dynamics

Economic Resilience: Despite the challenges posed by flooding, some farming households opt for return migration driven by economic resilience. The resilience of local economies can play a pivotal role in influencing these decisions. For instance, communities with diverse economic opportunities, such as small-scale businesses or alternative employment options, may attract returnees seeking stability and livelihood diversification.

Land Attachment: The deep-rooted connection to ancestral lands and agricultural holdings often serves as a compelling motivation for return migration (Silver, 2023; King 2015). Farming households, anchored by generations of cultivation on specific plots, may prioritize returning to rehabilitate and reclaim their land after the floodwaters recede. This land attachment reflects a profound sense of identity and belonging that outweighs the immediate challenges posed by flooding.

Community Support Networks: The social structure within communities contributes significantly to the motivations for return migration. According to Hare (1999), tight-knit community support networks provide emotional and practical assistance during times of crisis.

Returnees may be drawn back by the social bonds and shared experiences that foster a sense of belonging and mutual support, mitigating the challenges associated with post-flooding resettlement.

Cultural Identity and Heritage: Cultural ties and a sense of heritage can be powerful motivators for return migration (Kunuroglu *et al.,* 2016). In areas where cultural practices are deeply intertwined with agricultural traditions, the pull to preserve and perpetuate cultural identity may lead families to return to their ancestral lands, even in the face of recurring flooding. This motivation transcends immediate economic considerations and reflects a commitment to preserving a way of life.

In essence, the motivations for return migration amidst flooding are diverse and influenced by a multifaceted interaction of economic, social, and cultural elements. By exploring these motivations within specific communities, a richer understanding emerges, laying the groundwork for more targeted interventions and policies that respect the unique dynamics of each locality.

Patterns and Dynamics of return migration

Seasonal Movements: Return migration in the context of flooding often follows seasonal patterns, coinciding with periods of heightened flood risks. Individuals may temporarily leave flood-prone areas during the rainy season and return during the drier periods (McElwee *et al.,* 2017; Marengo and Espinoza, 2016).

Temporary Returns: Some individuals may engage in temporary return migration, where they migrate to other areas during the flood season and then return to their home region during less risky periods. This pattern allows for a dynamic response to environmental challenges (Entwisle, 2020; McElwee *et al*., 2017).

Economic Impacts and Livelihood Considerations

Agricultural Livelihoods: Return migration can be closely tied to agricultural livelihoods. Individuals engaged in farming activities may return to their agricultural practices during specific seasons, contributing to the cultivation and management of crops despite the challenges posed by flooding (Yizengaw *et al.,* 2015; Cole *et al*., 2015).

Income Diversification: The return migration may also be driven by the pursuit of diverse income sources. Individuals may engage in multiple economic activities, combining farming with other livelihood strategies, creating a dynamic economic landscape (King, 2015).

Coping Strategies and Resilience

Community Support Networks: Return migrants often play a crucial role in community support networks during times of flooding. Their experiences and insights gained from residing in different regions contribute to the development of coping strategies within their communities (Antwi *et al*., 2015; Kaniasty and Norris, 2013).

Adaptive Capacities: Return migration can enhance the adaptive capacities of communities by facilitating the exchange of knowledge and skills. Those returning may bring back innovations and practices that enhance the survivability of agricultural households amidst flooding (Gemenne and Blocher, 2017; Cox and Hamlen, 2015).

Policy Considerations

Government Interventions: Understanding the dynamics of return migration is vital for informing government interventions (Van Houte and Davids, 2013). Developing policies that both tackle the difficulties and harness the potential of return migration can play a key role in promoting sustainable development and enhancing community resilience (Rwelamira, 2015; Kaniasty & Norris, 2013). Return migration in the context of flooding is a multifaceted phenomenon influenced by environmental risks, cultural ties, and economic considerations (King, 2015; Mashi *et al*., 2020). Exploring the motivations, patterns, and impacts of return migration contributes to a holistic understanding of how individuals navigate and enhances the survivability of agricultural communities amidst recurring flooding challenges.

2.2.1 Coping Mechanisms in Response to Flooding

The coping strategies during flooding can take the form of traditional measures taken by farmers or innovative adaptive measures. These are discussed as follows.

1. **Traditional Coping Mechanisms**

In the face of recurrent flooding challenges, farming households have demonstrated resilience by relying on time-tested coping mechanisms, with a particular emphasis on crop diversification and water management (Sarku *et al.,* 2022; Ochieng *et al.,* 2020). These traditional strategies, deeply rooted in local agricultural practices, serve as adaptive measures to mitigate the impact of flooding and sustain agricultural productivity.

Crop Diversification: Crop diversification emerges as a cornerstone of traditional coping strategies employed by farming communities. The practice involves cultivating a variety of crops with different growth cycles, resistance to flooding, and nutritional profiles (Sarku *et al*., 2022; Kurukulasuriya and Rosenthal, 2013). By diversifying their crop portfolio, farmers aim to spread the risk associated with flooding, ensuring that a single catastrophic event does not lead to the complete loss of their agricultural output. Notably, this strategy not only enhances resilience but also contributes to maintaining local food security.

Water Management: Water management stands out as another vital traditional coping mechanism in places where flooding poses a persistent threat (Abegunde *et al.,* 2021; Rahman and Rahman, 2015). Farmers engage in meticulous water control practices to regulate the impact of inundation on their fields. Techniques such as constructing raised beds, contour ploughing, and utilizing irrigation systems allow farmers to exert a degree of control over water flow (Abegunde *et al.,* 2021; Rahman and Rahman, 2015). This not only minimizes immediate damage to crops during flooding events but also contributes to soil conservation and fertility in the long run.

Elevated Construction: Elevated construction is a traditional coping mechanism employed by people in flood-affected regions like Rivers State to mitigate the impact of rising floodwaters on homes and infrastructure (Ifabiyi & Ojoye, 2020; Patnaik and Narayanan, 2015). This architectural adaptation involves building houses on elevated platforms or stilts, a practice widely observed in regions vulnerable to flooding (Ifabiyi & Ojoye, 2020; Patnaik and Narayanan, 2015). By elevating structures above the potential flood level, communities aim to protect their homes and possessions during inundation. This strategy not only reduces the risk of flood damage but also provides a practical solution for shelter and refuge during extreme flooding events (Ifabiyi & Ojoye, 2020; Patnaik and Narayanan, 2015).

The use of elevated construction is deeply rooted in the local knowledge of flood dynamics and has evolved over generations as a response to the recurring threat posed by seasonal floods in Rivers State.

Use of Traditional Knowledge: The utilization of traditional knowledge is integral to coping with flooding. Local communities rely on indigenous wisdom passed down through generations to anticipate, understand, and adapt to weather patterns and flooding events. This traditional knowledge encompasses observations of natural indicators, such as animal behaviour, changes in atmospheric conditions, and river water levels, which communities interpret to forecast potential flooding (Mapfumo *et al.,* 2019; Adzawla *et al.*, 2022; Hiwasaki *et al.*, 2015; Mavhura *et al.,* 2013; Gómez-Baggethun *et al.,* 2013).

This grassroot approach to early warning systems, grounded in traditional knowledge, enables communities to take timely preventive measures, such as evacuation or safeguarding essential assets, contributing to their overall resilience in the face of flooding challenges (Mapfumo *et al.,* 2019; Adzawla *et al.*, 2022; Hiwasaki *et al.*, 2015; Mavhura *et al.,* 2013).

Flood-Resistant Crop Varieties: Flood-resistant crop varieties are a traditional coping strategy in agricultural communities, aiming to ensure food security in the aftermath of flooding events. Farmers selectively cultivate crop varieties known for their resilience to waterlogged conditions and inundation (Bimpong *et al*., 2022; Dar *et al*., 2020; Steenwerth *et al.,* 2014; Ismail *et al.,* 2013). These flood-resistant varieties exhibit traits such as tolerance to submersion, ability to recover after flooding, and adaptation to the local agro-climatic conditions.

The cultivation of flood-resistant crop varieties represents a dynamic interplay between traditional agricultural practices and local environmental challenges. This traditional knowledge of selecting and cultivating resilient crop varieties contributes significantly to sustaining agricultural productivity despite the recurrent threat of flooding in flood-prone areas. An example of such crop is flood-resistant rice variety.

2. **Innovative Adaptive Measures**

As the challenges posed by flooding continue to evolve, the agricultural communities have begun to explore innovative adaptive measures, incorporating technological advancements and new approaches to enhance resilience (Olabisi *et al.,* 2020; Ayanlade & Radeny, 2020). In response to the changing dynamics of flooding, the integration of forward-looking strategies becomes imperative, requiring a detailed exploration of global initiatives and their potential applicability to the unique agricultural landscape of an area.

Technological Advancements: The infusion of technology into agricultural practices offers a promising avenue for innovative adaptive measures in the face of flooding. Precision agriculture, for instance, utilises satellite photos, sensors, and data analytics to enhance agricultural practices (Shaikh *et al.,* 2022; Rezvani *et al.,* 2023). In the context of flooding, current information on soil moisture levels and weather patterns can equip farmers to make intelligent decisions, allowing for timely adjustments to mitigate the impact of flooding.

Remote sensing technologies are essential in monitoring flood-prone areas (Schumann, 2015; Rahman and Di, 2017). Drones outfitted with high-quality sensors and cameras offer an aerial perspective of fields, aiding farmers in assessing the extent of flooding and planning targeted interventions. These technological tools empower farmers to proactively manage the risks associated with flooding, marking a departure from reactive strategies.

New Approaches to Water Management: Innovative approaches to water management complement traditional strategies, offering sustainable solutions to cope with flooding. Water-sensitive urban design, for example, integrates urban planning and water management to minimize the adverse impacts of flooding in rural and urban areas (Abass *et al.*, 2022; Dada *et al.,* 2021). The principles of this approach, if tailored to the agricultural context, could contribute to more resilient farming practices.

Additionally, bioengineering techniques, such as the use of flood-resistant crop varieties or eco-friendly soil stabilization methods, showcase a modern approach to addressing the consequences of flooding on agriculture. Genetic modifications that enhance crops' resilience to waterlogged conditions and the use of environmentally friendly soil amendments represent a departure from conventional methods, offering novel avenues for safeguarding agricultural productivity (Bimpong *et al.,* 2022; Semenov *et al.,* 2021; Dhital *et al.,* 2013; Ahmed *et al.,* 2013).

Global Initiatives and Local Relevance: Examining global initiatives and projects that have successfully implemented innovative adaptive measures provides valuable insights for Rivers State. For instance, initiatives in flood-prone regions of Asia or other parts of Africa may offer lessons applicable to the local context (Shah *et al.,* 2021; Okonya *et al.*, 2020; Poff *et al.,* 2016). By adapting successful strategies to the specific environmental and socio-economic conditions, agricultural communities can draw inspiration from global best practices. Examining global and regional initiatives that have successfully implemented adaptive strategies offers valuable insights for Rivers State. For instance, Bangladesh's raised homestead model and early warning systems (UNDP, 2016), Mozambique's use of flood-tolerant seeds (FAO, 2001), and Vietnam's floating agriculture systems (ICEM, 2013) highlight practical, community-driven innovations that could inform local flood resilience measures. Closer to home, Nigeria's Sahel Adaptive Irrigation Initiative in Kano State (World Bank, 2019) demonstrates how community-managed irrigation and water harvesting can enhance resilience, even in the face of climate shocks. These examples provide transferable lessons that could inform the design of context-specific, flood-adaptive measures in Rivers State.

It is crucial to consider the scalability and affordability of these innovative measures in the local setting. While cutting-edge technologies may offer effective solutions, their widespread adoption hinges on factors such as cost, accessibility, and the capacity of local communities to implement and maintain them. Balancing technological sophistication with practical feasibility is essential to ensure the relevance and sustainability of these adaptive measures.

The exploration of innovative adaptive measures in response to flooding goes beyond the traditional coping mechanisms. By embracing technological advancements and drawing inspiration from global initiatives, agricultural communities can forge a path toward resilience that aligns with the evolving nature of environmental challenges. The integration of the innovative measures not only enhances the capacity to withstand flooding but also contributes to the sustainable development of agriculture.

2.2.2 Challenges of Return Migration

Contrary to the perception of migration as a straightforward coping strategy, the process of return migration in the aftermath of flooding presents returning migrants with a host of challenges during resettlement. These challenges, including issues related to land access, social reintegration, and resource competition, compound the complexities of rebuilding lives and agricultural livelihoods. (Tezcan, 2019; King, 2015).

Land Access Challenges: In the aftermath of flooding in the Bonny Island region of Rivers State, returning migrants often encounter challenges related to land access (Nkwunonwo, 2016; Ede & Edokpayi, 2021; Amadi and Ogonor, 2015). Displacement and alterations in land morphology due to flooding can lead to disputes over land ownership and boundaries. The need for clear and enforceable land tenure systems becomes pronounced to facilitate the smooth resettlement of returning families. In communities like Eleme, Rivers State, where agriculture is intricately tied to specific plots of land, returning migrants could face hurdles in reclaiming their original agricultural holdings. The lack of effective land-use planning exacerbates these challenges, posing obstacles to the equitable distribution of available arable land among returnees.

Social Reintegration Dynamics: Returning migrants face formidable challenges in social reintegration, with distinct nuances observed in both urban and smaller community settings. In Port Harcourt, the capital city of Rivers State, the disruptive impact of flooding triggers shifts in community dynamics, complicating the seamless reintegration of returnees (Nkwunonwo, 2016; Setrana and Tonah, 2014). The perceived temporariness of their return often leads to stigmatization and social isolation, exacerbated by the fast-paced urban lifestyle that may hinder the establishment of meaningful connections and support networks (Nkwunonwo, 2016; Setrana and Tonah, 2014).

On the other hand, in smaller communities like Okrika, Rivers State, characterized by tightly woven social bonds, returning migrants encounter a unique set of challenges. Here, changes in social structures, altered power dynamics, and the arrival of new migrants during the resettlement phase contribute to intricate social complexities (Nkwunonwo, 2016; Setrana and Tonah, 2014). The close-knit nature of the community, while fostering strong social ties, presents difficulties when established bonds undergo transformation due to the return migration process.

In both urban and smaller community contexts, the obstacles to social reintegration highlight the need for targeted interventions. Strategies aimed at facilitating the seamless return of migrants must address not only the immediate impacts of flooding but also the intricacies of social structures and community relationships that perform a crucial function in the successful reintegration of individuals and families affected by migration in the wake of flooding events (Nkwunonwo, 2016; Setrana and Tonah, 2014).

Resource Competition Post-Flooding: Resource competition intensifies in areas like Degema, where returning migrants compete for limited resources, both in terms of land and economic opportunities (Nkwunonwo, 2016; Setrana and Tonah, 2014). The influx of returnees strains existing infrastructure and services, leading to heightened competition for jobs and other income-generating activities. This competition can foster tensions within the community, affecting the overall resilience of the returning population.

In summary, this review delves into the intricate dynamics of flooding, migration, and coping mechanisms in Rivers State. It underscores the evolving nature of flooding, diverse motivations in return migration, and a range of coping strategies, including traditional methods like elevated construction and resilient crops that showcase community adaptability. The synthesis of perspectives highlights the delicate balance between migration benefits and challenges, emphasizing the resilience ingrained in traditional coping strategies rooted in local knowledge. Challenges in return migration, spanning urban reintegration to complexities in smaller communities, underscore the need for tailored strategies.

2.3 Empirical studies on flooding and coping strategies employed by farmers

Coping strategy refers to the advantageous utilisation of available resources by individuals and organisations in response to the adverse conditions of a disaster event. Families create a variety of ex-ante and ex-post risk coping strategies in mitigating the detrimental effects of natural disasters such as floods. Ex-post coping strategies aim to bridge the gap in household consumption following the post-disaster occurrence (Myint and Tun, 2017; Lekprichakul, 2007). Diverse ex-ante and ex-post risk coping strategies have been devised to mitigate the adverse effects of natural calamities such as flooding (Myint and Tun, 2017; Harvey & Rakotobe (2014). Reducing the degree of household consumption following the tragedy is the ex-post coping method. For example, producers manage agricultural output risks by using low-risk technologies, contracts, intercropping, and crop diversification. The goal of the ex-post risk coping techniques is to maintain the level of household consumption. Examples include: (1) cutting back on household expenses; (2) taking out a loan; (3) selling some assets following natural calamities (Myint and Tun, 2017; Harvey & Rakotobe 2014).

The two types of coping techniques that affected households could employ to deal with the economic crises caused by disasters are (1) raising income and (2) cutting expenses, according to the Global Facility for Disaster Reduction and Recovery (2013). The affected households are using various measures to boost their income, such as working more hours, moving, altering farming practices, selling assets, and changing their means of subsistence. Conversely, the cost-cutting measures mean that vulnerable households eat fewer meals, spend less on social services, and invest less in agricultural input.

Household's choice of coping mechanisms has been shown to be impacted by its income, lessons learned from the past, media recommendations, and attitudes towards natural catastrophes. The following factors considerably shorten the time it takes to recover from property damage: income of household, credit access (borrowing), usage of a flood warning system, availability of safe housing, involvement in a community organisation, adoption of particular actions, and comprehensive preventive strategies. There were no notable effects from evacuation, relief assistance, type of house, education, household size, or the area's frequency of floods (Myint and Tun, 2017; Francisco (2015).

There are restrictions on the kinds of coping mechanisms that can be successfully used. For instance, there are frequently few off-farm job prospects during planting season. In order to pay for rice in the market or to send family members to work as agricultural labourers in other farms, farmers also sell household assets, especially poultry, in order to raise money for consumption (Ogunniyi *et al.,* 2020; Antwi *et al*., 2015; Harvey & Rakotobe, 2014; Kamal, 2013),

Indigenous coping and recovery mechanisms have been significantly more important than outside help. People are increasingly looking for alternate livelihood strategies, despite having few possibilities, in order to cope with the significant interruption of their livelihoods. Households are relying more and more on social, human, and natural assets due to a shortage of financial and physical capital, but these capitals are insufficient to make them resilient. Therefore, risk reduction techniques must make use of the communities' innate social and cultural strengths (Myint and Tun, 2017; Kamal, 2013).

UNDP (2012) and Kumar & Landy (2020), reports that 40% of the impacted households in the provinces of Prey Veng, Siem Reap and Kratie in Cambodia, stated their households had taken out loans, and a greater majority were used in the purchase of farm inputs for replanting, while some went into food consumption. The household's prospective capacity to service the debts will suffer if loans are diverted to non-income producing activities or if they are used for debt servicing. It is reported also that many turned to labour migration, especially in Prey Veng and Siem Reap. There have also been reports of reduced food consumption and animal sales as coping mechanisms.

Regarding coping techniques in Myanmar, farm households affected by the flood in this study area reported receiving various forms of assistance from both government and non-government donor organisations, such as UNICEF, charity organisations, and donors across the nation

(Myint and Tun, 2017). While non-governmental organisations and the private sector primarily offered cash relief, food, purified water and general property for affected agricultural families, the Myanmar government primarily provided agricultural inputs, meals, and clothing. Among the several afflicted groups, the group that was least affected was situated close to Kambalu Township in Myanmar and had easy access to transportation. Nonetheless, those who were severely and moderately impacted lived far from Kambalu and had transportation challenges.

In reaction to the damage to property which includes crops, animals, and farm inputs, agricultural households utilised several coping strategies: (1) reducing family expenditures, (2) obtaining loans, and (3) liquidating family assets and livestock, among others. These findings demonstrated that cutting back on household expenses was the most popular coping approach employed by most of the households sampled in each group, while borrowing money from friends and family at variable interest rates was the second most popular strategy across all groups in Kambalu Township, Myanmar.

In the case of Cambodia, migration is generally viewed as a temporary coping strategy to address unforeseen challenges rather than as a medium-term or long-term process for raising the family's economic and social status. Generally, internal migration is characterised by interprovincial and short-distance movements (Middleton *et al.*, 2013; Maltoni, 2007). Although there isn't much information available on rural-to-rural migration in Cambodia, currently there is a level of awareness about rural-to-urban migration especially since mid-1990s when Phnom Penh's industry for garment manufacturing was established (Ministry of Planning and UNDP, 2007).

Research on migration patterns specifically originating from the communities around Tonle Sap Lake in Cambodia, remains scarce. Most existing studies (Heinonen, 2006; Un, 2011; Middleton *et al.*, 2013) tend to explore how environmental changes relate to migration trends. For instance, Heinonen (2006), drawing on village-level surveys conducted in 2002, highlighted how the flooding trends around the Tonle Sap Lake significantly influence the availability of natural resources. Heinonen (2006), also initiated an investigation into the connection between change in environment and both seasonal and permanent migration. The study focused especially on the connection between urbanisation in Cambodia, particularly in Phnom Penh, and migration from the area surrounding the Tonle Sap Lake. The study contended that factors such as rural unemployment and wage differences between urban and rural areas, population increase and rising rates of landlessness are what propel migration. While many push factors are economic, Heinonen (2006) noted that they also frequently have to do with rivalry for natural resource access, environmental changes and quality of the environment. Heinonen's study provided a useful foundation upon which to investigate in depth the ways in which various forms of annual floods impact livelihoods based on farming and fishing, and consequently influence decisions to migrate temporarily or permanently. Research by Un (2011) in three floating villages located on the Tonle Sap Lake in Cambodia's Battambang province reveals a growing trend of subsistence fishers migrating to Thailand. This shift is largely driven by declining fish catches, which have made it difficult for them to sustain their livelihoods—a significant development considering the lake's historically rich fishery resources.

Every hamlet visited for the Middleton *et al.* (2013) study is situated in a floodplain of the Tonle Sap and experiences flooding from the lake for three to four months out of the year. To better understand key migration patterns and their links to environmental changes and aspects of human security—especially food and economic security—these villages were selected as representative samples of the broader Tonle Sap Lake floodplain communities in their respective provinces. All of the villages were primarily rice-growing and fishing settlements with access to comparable natural resources, such as agricultural land, lakes, streams, rivers and wild-capture fisheries in the area; flooded forests; firewood, and other forest products that are non-timber. But throughout time, each village's resources—both in terms of quantity and quality—have evolved. When farmland is close to rivers or streams, water from these sources is directly pumped into fields during the dry season. This practice is known as irrigated agriculture. In addition to farming, the locals engage in family-sized fishing prior to, during, and following their harvest. This could take place in the village's designated communal fishing area or in the sections that have unrestricted access on Tonle Sap Lake (Middleton *et al.,* 2013; Access to Finance Consortium, 2012).

This Cambodia study was carried out in 2011 November, shortly after the Tonle Sap Lake experienced a significant flooding, that resulted in the loss of life and severe disruption to the daily routine of numerous individuals. For instance, the income of people decreased leaving them with a high level of indebtedness, frequently requiring to sell assets; children could not go to school and movement was hindered, even for roads that are normally dry; livestock perished and rice crops in thousands of hectares were destroyed; and urban and rural infrastructure was damaged (Middleton *et al.,* 2013; Access to Finance Consortium, 2012). These challenges necessitated migration out of these areas. So, migration in Cambodia is a coping strategy to flooding prone Tonle Sap Lake communities.

2.3.1 Flooding in Nigeria and coping strategies adopted by farmers

Between July and October 2012, Nigeria experienced one of the most devastating flood disasters in its history. Several states, including Rivers, Edo, Cross River, Bayelsa, Delta, Benue, and Kogi, were significantly impacted. Prior to the disaster, the Nigerian Meteorological Agency (NIMET) had warned that excessive rainfall could lead to flooding in 12 key states. Combined with the release of water from Cameroon's Lagdo Dam, the Niger and Benue Rivers overflowed, resulting in widespread inundation across the country (Erekpokeme, 2015; Odeh, 2014).

The consequences were severe—lives were lost, many individuals were displaced, farmland was submerged, water sources became polluted, and daily economic activities were brought to a halt. Transportation became increasingly difficult and expensive due to the limited options, which were largely restricted to local boats and canoes. In several regions, floodwaters brought dangerous reptiles such as snakes and crocodiles into residential areas. Farmers across the country suffered extensive financial losses. Food production, distribution, and storage all faced major disruptions, while the cost of basic goods surged. In some areas, schools had to close abruptly (Odidi, 2012; Famous, 2012).

The floods destroyed about 1.9 million hectares of farmland. Crop yields declined significantly, including a 22.4% drop in rice production, 14.6% in maize, 6.3% in cowpea, 11.2% in soybean, and similar losses in cassava output (Erekpokeme, 2015; Anugwara & Emakpe, 2013). In terms of livestock, the floods led to the death of 136 cattle, 3 million poultry birds, and 12 million goats. The National Emergency Management Agency (NEMA) estimated the total economic loss at approximately ₦2.29 trillion (Okoruwa, 2014).

The disaster severely threatened food security, displacing thousands of farming households and destroying their produce, making it one of the worst flood events in Nigeria's recent history. Key staple crops such as yam, maize, cassava, plantain, and pawpaw were especially hard-hit (IITA, 2012). In total, 32 out of Nigeria's 36 states were affected, with Rivers, Benue, Taraba, Kogi, Bayelsa, and Anambra being the hardest hit (Erekpokeme, 2015; Odeh, 2014).

Despite inadequate relief materials, state governments ordered the evacuation of residents from flooded areas and established temporary shelters. However, many victims were hesitant to leave due to fears of looting and theft in their absence (Odidi, 2012). Although floods also occurred in 2011, their impact was far less destructive. In 2012, for example, a flood in Kano State resulted in one fatality and the displacement of around 600 people, while in Katsina State, 55 farms were destroyed.

Some analysts believe the reported losses from the 2012 disaster may have been underestimated by as much as 50%. The broader West African region, including Nigeria, reportedly lost up to $2.5 trillion globally due to the flooding (Erekpokeme, 2015; Gbemudu, 2013). Given ongoing urbanization and population growth, the number of people at risk from such events is expected to rise.

The United Nations Office for Disaster Risk Reduction (UNISDR) projected in its 2015 Global Assessment Report that annual global economic losses from natural disasters could range between $250 billion and $300 billion (UNISDR, 2015). That same year, the Director-General of the Nigeria Hydrological Services Agency issued a national flood risk alert in Abuja. The country was divided into three risk zones: lowland, medium, and high-risk areas. Predictions indicated high flood risk in river basins like Niger-Benue, Sokoto-Rima, and Anambra; localized flooding in areas such as Biase, Munya, Chikum, Shinkafi, and Etiosa; and coastal flooding in states like Rivers, Lagos, Bayelsa, and Delta, largely due to rising sea levels and tidal surges.

Given these warnings and past experiences, it becomes crucial to assess the strategies currently employed by farmers to prepare for flooding, the role of institutions in mitigating its effects, and the interventions introduced by the government for effective flood management.

In coping, farmers frequently utilise mounds as a land management technique to lessen the consequences of floods, according to a study undertaken in Rivers, Akwa Ibom and Ondo states. This approach is used by 39% of female farmers and 30% of male farmers (Umoh, 2013). Famers in the wetlands of Ondo state, plant flood-resistant crop varieties. To deal with environmental risks, farmers have also broadened the sources of their revenue. In Ondo, Rivers and Akwa Ibom states' fishing villages, fishermen take along with them deep freezers to their fishing spots. This is to conserve their catch for the time they would be at sea, and they fish farther from the shore than they used to in order to adjust to flooding and rise in sea level (Umoh, 2013). In another study it was found that the coastal rural populations of the Ijaws, Itshekiris, and Ilaje tribes possessed undocumented knowledge of local meteorology, derived from observation, customs, and systems of belief. This knowledge aids in making long-term and seasonal flood predictions (Erekpokeme, 2015; Fabiyi & Oloukoi, 2013).

In Kwara state, Nigeria, a study was conducted to investigate the influencing factors of farmers' decisions on which adaptation method to use and also to access the adaptation techniques used by smallholder rice farmers in reducing losses due to flood. Semi-structured questionnaires were used to collect primary data from 240 smallholder rice farmers who had been chosen using a three-step sampling process. The data were analysed using a multinomial logistic regression model and descriptive statistics. According to the survey, about 79.5% of the rice farmers planted early-maturing rice seedling varieties. This is so as to enable them harvest early before rainfall peaks, which is when floods are observed. With only 2% of rice farmers using this technique, crop rotation and upland cropping are the least popular approaches. Early maturing rice varieties' adoption was positively influenced by educational status, savings from past flood-related losses, and changes in crop and upland cropping; on the other hand, access to information and household size had a negative influence on the practice of changing the planting date in relation to crop rotation and upland cropping (Ajibade *et al.,* 2019). The study suggests that it is imperative to educate the farmers in the area about locally appropriate coping techniques, such as planting alternative crops and upland cropping in order to address their continued reliance on flood-plain farming.

2.3.2 Flooding in Rivers State, Nigeria

The historical landscape of flooding in Rivers State signifies a transformative journey, transitioning from sporadic occurrences to a persistent and looming menace. The gravity of this issue necessitates a comprehensive exploration of the historical context and the dynamic patterns that have characterized flooding over time. By examining statistical evidence and drawing upon case studies, a more detailed perspective is gained, shedding light on the multifaceted nature of this environmental challenge (Nwiyii *et al*, 2022; Nkwunonwo, 2016).

Historically, Rivers State has witnessed a series of sporadic flooding events that have left an indelible mark on its landscape. However, a notable shift has occurred, transforming these events into a recurrent and pressing issue, demanding heightened attention and analysis. Statistical evidence becomes a crucial tool in unravelling the extent and frequency of these events, providing a quantitative foundation to grasp the severity and evolving nature of flooding in the region (Nwiyii *et al*, 2022; Nkwunonwo, 2016).

Beyond mere statistical representations, delving into the historical context allows for a deeper exploration of the factors contributing to the recurrent flooding menace. Identifying patterns and trends becomes imperative, offering insights into the drivers behind the increased frequency of flooding events in Rivers State. Historical analyses may uncover shifts in climate patterns, land-use practices, or infrastructural changes that have collectively contributed to the altered dynamics of flooding (Tempels, 2016; Brody *et al*., 2014).

Case studies play a pivotal role in augmenting the statistical narrative, providing a qualitative dimension to the historical evolution of flooding in Rivers State. By examining specific instances of flooding around the world, researchers can discern the localized impacts on communities, agriculture, and infrastructure. These case studies act as microcosms, illustrating the broader implications of flooding and offering valuable context to complement the quantitative data.

The intertwined nature of socio-economic and environmental factors further complicates the understanding of flooding. Rapid urbanization, changes in agricultural practices, and infrastructural developments can exacerbate the region's susceptibility to flooding (Zope *et al*., 2016; Ikechukwu, 2015). Investigating these interdependencies becomes paramount in constructing a holistic narrative of how Rivers State has transformed from sporadic flooding events to a recurrent environmental challenge.

2.3.3 Government Interventions

Institutions and governmental agencies realised the need to implement suitable flood prevention measures following the 2012 floods. Inputs for farming were provided by a few well-meaning organisations to assist farmers in rebuilding their lives following the catastrophic flood. The International Institute of Tropical Agriculture (IITA) was called upon to assist farmers in the Nigerian state of Bayelsa. To evaluate the magnitude of the damage, a group of IITA experts travelled to the state. After meeting with state representatives, the team promised to provide better plantains cuttings, maize and cassava cuttings to the state in less than a month. Early maturing maize varieties will enable farmers to make quick adjustments by putting food on the table (IITA, 2012). In order to lessen the suffering of internally displaced farmers, the Delta state government of Nigeria sent high-yielding yam seedlings, cassava cuttings and planting materials. A number of brainstorming sessions were held around the nation to discuss strategies for the management of flood which will be competitive with international standards. The Flood Research Group of the Federal University, Otuoke, Bayelsa state, located in the Niger Delta region and one of the states affected by the 2012 flood, in partnership with Bayelsa state government, conducted a workshop on post-flood management. The recommended approaches for reducing the impact of flooding include installing appropriate drainage systems, erecting buffer dams in key locations, designing homes to avoid impediments to natural drainage and waterways, the mitigation of siltation in rivers, creeks, and other waters bodies through dredging, and the formulation of a comprehensive community flood readiness, consciousness, and control program to be executed state-wide. Consistent assessment of soil moisture and water levels, efficient local weather report information, mandatory evacuation exercises, and a crisis self-assistance and survival community orientation are all important components of this project (Federal University, Otueke, 2013).

In reaction to flooding in major cities such as Lagos, Kano, and Kaduna, the federal government introduced an early warning system aimed at reducing the effects of floods across the country. The Ministry of the Environment implemented 307 web-based flood warning systems throughout the nation. Additionally, states including Rivers, Ondo, Cross River, Niger, Imo, Lagos, Anambra, Oyo, Ogun, Osun, Nassarawa, Akwa Ibom, Kwara, Enugu, and Abia were provided with community-based flood warning systems. The Ministry also acquired and deployed four autonomous automatic, functional, flood early warning systems throughout the Eruwa, Owena, and Alamutu River basins (Okoruwa, 2014). The federal government equipped the Nigerian Meteorological Agency (NIMET) to give accurate meteorological forecasts, with the aim of warning the population about the impending threat of flooding. In addition, 17 billion naira was disbursed to pertinent stakeholders and the affected states in order to mitigate the aftermath of the 2012 floods. Construction of the Ose Dam, the Kashimbilla/gamovo multifunctional dam, and the Taraba state hydropower project are all planned to handle the occasional burst of excessive water flow from Cameroon. The dams will improve irrigation, mitigate flooding, produce power, create jobs, and increase Nigeria's agricultural output (Anugwara and Emakpe (2013). The government has attempted to move residents from locations susceptible to flooding. In South Eastern Benue state, government officials moved 40 communities to more secure areas. The Kogi state government encouraged those living along the riverbanks to migrate, following a notification of water expected to be released from the Jebba Dams and Kainji. Additionally, the state's residents were urged by the government to clean up the drainage systems so as to provide unimpeded water flow and avert flooding (Anugwara & Emakpe, 2013). The flooding episode of 2012 imparted significant lessons to agencies like the Red Cross that improved their emergency response. The Nigerian Red Cross trained 22,000 volunteers, and supplies for assistance were stacked in warehouses. In order to reduce the risk of flooding, NEMA advised dam maintenance personnel to promptly lower water levels and to refrain from delaying until the levels exceed the dam's capacity before initiating release. In facilitating speedy evacuation, areas susceptible to flooding received training and basic supplies (Erekpokeme, 2015). NEMA utilised a floodplain and vulnerability map developed by the National Space Research and Development Agency (NASRDA) to aid in the rehabilitation of those impacted by the 2012 flooding episode. In the year 2015, NEMA sponsored a pre-flood awareness event for relevant stakeholders in Ilorin, the capital of Kwara State in North Central Nigeria. The state administration was urged to remove all garbage bins from the state in order to create a cleaner and healthier environment, and participants were counselled to pay attention to early warning systems and refrain from illegally throwing trash into waterways to obstruct them (Odeh, 2014; Akanbi, 2015).

2.3.4 Impact of Flooding on Agriculture

The impact of flooding on agriculture transcends mere disruption of fields; it permeates the very framework of livelihoods, food security, and the broader economy. Understanding the multifaceted repercussions requires a comprehensive exploration that delves into the direct and indirect consequences of flooding on the agricultural landscape. By incorporating specific examples and studies, a fuller understanding comes into view, portraying the severity of these impacts and underscoring the intricate interconnections between agriculture and the well-being of the region (Nwiyii *et al*, 2022; Nkwunonwo, 2016).

At its core, flooding manifests as a formidable adversary to agricultural activities. The inundation of fields during flooding events inflicts immediate damage to crops, compromising yields and diminishing the economic viability of farming endeavours. The direct impact on crop production is a pivotal aspect, as staple crops that form the backbone of local agriculture may face substantial losses, thereby threatening food security (Anderson *et al.,* 2020; Ikechukwu, 2015).

Beyond the visible devastation, the alteration of soil conditions due to flooding introduces a layer of complexity to the challenges faced by agricultural communities. Soil erosion, sediment deposition, and changes in nutrient composition become pronounced issues, affecting the long-term fertility and productivity of arable land (Batung, 2021; Ullah *et al.,* 2019). The repercussions extend beyond the immediate aftermath of flooding, posing enduring challenges to sustainable agriculture in the region.

The consequences of flooding on agriculture reverberate through the socio-economic framework of an area. Livelihoods dependent on agriculture experience a sudden and profound disruption, as farmers grapple with the loss of crops and the diminished capacity to generate income. Smallholder farmers, constituting a significant portion of the agricultural landscape, are particularly vulnerable, facing heightened economic uncertainty and potential impoverishment (Batung, 2021; Opiyo *et al*, 2014).

Food security, a critical concern for any region, becomes increasingly precarious in the wake of flooding. The disruption of agricultural activities contributes to a decline in local food production, necessitating external sources to meet the nutritional needs of the population. This dependence on external food supplies not only strains resources but also leaves communities susceptible to fluctuations in market prices, exacerbating the vulnerability of already marginalized households (Batung, 2021; Ebhuoma and Simatele, 2017).

The economic ramifications extend to the broader economy of Rivers state. Agriculture serves as a mainstay, and any upheaval in this sector ripples through related industries and markets. Reduced agricultural output translates to diminished income for farming households, influencing their purchasing power and, consequently, impacting local businesses.

2.4 Food security

Food security is widely recognised to be founded on six critical pillars: availability, access, utilisation, stability, agency and sustainability (FAO, 2016).

Availability: A household's ability to obtain the food it needs, which is mostly satisfied by the household's capacity to produce the food itself, is referred to as the availability component of food security. Any family-level effort that contributes to increased food supply or agricultural productivity should be included in the food availability strategy (Juhar, 2012). The availability dimension is frequently utilised in relation to the national or regional food supply. Any factors that affect local food production and stockpiling, importation of food and food support, together with the variables that affect these aspects, all have an effect on food availability (Carrillo-álvarez *et al.*, 2021; Wineman, 2013).

The assertion is that sufficient food accessibility cannot be guaranteed without sufficient food supply. The achievement of this dimension is hampered by a number of issues, including yield gaps, diminishing investment by the government in agriculture, environmental degradation, depletion of natural resources and biodiversity, the effects of climate change on productivity, loss of food and wastage, and inadequate storage infrastructure (HLPE, 2020), to name just a few. According to FAO, per capita food availability can be measured using the indicator Daily Per Capita Dietary Energy Supply (FAO, 2016). This indicator is discussed below.

Daily Per Capita Dietary Energy Supply: At the household level, food availability refers to the provision of adequate quantities of food, both in terms of quality and quantity, sourced from domestic production or importation (purchased outside the household or reference scale). The food availability indicator assesses the amount of food produced by the household, along with the quantities bought and sold per capita, to determine the calories and nutrients available per person (Remans *et al.*, 2014; Stewart *et al.*, 2018).

To measure Per Capita National Food Availability in a related study by Smith and Haddad, (1999), daily per capita dietary energy supplies (DES) of 63 countries were used. This measure was obtained using food balance sheets prepared by the United Nations Food and Agriculture Organisation (FAO) utilising country-specific data on food commodity production and trade. A supply account was developed for each commodity based on data regarding wastage, stock fluctuations, and various forms of food commodity utilisation, detailing the weight available for human consumption annually. The total energy availability was calculated by transforming the weights of each commodity into energy values and combining these values across commodities. The total energy supply was subsequently divided by the population size to obtain per capita DES (Smith and Haddad, 1999).

Accessibility: The food security (FS) component access, measures the ability of a household to obtain food by taking into account both the household's ability to buy food to meet their basic needs and the accessibility of food commodities on the local market (Juhar, 2012). Access to food is influenced by a variety of factors, including the range of food alternatives available to households based on their income, market price, accessibility, employment, income disparities, and structured or unstructured safety net systems (Carrillo-álvarez *et al.,* 2021; Wineman, 2013). Wineman (2013), claims that the demand side of food production is represented by FS accessibility, which really leads to an uneven distribution of food among and within households.

The availability and access to food and energy in a region depend on a number of factors, including quantity, quality, safety, and cultural acceptance and choices (Leroy *et al.,* 2015). According to HLPE (2020), issues affecting food access include a lack of readily available, healthful food at an affordable price; reliance on imported food; poverty and unstable livelihoods; disparities in the standard of food environments; plus, access within households, by gender, class, age, and other categories. Small-scale producers also face barriers to market access and distribution because of a lack of infrastructure. Per capita food expenditure is typically used to measure this component (Akukwe, 2020). Experience-based indicators, such as the household food security scale module (HFSSM), household dietary diversity score (HDDS), food consumption score (FCS), and many others, can also be used to measure this component (Leroy *et al.,* 2015). Two indicators, Household Food Insecurity Access Scale (HFIAS) and farm revenue as proxy are discussed.

HFIAS: The Household Food Insecurity Access Scale is a tool designed to capture the level of food insecurity in households, specifically focusing on the "access" dimension of food security. Specifically, HFIAS measures the perceptions and experiences of food insecurity due to insufficient access to food, typically over the past 30 days. HFIAS focuses on three key domains; Anxiety and uncertainty about household food availability, inadequate quality (including diversity and preferences of food types), and inadequate food intake together with its physiological consequences.

It consists of 9 questions that assess increasing levels of severity of food insecurity. These questions help identify whether households have experienced problems like worrying about not having enough food, eating fewer meals than needed, eating foods they did not prefer, going to bed hungry, and going for an entire day and night without eating (Coates, *et.al*., 2007).

Farm revenue: This mainly measures the economic access dimension of food security. Economic access refers to people's ability to afford food, based on their income levels relative to food prices. When farmers earn higher revenues, they are better able to access sufficient and nutritious food for themselves and their households, either by producing it directly or purchasing it from markets. Farm revenue also affects the local food economy — profitable farms can invest more in production, contributing to food availability and stability over time.

According to the Food and Agriculture Organization (FAO), food security exists when all individuals, at all times, possess physical, social, and economic access to adequate, safe, and nutritious food (FAO, 2006). Economic access is the ability of individuals and households to afford food, which is closely tied to income.

Farm revenue reflects the income farmers earn from selling agricultural products. Higher farm revenue generally increases farmers' ability to purchase food, invest in farm improvements, and build resilience against shocks, thus strengthening their economic access to food (FAO, 2008; Maxwell & Smith, 1992).

In research by Barrett (2010), farm incomes are discussed as a core determinant of household food security, particularly in rural areas where farming is the primary livelihood. Barrett emphasized that increased income from farm revenue improves the affordability of a diverse and sufficient diet. Therefore, farm revenue primarily captures the economic access aspect of food security.

Smith *et al.* (2006) show that income growth, particularly from agriculture, has been historically significant for enhancing household food security, specifically through improving the ability to buy food.

Utilisation: Utilisation is related to health and raises questions about how well people are using the foods they have access to on a daily basis. Wineman (2013) explained that there are two categories of food utilisation: biological and physical. Physical utilisation quantifies how well a household uses food and is contingent upon hygiene standards throughout the food chain, which are influenced by things like adequate housing, cooking utensils, food preparation knowledge and skill, and access to potable water. Conversely, dietary quality and hygienic practices have an impact on biological utilisation, which is a measure of the ability of the body to efficiently use the nutrients it consumes (Wineman, 2013; FAO *et al*., 2021).

FAO *et al.* (2021) state that a person's nutritional status is based on their body's capacity to utilise the food they eat as well as their ability to get enough energy and nutrients from a variety of sources, such as proper care and feeding, food preparation, a varied diet, food distribution throughout the family, and access to clean water, sanitation, and medical care. Hidden hunger and micronutrient deficiencies; rising obesity rates; lack of nutritional diversity; food safety issues; unhealthy and unsustainable diets; Changing food habits as a result of rising wages and urbanisation etc. are the challenges facing this component (Fanzo *et al*., 2022; HLPE, 2020).

Stability: It was argued that stability difficulties can be short-term, causing severe food insecurity, or medium- to long-term, causing chronic food insecurity. Stability is defined as the state in which the entire structure is steady, guaranteeing that households have food security at all times, when the other three dimensions (availability, accessibility, and utilisation) are all adequately satisfied (FAO *et al*, 2021). Furthermore, Carrillo-álvarez *et al.* (2021) contended that achieving food security necessitates the occurrence of all the aforementioned aspects simultaneously and continuously. Conflicts, migration and economic instability; periodicity in the supply of food; climatic disasters, natural and anthropogenic calamities; financial instability, trading disruptions, unexpected food costs; year-to-year income volatility, etc. are some of the issues that HLPE (2020) identified.

Agency: One of the two new extra aspects of food security that the high-level panel of experts (HLPE) suggested is agency, however the FAO and other international organisations have not yet formally approved it. According to their report, agency is the capacity of individuals or groups to decide for themselves what foods to produce and eat, as well as how those foods are produced, refined, and disseminated across food systemsIt also encompasses the ability to participate in the processes that shape the policies and administration of food systems. According to HLPE (2020), it encompasses more than just having access to monetary resources; it also includes empowerment, which is the ability for people to engage in social interactions that affect the larger context, making their voices heard and influencing public policy.

Clapp *et al.* (2021) further stated that a number of researchers have been compelled to examine food security through the lens of human development, enabling individuals to influence their interactions with food production systems, confront power imbalances, and coexist within those structures. A few obstacles to achieving this dimension are the unequal distribution of wealth and income, which influences decision-making; gender differences that restrict decision-making; erratic trade regulations that may penalise certain farmers and consumers; ineffectual and disjointed governance of food systems; feeble political structures; unequal distribution of land and resources; unequal access to information and technology; and so on (HLPE, 2020).

Sustainability: Sustainability is a component of food security that involves long-term efforts to maintain and conserve ecosystems within the food system, together with the establishment of the necessary economic and social institutions to guarantee food security and sustenance for all people (HLPE, 2020). According to HLPE, ecosystems' ability to interact with economic and social systems in ways that support varied and efficient agricultural output and food system livelihoods for the long term is threatened by climate change, environmental degradation, and growing social and economic inequities.

Long-term food security cannot be attained without sustainable agricultural systems that safeguard social, economic, and environmental factors, according to El Bilali *et al.* (2018). Climate change implications for future production; biodiversity loss that damages genetic diversity; depletion of natural resources; resource inefficiencies and pollution from the overuse of agrochemicals; urbanisation and population change, etc. are some of the concerns of sustainability (HLPE, 2020).

2.5 Empirical review of impact studies on migration, agricultural production and food security

Ren *et al*. (2023) examined the effects of migration on farm performance, specifically focussing on rice farmers in China, by estimating the causal relationship between migration and both economic and environmental performance, utilising metrics of technical efficiency and fertiliser use efficiency. A stochastic frontier analysis, utilising survey data from four locations in China, revealed an average technical efficiency of 0.92 and a fertiliser use efficiency of merely 0.22. According to propensity score matching data, farmers who engaged in migration more frequently saw a greater increase in the influence of migration on their rice production's technical efficiency and fertiliser use efficiency.

In the Northern Province of Thailand, Nonthakot and Villano (2008), looked into the connection between labour migration and agricultural productivity. Utilising data on maize production from a household survey, they estimated a stochastic production function to assess the impact of migration, remittances, and notable migrant attributes on the average yield of maize and technical efficiency levels. They found that the number of migrant workers and their remittances facilitate maize production. It was also discovered that the productive potential of maize farmers is increased by remittances, length of migration, gender, and education of migrants.

Adaku (2013) utilised sample data from the Ghana Living Standards Survey 5 (GLSS 5) to analyse the socioeconomic characteristics of households without migrants, households with temporary migrants, and households with permanent migrants, investigating the impact of rural-urban migration on agricultural production at the migration origin. The research employed a two-stage least squares regression model with the Cobb-Douglas production function to delineate the correlation between agricultural output and migration. The results showed that households with members who temporarily migrated had significantly reduced farm production, while households with permanent migrants had no significant effect on production.

With data collected from Malawi, Amadu, (2018) estimated the impacts of Climate Smart Agriculture (CSA) adoption on food security, in terms of agricultural yields and household income, using endogenous switching regression and endogenous treatment effect. He discovered that those who adopted had more yield and were more food secure than those who did not. He found that on average, CSA adopters obtained yield and household income increases of 90% and 41% respectively.

Employing an endogenous switching regression methodology to address selectivity bias, Issahaku (2019) examined the determinants influencing farmers' choices to adopt climate-smart practices and the impact of such adoption on food and nutrition security among agricultural households across three agro-ecological zones in Ghana. The study used farm revenue as a proxy for food access and HDDS and HFIAS as proxies for nutrition security. He used these three indicators to capture the multifaceted nature of food and nutrition security. In order to ensure that households have access to food for consumption, he first employed farm revenues, assuming that higher farm revenues tend to improve food security (Di Falco *et al.* 2011). Sen (1981) contended that both the degree of production and the market accessibility of food through purchase determine an individual's capacity to obtain food at the household level. According to certain research, eating their own produce helps smallholder farmers attain food security (Hawkes and Ruel 2008). On the other hand, Brown *et al.* (2017) noted that buying food from the markets contributes significantly to smallholder farmers' increased dietary diversification. Therefore, farm revenue can be a good indicator of food access, particularly if farmers are able to make enough money and buy from markets to diversify their diets.

The secondary metric used by Issahaku (2019) for assessing food security was the Household Food Insecurity Access Score (HFIAS). The HFIAS is an index that quantifies and summarises many behavioural and psychological aspects of food insecurity (access) into a scale (Coates *et al.* 2007; Maxwell et al. 2014). The minimum score is 0 for a household with no documented food insecurity (indicating superior food access). The highest score for a household is 27, indicating food insecurity characterised by a high frequency of consuming less favoured food and meal skipping due to insufficient availability to food (Coates *et al.* 2007). The third metric employed is the household dietary diversity score (HDDS), following the methodology outlined by Swindale and Bilinsky (2006). The results demonstrated that the implementation of climate-smart techniques had a favourable and noteworthy effect on HDDS, HFIAS, and farm revenues with regard to food and nutrition security.

2.5.1 Estimating production frontiers

There are various functional forms used in the estimation of stochastic production frontiers. The most popular are Cobb-Douglas and Translog production functions (Coelli *et al*., 2005; Kumbhakar *et al.,* 2015). The Cobb-Douglas production function is a double-logarithmic function with output and inputs expressed in logarithms. The model is implicitly expressed as:

$$Y = aX^b \quad \ldots\ldots 2.1$$

Where;

Y is output quantity, X is the input used in production, a and b are the parameters to be estimated.

This model when transformed to log is specified as:

$\text{Ln } Q = \beta_0 + \sum_{i=1}^{n} \beta_i \ln X_1$ ………………………………………………………………….. 2.2

Where;

β_1 is the elasticity of input used.

The translog production function in general form is expressed as;

$\ln Y = \beta_0 + \sum_{i=1}^{n} \beta_i \ln X_1 + 1/2 \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln X_1 \ln X_j$ ………………………………….. 2.3

The functional form must have flexibility because flexible functional forms impose no constraints on the values of the function or its first and second derivatives. The linearity, regularity and robustness of the function should also be some of the principles of selection.

The Stochastic Frontier Analysis estimates technical efficiencies on the assumption that firms operate under a single technology or under the same geographical location (Coelli *et al*., 2005; Kumbhakar *et al.,* 2015). Therefore, in situations the firms operate under varying technologies or geographical locations it may not applicable. In cross-country, cross-regional or multiple technology efficiencies, stochastic frontier cannot be used. Meta-Frontier analysis will suffice in these scenarios.

Stochastic frontier analysis for technical efficiency can be done using several analytical software like Stata, SAS, etc

2.6 Summary of key findings

In summary, contrary to the perception of migration as a straightforward coping strategy, the process of return migration in the aftermath of flooding presents returning migrants with a host of challenges during resettlement. These challenges, including issues related to land access, social reintegration, and resource competition, compound the complexities of rebuilding lives and agricultural livelihoods (King, 2015).

Several attempts have been made at researching into coping strategies of flooding-prone communities. Crop diversification emerges as a cornerstone of traditional coping strategies employed by farming communities. The practice involves cultivating a variety of crops with different growth cycles, resistance to flooding, and nutritional profiles (Kurukulasuriya and Rosenthal, 2013).

The measurement of food security has been done by several researchers like Issahaku (2019) who used HDDS and HFIAS as proxies for nutrition security and farm revenue as food accessibility. Smith and Haddad (1999), used daily per capita dietary energy supplies (DES) to measure Per Capita National Food Availability. These works measured various dimensions of food security.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter outlines the methodologies employed in the research. Section 3.2 outlines the theoretical background of the study. Section 3.3 discusses the method of data analysis for the study. It also outlined analytical tools and estimation procedures to address the stated research objectives. Section 3.4 outlines the research design. Section 3.5 highlights the study area, its climate, economic situation, demography and geographical location.

3.2 Theoretical framework

3.2.1. Push-Pull Theory of Migration

The Push-Pull Theory of Migration, first introduced by Lee (1966), offers a comprehensive framework for analysing the intricate dynamics that affect return migration. Lee (1966) posits that migration is influenced by a confluence of "push" elements that necessitate individuals' departure from their existing locale and "pull" variables that entice them to a new place (Van Hear *et al.,* 2020). This theory allows for a nuanced exploration of the motivations behind return migration and aids in comprehending how individuals navigate the challenges posed by escalating flooding. In the context of return migration after flooding, individuals may be pushed away by adverse environmental conditions and economic challenges resulting from flooding-induced losses, while the desire to reconnect with the homeland and contribute to post-flood recovery acts as a significant pull factor (Lee, 1966).

Push Factors: These could encompass adverse environmental conditions, economic challenges arising from flooding-induced losses, and disruptions to livelihoods (Van Hear *et al.,* 2020). Individuals may feel compelled to migrate due to the deteriorating conditions in their current location.

Pull Factors: Conversely, pull factors might involve the desire to reconnect with the homeland, rebuild communities, and capitalize on improved post-flood conditions (Van Hear *et al.,* 2020). The prospect of contributing to the restoration and recovery of the region could act as a significant attractor.

Understanding the interplay between these pushes and pull factors provides a nuanced perspective on the motivations driving individuals to return after flooding.

The push–pull theory of migration provides an important theoretical lens for understanding the migration dynamics observed in this study. The theory posits that migration decisions are shaped by a combination of push factors that compel individuals to leave their place of origin and pull factors that attract them to alternative locations (Lee, 1966).

In the context of this study, recurrent flooding serves as a dominant push factor. Flooding undermines agricultural production through crop losses, land degradation, disruption of farming calendars, and heightened livelihood insecurity. These adverse conditions reduce the viability of farming as a means of sustenance, thereby compelling farming households to temporarily or repeatedly migrate out of flood-prone communities. The loss of farm output, income instability, and food insecurity documented among migrant households in this study are consistent with the push-factor mechanism described by the theory.

Conversely, pull factors influencing migration during flooding episodes include the availability of temporary shelters such as internally displaced persons (IDP) camps, relocation to family members' residences in safer communities, and movement to urban areas where access to basic services, relief assistance, and alternative livelihood opportunities may be perceived to be better. These destinations offer relative safety and short-term survival options, even though they may not necessarily provide sustainable income-earning opportunities.

By applying the push–pull framework, this study conceptualizes migration as a response to environmental stress rather than a voluntary economic choice. The theory helps explain why migration in the study area is widespread, recurrent, and largely involuntary, affecting entire households during flooding episodes. It also provides a basis for linking migration to observed outcomes such as reduced farm technical efficiency, disrupted agricultural activities, and heightened food insecurity among migrant households.

Overall, the push–pull theory strengthens the analytical foundation of this study by clarifying how flooding-induced environmental pressures interact with destination-specific factors to shape migration patterns and their subsequent impacts on agricultural productivity and household welfare.

3.2.2. Resilience Theory

The Resilience Theory, pioneered by Holling (1973), serves as a foundational pillar to elucidate the coping strategies employed by agricultural households in response to flooding challenges. This theory posits that individuals and communities possess inherent capacities to adapt, recover, and even thrive in the face of adversity (Holling, 1973; Folke, 2006). In the area of flooding, the Resilience Theory provides a lens for understanding how agricultural communities leverage their innate adaptive capacities to navigate the multifaceted impacts of escalating flooding (Southwick *et al.*, 2014).

Following Bang *et al.* (2018), resilience, in the context of this study, encompasses the ability of farming households not only to withstand the immediate shocks of flooded fields but also strategically and sustainably adapt their agricultural practices over time. The theory emphasizes the dynamic nature of resilience, highlighting the ongoing process of adjustment and learning within communities facing environmental challenges.

The theoretical framework in Figure 3.1, guides the exploration of how agricultural households confronted with the recurrent threat of flooding, harness their resilience to develop coping strategies that extend beyond survival to aiming for sustained productivity and community well-being.

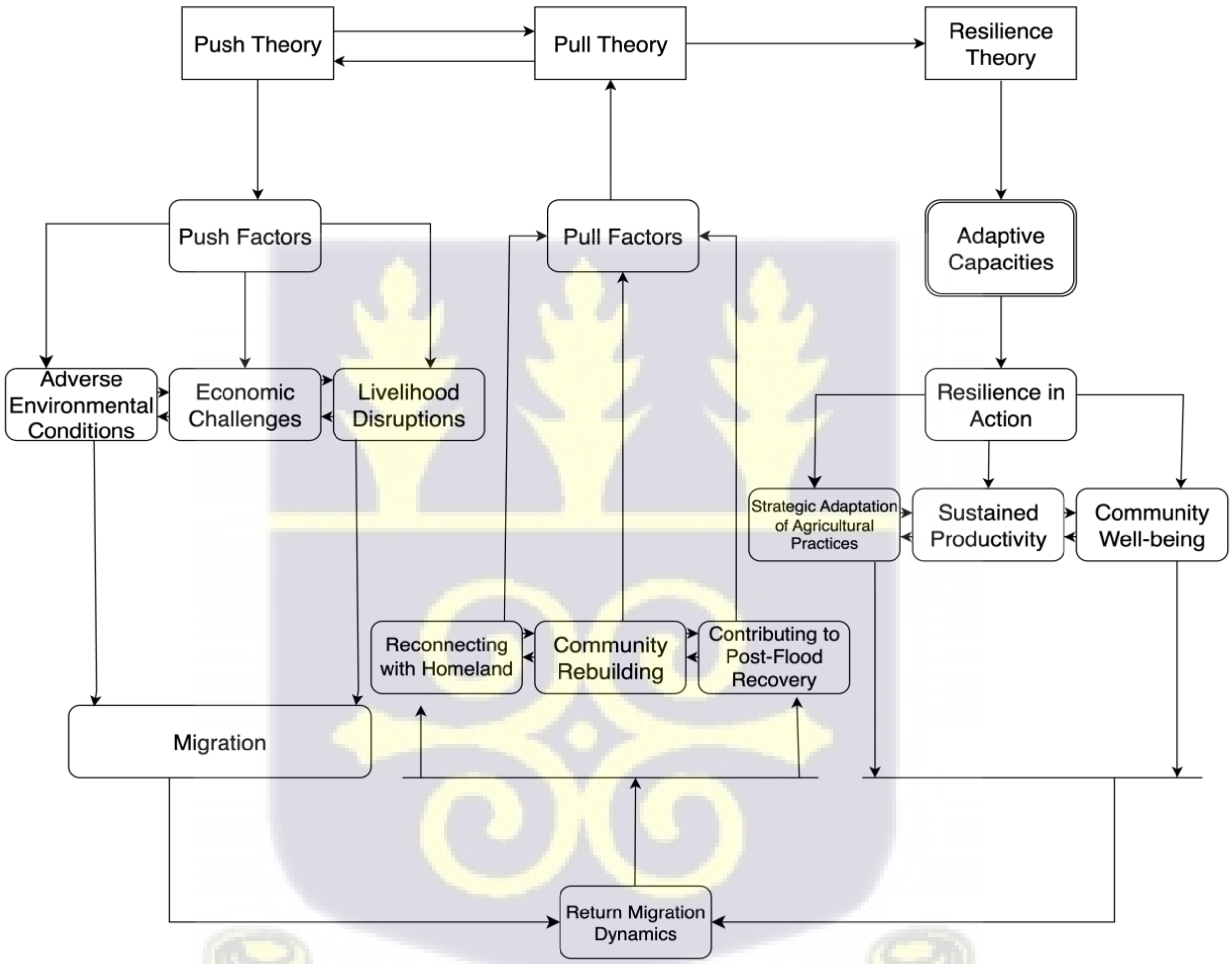

Figure 3.1: Theoretical Framework

Source: Author (2024)

By integrating the Push-Pull Theory of Migration and Resilience Theory, the theoretical framework in Figure 3.1 provides a comprehensive lens to analyse the nuanced dynamics of return migration and the coping strategies adopted by agricultural households in Rivers State.

It offers a theoretical scaffold to explore motivations, adaptive responses, and the sustainable resilience of communities facing the challenges of escalating flooding. The framework begins with Push-Pull Theory, which categorizes the initial motivations for migration into push and pull factors. On the left side of the figure, push factors emerge from environmental and socio-economic stressors, including adverse environmental conditions, economic challenges, and livelihood disruptions. These elements represent the main triggers of temporary migration during flood events.

These push factors connect to the pull factors, which include motivations for return such as reconnecting with homeland, community rebuilding, and contributing to post-flood recovery. These represent the conditions or aspirations that draw displaced agricultural households back to their original communities after the flooding subsides.

The central component of the framework "Return Migration Dynamics" is the convergence point of both the push and pull factors. It highlights the transition from displacement back to resettlement and the beginning of recovery.

To the right of the figure, Resilience Theory comes into focus. It begins with adaptive capacities, which reflect the internal strengths, coping mechanisms, and institutional supports that households and communities rely on during post-flood recovery. These capacities give rise to resilience in action, manifested in three interrelated outcomes: strategic adaptation of agricultural practices (e.g., adjusting cropping patterns or input use), sustained productivity (ability to maintain farm output despite displacement), and community well-being (broader social and economic recovery post-flood).

Finally, arrows connect these outcomes back to Return Migration Dynamics, emphasizing that the return process does not merely close the migration loop but contributes to long-term recovery, adaptation, and improved food security outcomes. The cyclical nature of this framework reflects the recurring pattern of displacement and return that characterizes agricultural households' experiences in flood-prone regions.

3.2.3 Production Theory

This study is grounded in classical production theory, which defines the technology that maps inputs into the maximum feasible output. To operationalise this theoretical framework, parametric production frontiers (Cobb–Douglas and Translog) is estimated and measures of technical efficiency derived as the ratio of observed to maximal feasible output. The stochastic frontier specification explicitly separates random noise from one-sided inefficiency, allowing consistent estimation of both the production technology and farm-level inefficiency. Test for functional form (Wald test for Translog versus Cobb–Douglas) was conducted to ensure the chosen specification aligns with underlying production-theory implications.

Production theory is the branch of microeconomics that describes how firms (or production units such as farms) transform inputs into outputs. It formalises the technology available to producers and provides the conceptual tools to analyse productivity, returns to scale, input demand and the marginal contribution of each input to output. At its heart is the production function, a mapping from input vectors to the maximum feasible output given technology and management:

$$Y = f(X_1, X_2, \ldots, X_n)$$

where Y is output and X_j are inputs (for example seed, labour, fertiliser, land).

The production function embodies the technological possibilities and is the benchmark against which observed output is compared. Classical objectives of production theory include deriving marginal products, elasticities of output with respect to inputs, and understanding behaviour under input or output price changes. Functional forms commonly used are Cobb–Douglas and Translog (Transcendental logarithmic) functions. Choice of functional form is a modelling decision informed by production theory and empirical flexibility.

Production theory defines the feasible maximum output given inputs and technology. Technical efficiency (TE) measures how close an observed producer is to this frontier (the maximum feasible output):

Technical efficiency$_i$ $= \frac{Yi}{Yi*}$ with $0 < \mathrm{TE}$

where Y_i is observed output and Y_i* is the maximum feasible output for inputs X_i given the technology. A TE of 1 means the farm operates on the production frontier (technically efficient); values below 1 indicate inefficiency.

To estimate the production frontier and obtain TE measures, production theory is extended into a stochastic frontier econometric model (Aigner, Lovell & Schmidt, 1977). The typical SFA specification introduces two error components:

$\mathrm{Ln}\ Y_i = f(\ln X_i) + V_i - U_i$

V_i captures symmetric statistical noise (measurement error, weather shocks, random events and is usually assumed $V_i \sim N(0, \sigma^2{}_V)$

$U_i > 0$ captures bon-negative technical efficiency (distance from the frontier) often assumed to follow a truncated-normal, half-normal, or exponential distribution.

This decomposition rests on production theory (the frontier f(.) and recognises that observed output may be below the frontier due to both inefficiency and random shocks.

Because the production function indicates the technologically feasible maximum output for given inputs, the estimated frontier $\hat{f}(.)$ is the empirical representation of that maximum. Technical inefficiency U_i is therefore the shortfall from the production-theory-implied maximum; inference about TE and the determinants of inefficiency relies on this production-theory foundation.

3.3 Method of data analysis

To realize the specific objectives of the study, a number of analytical and estimation tools have been put together. These methods and tools of analysis are explained in this section and used in analysing the secondary data and also primary data collected from the study area.

3.3.1 Description of trends in flooding episodes, migration and return migration of farming households in the study area between 2011-2022

To describe the trend in flooding episodes, migration and return migration in the study area, tables, graphs, mean differences and percentages were used. Secondary data analyzed were collected from National Emergency Management agency (NEMA) and primary data gathered from the individuals who participated in the study (respondents) in the study area.

This study was guided by several hypotheses, and for this objective, the study tested the hypotheses that flooding episodes have no influence on the livelihood of farming households in the study area. This was done using descriptive and inferential statistics drawn from household survey data. Indicators of livelihood disruption such as crop loss, farm abandonment, and income reduction due to annual floods were analyzed.

3.3.2 The coping strategies adopted by farming households in Rivers State, in mitigating the impacts of flooding

To identify the coping strategies adopted by farming households, in mitigating the impacts of flooding, simple statistical tools like percentages and tables were used in analysing the responses to questions presented to the respondents. Coping strategies like crop diversification (e.g early-maturing varieties), water management, use of traditional knowledge, technological advancement etc, were analysed using tables and percentages. This method aligns with various works that used descriptive statistics to describe the coping strategies adopted by farmers during flood (e.g., Ajibade *et al*., 2019; Myint and Tun, 2017; Middleton *et al.,* 2013).

The hypothesis tested for this objective is that farmers' coping strategies are not characterized by crop diversification, community support networks, adaptive capacities, and government interventions. This was realized by using descriptive statistics drawn from household survey data.

3.3.3 Effects of flooding-induced migration and return on farm productivity (technical efficiency)

Ren et al. (2023) conducted a study in China where they applied both Cobb-Douglas and Translog stochastic frontier models to evaluate how migration affects the performance of rice farms. In addition, they assessed the impact of migration on technical efficiency using Propensity Score Matching (PSM) alongside the Radius Matching technique. Drawing on this framework, the current study adapted their methodological approach by incorporating Endogenous Switching Regression (ESR) to enhance analytical robustness. The ESR method was introduced to address a key limitation of PSM-its reliance solely on observable variables and sensitivity to matching quality-by allowing for the simultaneous control of both observed and unobserved influences on treatment selection and outcomes.

In the context of Rivers State, Nigeria, the effects of flooding-induced migration and return on farm productivity, measured through technical efficiency, were examined. The analysis involved fitting both Cobb-Douglas and Translog stochastic production frontiers, from which the better-performing model was selected. The ESR model was then employed to estimate the influence of migration on farm-level technical efficiency, complemented by PSM as a robustness check. Technical efficiency here refers to the farm's ability to minimize input usage relative to output production. To quantify this, the first step involved specifying a production function, with the Translog functional form detailed below:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{n} \sum_{s=1}^{n} \beta_{js} \ln X_{ij} \ln X_{is} + \sum_{k=1}^{n} \alpha_k D_k + V_i - U_i \qquad \text{………… (3.1)}$$

Where;

Y denotes farm output, measured in kilograms per hectare;

X_1 indicates the total quantity of seed used (in kilograms);

X_2 represents the total land area cultivated (in hectares);

X_3 captures the amount of fertilizer applied, comprising nitrogen, phosphorus, and potassium. Measured in kilograms;

X_4 refers to the total labour input, quantified in man-days.

To account for qualitative influences on production, dummy variables are introduced following Battese (1997), allowing for unbiased parameter estimation:

D_1 is a binary variable for fertilizer use: 1 if fertilizer was applied, 0 otherwise;

D_2 indicates soil fertility: 1 if the respondent reported fertile soil, 0 if not;

D_3 captures access to agricultural extension services: 1 if the farmer had contact with an extension agent, 0 otherwise;

D_4 represents migration status: 1 if the household experienced migration, 0 if it did not.

The indices j, i, and k refer to the j-th input (where j = 1, 2, …, 4), the i-th respondent (i = 1, 2, …, 440), and the k-th dummy/control variable (k = 1, …, 4), respectively.

The parameters α and β are to be estimated through the Stochastic Frontier model. The error term is split into two components:

V_i captures random statistical noise,

U_i denotes technical inefficiency, assumed to be a non-negative value.

The technical efficiency (TE) of the i-th farm is defined as follows:

$TE_i = \exp(-u_i)$ ………………………………………………… (3.2)

The technical efficiency index (TE_i) which ranges from 0 to 1 equals 1 when the farm operates at optimal efficiency and equals zero when it is completely inefficient.

The subsequent phase of the empirical analysis focused on estimating the effect of migration on farm technical efficiency using an endogenous treatment effect framework. Technical efficiency was used here as the outcome variable and serves as a measure of farm-level economic performance. The key explanatory (treatment) variable is migration (Mi), defined as 1 if a household relocated during the most recent flood event and 0 otherwise.

However, migration decisions are influenced by a variety of household-specific and contextual factors, implying that the choice to migrate is not random. To account for this non-random selection and to obtain unbiased estimates of migration's effect on farm efficiency, the Endogenous Switching Regression (ESR) approach was adopted. In the first stage, a selection model is estimated as:

$$\boldsymbol{G_i^*} = \boldsymbol{\alpha X_i} + \varepsilon_i \text{ , where } \boldsymbol{G_i} = \begin{Bmatrix} 1, if\ \boldsymbol{G_i^*} > 0,\ and \\ 0, \quad if \quad otherwise \end{Bmatrix} \text{ ……………………………… (3.3)}$$

Where:

$\boldsymbol{G_i^*}$ is an unobserved (latent) continuous variable representing the propensity to migrate;

$\boldsymbol{G_i}$ is the observed binary migration outcome (1 = migrated, 0 = otherwise);

$\boldsymbol{X_i}$ is a vector of exogenous variables describing household and farm characteristics;

$\boldsymbol{\alpha}$ is the vector of parameters to be estimated;

ε_i denotes the error term.

The two regimes for the technical efficiency outcomes are specified in eqns. (3.4) and (3.5) as:

$$\mathrm{TE}_{1i} = \beta_1 Z_{1i} + \mu_{1i}, \quad \text{if G = 1 and ………………………………….. (3.4)}$$

$\mathrm{TE}_{0i} = \beta_0 Z_{1i} + \mu_{0i}$,   if G = 0, ……………………………………….. (3.5)

Where;

TE_{1i} and TE_{0i} represent the technical efficiency outcomes for households that experienced migration and those that did not, respectively.

The variable $\boldsymbol{Z_i}$ denotes a set of exogenous factors assumed to influence both TE_{1i} and TE_{0i} Importantly, at least one variable from the selection equation (X_i) is excluded from the outcome equations (Z_i) to correct for potential selection bias stemming from unobservable differences between migrant and non-migrant households.

The error terms (ε_i, μ_{1i} and μ_{0i}) are assumed to be jointly normally distributed with a mean of zero and a non-singular covariance matrix, following the specification by Lokshin and Sajaia (2010).

$$Cov\ (\varepsilon_i, \mu_{1i}, \mu_{0i}) = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\varepsilon} \\ \sigma_{10} & \sigma_0^2 & \sigma_{0\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{0\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix} \text{……………………………..} \quad (3.6)$$

Where σ_ε^2 is the variance of the error term in the selection equation (3.3), and σ_1^2 and σ_0^2 are the variances of the error terms in the two regimes (3.4) and (3.5) (Lokshin and Sajaia, 2010). Also, σ_1^2 = var (μ_1), σ_0^2 = var (μ_0), σ_{10} = var ($\mu_1 . \mu_0$), $\sigma_{0\varepsilon}$ = var ($\mu_0 . \varepsilon$), $\sigma_{1\varepsilon}$ = var ($\mu_1 . \varepsilon$) and σ_ε^2 is assumed to be 1 because $\mathrm{TE}_{1i}$and TE_{0i} are not simultaneously observed (Amadu, 2018; Belayneh, 2012).

The error terms μ_{1i} and μ_{0i} in equations (3.4) and (3.5) respectively are therefore, expected to have values of zero.

These are expressed as:

$$E[\mu_1 |\ G_i = 1] = \sigma_{1\varepsilon}\lambda_{1i} \qquad \text{……………………………..} \ (3.7)$$

$$E[\mu_0 |\ G_i = 0] = \sigma_{0\varepsilon}\lambda_{0i} \qquad \text{……………………………..} \ (3.8)$$

where;

$\lambda_{1i} = \frac{\phi[\alpha X_i]}{\Phi[\alpha X_i]}$ and $\lambda_{0i} = \frac{\phi[\alpha X_i]}{1-\Phi[\alpha X_i]}$

ϕ *is the standard normal probability density function*
Φ is the standard normal commulative density function

Conditional on the selection equation, these two parameters (λ_{1i} and λ_{0i}) constitute the inverse Mills ratios (IMRs), which are used in equations 3.4 and 3.5. IMRs are used in the model for correction of error due to self-selection bias associated with migration. Also, ESR method apply the full information maximum likelihood (FIML) estimation, to perform a simultaneous equation system to produce more efficient parameter estimates (Amadu, 2018; Issahaku, 2019). Di Falco *et al*. (2010) stated that, If the estimated covariances $\hat{\sigma}_{1\varepsilon}$ and $\hat{\sigma}_{0\varepsilon}$ are statistically significant, then there is evidence of endogenous switching and we reject the null hypothesis of absence of sample selectivity bias. This means that migration and the technical efficiency outcomes are correlated.

ESR is able to establish hypothetical or counterfactual outcomes for the two regimes of migrants and non-migrants. The study therefore, compared the expected technical efficiency outcomes of actual migrants and their counterfactuals, and this was used to compute the average treatment effect on the treated (ATT) and the average treatment on the untreated (ATU). Similar studies used ESR for treatment effect estimation like Amadu, 2018; Issahaku, 2019; and Israel, 2019. The model is specified as follows:

Migrants observed in the sample

$$E(\mathrm{TE}_{1i}\,|G_i = 1) = \beta_1 Z_{1i} + \sigma_{1\varepsilon}\lambda_{1i} \tag{3.9}$$

Non-migrants observed in the sample

$$E(\mathrm{TE}_{0i}\,|G_i = 0) = \beta_0 Z_{0i} + \sigma_{0\varepsilon}\lambda_{0i} \tag{3.10}$$

Farm households if they had not migrated (counterfactual situation), then the equation will be

$$E(\mathrm{TE}_{0i}\,|G_i = 1) = \beta_0 Z_{0i} + \sigma_{0\varepsilon}\lambda_{0i} \tag{3.11}$$

Farm households if they had migrated (counterfactual situation), then the equation will be

$$E(\mathrm{TE}_{1i}\,|G_i = 0) = \beta_1 Z_{1i} + \sigma_{1\varepsilon}\lambda_{0i} \tag{3.12}$$

The average treatment effect on the treated (ATT) will be calculated by taking the difference between equations 3.9 and 3.11 as follows:

$$ATT = E(\mathrm{TE}_{1i}\,|G_i = 1) - E(\mathrm{TE}_{0i}\,|G_i = 1)$$

$$= Z_{1i}(\beta_1 - \beta_0) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{0\varepsilon}) \tag{3.13}$$

The average treatment effect on the untreated (ATU) will also be computed by taking the difference between equations 3.10 and 3.12 as follows:

$$ATU = E(\mathrm{TE}_{0i}\,|G_i = 0) - E(\mathrm{TE}_{1i}\,|G_i = 0)$$

$$= Z_{0i}(\beta_1 - \beta_0) + \lambda_{0i}(\sigma_{1\varepsilon} - \sigma_{0\varepsilon}) \tag{3.14}$$

Endogeneity was assessed using the two-stage residual inclusion (2SRI) technique, also referred to as the control function approach. This method helps account for unobserved variables that might simultaneously affect both the treatment variable (migration) and the outcome variable (technical efficiency). The process entailed first estimating a logistic regression model for migration using appropriate instrumental variables. The residuals from this first-stage regression were then incorporated into the second-stage technical efficiency model as an additional covariate. A statistically significant residual term implies that migration is endogenous and associated with unmeasured influences on technical efficiency. In such cases, assuming exogeneity would bias the estimated results. To correct for this, the subsequent analysis employs an endogenous treatment effect framework.

Endogenous treatment effect

To analyse how migration affects technical efficiency, the study employed an endogenous treatment effect model. In Stata, this model is implemented in two simultaneous stages while accounting for selection bias. The first stage involves estimating a logistic regression to model the probability of migration, followed by separate outcome equations estimated for each migration group (migrants and non-migrants) in the second stage. The selection equation is estimated using the full sample, whereas the outcome equations are estimated within their respective sub-samples. The outcome specification for each migration status is given as;

$$E(TE_i = 1 \mid d_{ik}, z_i, \bar{z}_i, \varepsilon_i) = z_i\beta + \sum_{k=1}^{k} Y_k\, d_{ik} + \sum_{k=1}^{k} \lambda_k\, \xi_{ik} + \varepsilon_i \quad \text{......................} (3.15)$$

Where;

TE_i is the technical efficiency.

z_i denotes a vector of exogenous covariates with an associated parameter vector β.

The binary indicators d_{ik} represent observed treatment status (e.g., migration versus non-migration).

The parameter Y_k captures the treatment effect relative to the base category of non-migrants.

The term ξ_{ik}represents a set of unobserved (latent) factors that potentially may influence both treatment assignment and outcome.

The expected technical efficiency outcome for an individual, conditional on treatment status and covariates, is expressed as $E(TE_i = 1 \mid d_{ik}, z_i, \bar{z}_i, \varepsilon_i)$, which is modeled as a function of the latent factors ξ_{ik}.

The endogenous treatment model was estimated in Stata using the Maximum Likelihood Estimation (MLE) approach.

Propensity score matching (PSM)

The final step in the empirical strategy to estimate the effect of migration on farm technical efficiency entails using the propensity score matching (PSM) approach as a robustness check for the treatment effect estimates derived from the Maximum Likelihood method, particularly focusing on the Average Treatment Effect on the Treated (ATT). Introduced by Rosenbaum and Rubin (1985), PSM constructs a simulated control group to estimate the counterfactual outcomes of a program. By matching treated and untreated households based on observable exogenous factors influencing migration, PSM facilitates causal inference through the comparison of outcome differences between the two groups.

In this study, households are categorized as either migrants (Mi = 1) or non-migrants (Mi = 0), and each household has two potential outcomes: Z0i when untreated, and Z1i when treated. The impact of migration on the outcome (technical efficiency) for migrant and non-migrant households can be represented as:

$E(Z_{1i}| M_i = 1) - E(Z_{0i}| M_i = 1)$, for the migrant group……………………… (3.16)

$E(Z_{1i}| M_i = 0) - E(Z_{0i}| M_i = 0)$, for the non-migrant group…………………... (3.17)

However, from the survey data, only the actual outcomes are observed—namely;

$E(Z_{1i}| M_i = 1)$ for treated households and $E(Z_{0i}| M_i = 0)$ for the controls. The counterfactuals (i.e., $E(Z_{0i}| M_i = 1)$ and $E(Z_{1i}| M_i = 0)$) remain unobserved. PSM helps estimate these unobservable outcomes, thereby allowing for causal inference on the effect of migration on technical efficiency.

To construct the counterfactuals, the study first estimated the determinants of migration using a logit model:

$M_i = \alpha_0 + \alpha_i W_i + \omega_0$ ……………………………………………… (3.18)

Here, Wi includes the variables influencing the decision to migrate. Based on these, the probability of each household migrating—its propensity score—is calculated: Pi(Wi) = Pr(Mi = 1 | Wi). Households in the treatment group are paired with comparable counterparts from the control group having similar propensity scores, thereby ensuring comparability. The counterfactual outcomes for each treated household are then inferred from the outcomes of the matched controls. The causal effect, i.e., ATT, is estimated as:

$$ATT = E_{P_i(W_i)|M_i=1}\{E[Z_{1i}| M_i = 1, P_i(W_i)] - E[Z_{0i}| M_i = 0, P_i(W_i)]\} \qquad (3.19)$$

Two crucial assumptions must hold for PSM to yield valid causal inferences (Khandker *et al.*, 2009). First is the "conditional independence assumption"—potential outcomes ($Z_{1}i$, $Z_{0}i$) must be independent of treatment assignment (Mi) conditional on the observed covariates (Wi), or $Z_{1i}, Z_{0i} \perp M_i| W_i$. Second is the "common support assumption", which ensures overlap in the spread of propensity scores across the treated and control groups. For estimation, the Nearest Neighbour (NN) matching method is applied, specifically matching each treated unit with two control units within the range where both groups share common characteristics.

The hypothesis tested in this objective is that flooding-induced migration and return have no effect on the productivity (technical efficiency) of farms in the study area.

This hypothesis was tested using Stochastic Frontier Analysis, where migration status was introduced into the technical inefficiency model.

Description of variables for the production function estimation

The variables used in the analysis of the production function of farms in the study area are presented in Table 3.1.

Table 3.1: Description of variables for the Translog stochastic frontier analysis for farm production in Rivers State, Nigeria

Variables	Description	Measurement	a-priori expectation
Production function model			
Crop output	Total quantity of produce of crops	Kg	
Farm size	Farm size of respondent	in hectares	+
Seed	Quantity of seeds planted	Kg	+
Fertilizer	Quantity of fertilizer used for the total farm size	Kg	+
Labour	Quantity of labour used	Mandays	+
Inefficiency Model			
Dummy:Soil fertility	Perception of soil fertility of respondents' farm	1 = fertile, 0 = otherwise	+/-
Dummy;Extension contacts	Extension services respondents had	1 = had access, 0 = otherwise	+
Dummy:Migration	Migration index	1 = migrated, 0 = otherwise	-
Type of family	Monogamous or polygamous family	1 = monogamous, 0 = otherwise	+/-
Household Size	Number of people in a household	Number/household	+/-
Gender	Sex of respondents	1 = female, 0 = otherwise	+/-
Age	Age of respondents	Years	+
Education	Level of education of respondents	1 = educated, 0 = otherwise	+/-
Years of experience	Respondents' farming experience	Years	+

Source: Author's compilation

Table 3.1 shows the variables used in the Translog production frontier analysis for crop production in the study area for the 2022 planting season.

Crop output is the total quantity of produce from all crops grown by the respondents. The output here was normalized by dividing the total outputs harvested with the total farm size in hectares. The output used in the analysis then became output per hectare of farm land (yield). The yield here is the total yield in grain weight equivalents, for all the crops grown by the farmers on their lands utilizing the same labour and fertilizer without separation (composite inputs). Ojo, (1991) used 0.96 coefficient as conversion factor for cereals (maize, millet, sorghum, rice, wheat and fonio) and 0.26 for roots and tubers (cassava, yam, plantain, potatoes and cocoyam) to convert the various crops into grain weight equivalents. These conversion coefficients were adopted in this study to convert the weights of cassava, maize, yam and plantain into grain weights equivalents.

Seed is the quantity of seeds planted for all crops grown. This was measured in kilograms per hectare of farm size.

Fertilizer measured the amount of fertilizer used by the respondents for the planting season under study. This was captured in kilograms per hectare of farm size.

Labour is the estimated number of people who were engaged in all the farm operations for the planting season under study. It was measured in man-days. The farming operations here includes, land clearing and ploughing, planting, chemical application, weeding and harvesting. For the inefficiency model, soil fertility is a dummy which measures the responses to the question of whether the soil is fertile or not. It takes the value of one if the farmer's farmland is fertile or zero if otherwise. Extension contact is an index for measuring if a farmer had contact with an extension agent. It takes the value of one if the farmer had at least one contact with an officer of zero if otherwise. The variable migration is a dummy which took the value of one if the farmer migrated or zero if otherwise. Farming experience measures how many years of experience the farmer has with farming operations. It is expressed in years. All other variables for the inefficiency model are as captured in the respondents' socio-economic attributes in the study area (age, educational level, household size, family type, etc).

3.3.4 Effects of migration on the food security status of farming households

To estimate how migration affects the food security status of farming households in Rivers State, with a focus on distinguishing effects between migrant and non-migrant households following flooding, the Endogenous Switching Regression (ESR) model was similarly used. Household Food Insecurity Access Scale (HFIAS), Farm revenues, and Daily Per Capita Dietary Energy Supply were used as indicators for food security. HFIAS was used as a proxy for food access to measure the level of food insecurity, and farm revenues a proxy mostly for food accessibility, to measure economic access to food. This was adopted from Issahaku (2019) who used HFIAS, and farm revenue to capture the impact of adoption on food security. Daily Per Capita Dietary Energy Supply was used to measure food availability at the household level. These three indicators were used to capture the multifaceted nature of food security. The

HFIAS is an index that quantifies and summarises many behavioural and psychological aspects of food insecurity into a scale (Coates *et al*., 2007; Maxwell et al., 2014). In order to ensure that households have access to food for consumption, farm revenue was employed, assuming that higher farm revenues tend to improve food security (Di Falco *et al.,* 2011). Sen (1981) contended that both the degree of production and the market accessibility of food through purchase determine an individual's capacity to obtain food at the household level. Daily Per Capita Dietary Energy Supply captured the food supplied by households in dietary energy equivalence (DES). The average supply from own food production was added to foods purchased from the market and with the household size, the per capita household food availability was measured in kilocalorie.

HFIAS

This approach uses respondents' responses to questions about how much food a household feels like it has and whether or not they are concerned about running out of food to quantify food security.

The responses are compiled into a scale, and a cut-off point is established and used to categorize families based on their degrees of food security. This process produces a continuous indication of the degree of food insecurity in households. In general, the purpose of this measure is to record how households behave when there is a lack of food, both in terms of quantity and quality, as well as anxiety over food shortages.

It is used to measure households' level food security and accounts for the food availability and utilization dimension of food security.

The level of food insecurity experienced by a household over the past 30 days is assessed using the Household Food Insecurity Access Scale (HFIAS) score, which is treated as a continuous variable. To compute the HFIAS score, the numeric codes assigned to each of the frequency-of-occurrence responses are summed. If the corresponding occurrence question was answered "no," the frequency question is automatically coded as zero (e.g., if Q1 = 0, then Q1a = 0; the same applies for Q2, and so forth). The total score ranges from 0 to 27. A score of 27 represents the most severe food insecurity, indicating that the household answered "yes" to all nine frequency-of-occurrence questions and selected the highest frequency response (coded as 3) for each. A score of 0 reflects no reported experience of food insecurity. Therefore, higher scores correspond to greater food insecurity, while lower scores indicate improved household food access.

As a categorical variable, households are categorized as food secure, mildly food insecure, moderately food insecure, or severely food insecure. For this objective, the indicator for use is HFIAS score and not the prevalence indicator which captures the categorizations, although categorization was done for clarity of subject matter.

The Household Food Insecurity Access Scale (HFIAS) Score, ranging from 0 to 27, is computed by summing the response codes for the frequency-of-occurrence questions related to food insecurity conditions, as shown below:

$$\text{HFIAS Score (0-27)} = Q1a + Q2a + Q3a + Q4a + Q5a + Q6a + Q7a + Q8a + Q9a \quad \ldots\ldots (3.20)$$

(This total reflects the sum of reported frequencies for nine food insecurity-related experiences within the past 30 days.)

Next, the average HFIAS score is derived by calculating the mean of the individual household scores obtained from the formula above.

$$\text{Average HFIAS Score} = \frac{\textbf{Sum of HFIAS Scores in the sample}}{\textbf{Number of HFIAS Scores (households) in the sample}} \quad \ldots\ldots (3.21)$$

(Calculate the average of the Household Food Insecurity Access Scale Scores).

Farm revenue

Primary data were collected from 440 respondents on their 2022 production activities. The households included in the sample were given a structured questionnaire. The questionnaire gathered a variety of data regarding their production activities which includes number of crops grown, size of farmland, quantity of output harvested per crop, price of a unit quantity of each crop output sold, etc. The farm revenue was then computed for each household, from the data collected. This was further divided by each household size to get the households revenue per head. This value was used as a proxy for food accessibility in determining the food security status of the respondents in the study area.

Daily Per Capita Dietary Energy Supply (DES)

This was adopted to capture food availability at the household level (Smith and Haddad, 1999; Stewart *et al*., 2018). Data for estimating this indicator was gathered through a household-level survey. The essential data required from the surveys for computation comprises the following: the quantity of crops produced by the household in standard metric units (kilogrammes), the volume of crop produce sold, the amount of food acquired from the market for consumption, and household composition. The data regarding household composition, including the age and gender of members, is crucial in assessing the food intake of each individual, emphasising caloric and nutrient consumption. Food composition tables are used in estimating the amount of calories in a 100 g of a given crop (e.g., maize) and the nutrients contained in that crop. The Food Composition Tables were created by the Food and Agricultural Organisation (FAO) (FAO, 2016). The food composition tables present statistics on the caloric content and nutrient makeup of each food item. This study concentrates on the calorie consumption of household members derived from their own food produced in equal DES. An adult equivalent scale was used to estimate total food requirements of an individual. The adult equivalent values provide an estimate by age and gender of an individual caloric requirement based on the mean requirements by age and gender (Claro *et al*., 2010).

The food availability indicator is scored from 0 to 1. In percentage, this gives the food energy available at the household in kcal/day and shows if the household has enough food available to meet its food energy requirement daily or if a shortfall exists.

The calories available per capita were estimated as follows:

Amount of food available per crop = Total amount produced by the household - (Amount sold + amount lost) ……………………………………………………………….…… (3.22)

Total food available = Amount of food available per crop + total amount of this crop that the household bought for consumption ………………………………………………….. (3.23)

The total number of food items were subsequently multiplied by the data from the food composition table to derive the caloric contents (in kilocalories per 100 grammes). To calculate the per capita daily caloric intake for households, the total calories from all food products were summed up and divided by the adult equivalent of the household.

$$\text{Amount of calories available per capita per day} = \frac{\text{Total food available (kcal)}}{365 \text{ x Household size}} \qquad (3.24)$$

The Average dietary energy requirement (ADER) for Nigeria is 2160kcal/person/day.

The ratio of the calorie available per capita per day as against Nigeria energy requirement, lies between 0 and 1 and in percentage explains the amount of energy supplied by the household per capita per day. This food availability indicator was compared for the migrants and non-migrants using endogenous treatment effect and propensity score matching. The technicalities are described in sub-section 3.3.3.

The hypothesis tested in this objective is that migration has no effect on the food security status of migrant households in the flooding-prone study area. The effect of migration on food security (measured by HFIAS, farm revenue and food availability) was evaluated using both Endogenous Switching Regression and Propensity Score Matching.

3.4 Research Design

3.4.1 Data types and data collection

Both primary and secondary data were utilized in this study. The primary data were collected from rural farming households within one of the agricultural zones in Rivers State, Nigeria, an area notably affected by recurrent flooding and predominantly engaged in crop production (Ahoada zone). Data collection was conducted in 2024 using a structured questionnaire programmed into KoboCollect software. The questionnaire gathered comprehensive information on households' socioeconomic characteristics, agricultural production practices, and the coping strategies employed to mitigate the impacts of flooding. In addition to households residing in flood-prone communities, the sample also included households from non-flooded communities to serve as a control group for comparative analysis.

Eligible respondents included head of households aged 18 years and above, regardless of gender. The study focused exclusively on crop farmers; individuals involved solely in livestock rearing were excluded to maintain consistency in the production context under investigation. Ethical clearance was also done before the data collection and the respondents gave consents before the study proceeded. The respondents were interviewed and also group discussions were held to corroborate the information from individual respondents to avoid recall bias. Pretesting of instruments were also done before the data collection to ensure all details included were valid.

Secondary data were obtained from the National Emergency Management Agency (NEMA), providing records on historical flood events in the study area spanning the period from 2011 to

2022. These data were used to complement the primary dataset and provide contextual understanding of the frequency and severity of flooding episodes over time.

3.4.2 Sample size determination

A total of 440 farming households were included in the study. The sample size was derived from the sampling frame using the mathematical formula proposed by Miller and Brewer (2003), which provides a systematic approach for determining appropriate sample sizes in social research. This ensured that the selected sample was statistically representative of the target population within the study area.

The following is the formula; $n = \frac{N}{1+N(\alpha)2}$ .... (3.42)

Where;

N= Sample frame

n = Sample Size

α = Confidence Interval

A 95% confidence interval and a 5% margin of error (α = 0.05) were adopted in this study to ensure statistical precision. This level of confidence is standard in social and agricultural research, particularly because the study involves human subjects, where responses are susceptible to recall and reporting biases. Based on available demographic estimates, approximately 70% of the total population in the study area are engaged in farming activities, yielding a sample frame of 1,258,670 individuals (total population is 1,798,100). This informed the determination of the sample size using the standard formula by Miller and Brewer (2003), resulting in a sample size of 440 respondents. Farming remains the dominant livelihood in rural flood-prone communities of Rivers State. In these locations, estimates suggest that up to 70% of the adult population are engaged in farming activities, justifying the use of this proportion in sample size determination.

Consequently,

n = 399.87 (approx. 400)

Based on the predetermined confidence level (95%) and margin of error (5%), a sample size of 400 farmers was calculated using the Miller and Brewer (2003) formula. To account for potential non-response and data inconsistencies, an additional 10% was added, resulting in a final sample size of 440 farmers. The breakdown of this calculation is presented in Table 3.2.

3.4.3 Sampling procedure

A total of 440 households were selected for this study from one of the three designated agricultural zones of Rivers State (Ahoada, Degema, and Eleme). These zones possess vast and fertile farmlands supporting the cultivation of various crops such as vegetables, plantains, rice, cassava, yam, and cocoyam. However, natural variations in soil fertility and ecological conditions influence agricultural productivity across these regions (Ikechukwu, 2015). Rivers State comprises 23 Local Government Areas (LGAs): 7 in the Ahoada zone, 8 in Degema, and 8 in Eleme. Given that Degema is predominantly known for its fishing-related activities, and flooding episodes are not experienced in Eleme, these two zones were excluded from the study. Consequently, the study focused exclusively on the Ahoada agricultural.

A multi-stage random sampling technique was employed to achieve inclusive representation of the farming population. At the initial stage, farming households in the Ahoada zone were clustered into two groups: migrants (from flood-affected areas) and non-migrants (from non-flooded areas). Three LGAs that regularly experience flooding were purposively assigned to the treatment group (migrants). For the control group (non-migrants), three LGAs were randomly selected from the remaining four LGAs that do not experience flooding, resulting in six LGAs in total, three for each group.

In the second stage, a simple random sampling technique was employed to choose two communities from each of the six LGAs. Community names were written on slips of paper, shuffled in a container, and randomly drawn to ensure unbiased selection. This process yielded 12 communities: six from flood-prone areas (treatment) and six from non-flooded areas (control).

In the third stage, a systematic random sampling method was used to select a total of 440 households from the 12 communities. In each selected community, every third household was included in the sample. Based on proportional population sizes, 246 households were selected for the treatment group and 194 for the control group. Further details of the sampling process are presented in Table 3.2.

Table 3.2: Sampling procedure

Captured LGAs (Migrant group)	Farming Population (70%)	Sample size	Captured LGAs (Non-migrant group)*	Farming Population (70%)	Sample Size
Ahoada East	167,440	58	Emohua	202,440	71
Ahoada West	250,880	88	Omuma	101,080	35
Ogba-Egbema-Ndoni	285,180	100	Etche	251,650	88
Total	**703,500**	**246**		**555,170**	**194**

Source: Author's computation.
*Control group.

3.5 Study Area

Rivers State, situated in Nigeria's South-South geopolitical zone, is one of the country's 36 states, with Port Harcourt as its capital. It shares boundaries with Abia and Akwa Ibom States to the east, Bayelsa and Delta States to the west, Anambra and Imo States to the north, and the Atlantic Ocean to the south. Geographically, Rivers State lies between Latitude 4.75°N and Longitude 6.50°E, covering an area of approximately 11,077 km² (4,277 mi²). According to the 2006 national census, the population stood at 5,198,716, with projections estimating it at 7,492,366 in 2023.

The state is inhabited by diverse ethnic groups, including the Ijaw, Ikwerre, Etche, Ogoni, and Ogba/Egbema, among others. Agriculture is the primary source of livelihood for most residents, and food production remains a central focus of the state's agricultural policy. Rivers State ranks as the seventh most populous state in Nigeria and is renowned for its rich linguistic and cultural diversity. It is estimated that approximately 28 indigenous languages are spoken across the state, including Ikwerre, Ogba, Etche, Abua, Ogoni, Igbo, and Ijaw languages.

Topographically, Rivers State is interlaced with numerous rivers, most notably the Bonny River, which plays a significant role in shaping the region's landscape and ecology. A map of Nigeria highlighting Rivers State is presented in Figure 3.2.

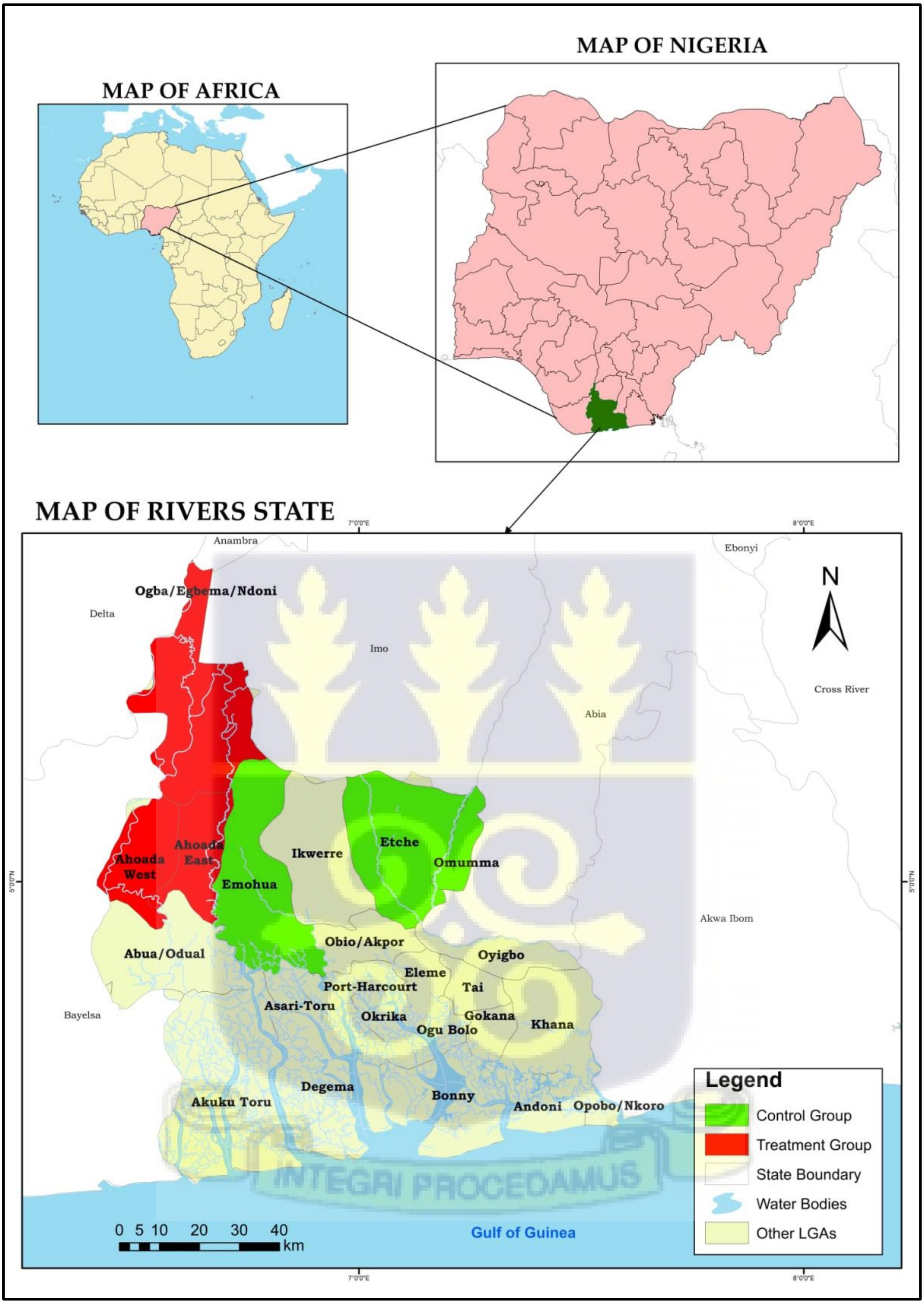

Figure 3.2: The Nigerian map displaying the study area, Rivers State.

Source: Centre for Remote Sensing and Geographic Information Services (CERGIS), 2024.

CHAPTER FOUR

RESULTS AND DISCUSSION[1]

4.1 Introduction

The empirical findings of the thesis are outlined and discussed in this chapter. Section 4.2 presents the descriptive characteristics of the farmers. It also includes description of trends in flooding episodes, migration and return migration of farming households in the study area between 2011-2022. Section 4.3 deals with the coping strategies adopted by farming households, in mitigating the impacts of flooding. In section 4.4, the effects of flooding-induced migration and return on farm productivity (technical efficiency) was analysed and finally, the last section presents and discusses the effects of migration on the food security status of farming households following flooding.

4.2 Descriptive characteristics

4.2.1 Farmer characteristics

The socio-economic details of the farmers included in the research are shown in Table 4.1.

[1] Section 4.2.3 and 4.4 of this chapter have been published in the Journal of Agriculture and Food Research. (Jacinta Nmutaka Umechukwu, Daniel Brucee Sarpong, Akwasi Mensah-Bonsu, Ama Ahene-Codjoe, Taeyoon Kim, (2025). Effects of flooding-induced migration on farm technical efficiency in Rivers State, Nigeria. *Journal of Agriculture and Food Research,* Volume 23, 2025, 102189
https://doi.org/10.1016/j.jafr.2025.102189.)

Table 4.1: Descriptive statistics of respondent farmers in the study area

	Migrants (Treatment)				Non-migrants (Control)					
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Diff. in mean	P-value
Family type									0.012	0.9140
Nuclear	0.9146	0.2800			0.9175	0.2758				
Extended	0.0854	0.2800			0.0825	0.2758				
Marriage type									2.9560*	0.0860
Polygamous	0.2900	0.4540			0.2200	0.4130				
Monogamous	0.7114	0.4540			0.7835	0.4129				
HHSize	7.7114	2.9294	2	20	6.8402	2.6760	2	20	-0.871***	0.0010
Gender									4.7685**	0.0290
Male	0.9756	0.1546			0.9330	0.2507				
Female	0.0244	0.1546			0.0670	0.2507				
Age	62.8821	9.7197	33	88	60.0412	11.2101	27	88	-2.841***	0.0050
Marital status									8.3934*	0.0780
Married	0.9634	0.1881			0.9588	0.1994				
Separated	-	-			0.0206	0.1425				
Divorced	-	-			0.0052	0.0718				
Widowed	0.0325	0.1777			0.0155	0.1237				
Never married	0.0041	0.0638			-	-				
Age with married partner	31.8211	4.1797	20	47	30.9124	4.1858	18	20	-0.909**	0.0240
Years of farming experience	28.7800	9.5204	3	51	28.1700	9.6457	5	52	-0.6155	0.5040
Religion									3.0195	0.6970
No religion	0.0244	0.1546			0.0464	0.2109				
Catholic	0.3740	0.4848			0.4175	0.4944				
Protestant	0.2967	0.4578			0.2577	0.4385				
Ch'matic	0.2154	0.4120			0.2010	0.4018				
Islam	0.0081	0.0900			0.0052	0.0718				
Traditionalist	0.0813	0.2739			0.0722	0.2594				
Ethnic groups									427.9539***	0.0000
Ekpeye people	0.2358	0.4253			0.0052	0.0718				
Ikwerre	-	-			0.3608	0.4815				
Igbo	0.0041	0.0638			0.6186	0.4870				
Ijaw	-	-			0.0052	0.0718				
Ogba	-	-			0.0052	0.0718				
Other	0.7602	0.4279			0.0052	0.0718				
Education									30.7535***	0.0000
None	0.0569	0.2321			0.0155	0.1237				
Primary	0.5488	0.4986			0.4536	0.4991				
Secondary	0.3089	0.4630			0.2732	0.4468				
Polytechnic	0.0244	0.1546			0.0258	0.1589				
University	0.0610	0.2398			0.2268	0.4198				
Uni. (postgraduate)	-	-			0.0052	0.0718				

Source: Author, 2024.

Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively.

The findings indicate that most farmers in the study area enter into farming upon marriage, as land is typically allocated to them within the community at that point. Among both migrant and non-migrant groups, 96% are married. Monogamous unions are predominant, with 71% of migrants and 78% of non-migrants in such arrangements. The average age at marriage for migrants is approximately 32 years, compared to 31 years for non-migrants. The mean age of migrant farmers is 63 years with standard deviation (SD) of 9.7, while non-migrant farmers have a slightly lower mean age of 60 years (SD = 11.2). Males dominate both groups, comprising 98% of the migrant group and 93% of the non-migrant group.

In terms of farming experience, migrant farmers average 29 years (SD = 9.5), while non-migrants average 28 years (SD = 9.6). The average household size is 8 persons (SD = 3) for migrant households and 7 persons (SD = 3) for non-migrants. Educational attainment is relatively high in both groups, with only 6% of migrant farmers and 2% of non-migrants having no formal education; the remainder have received education at various levels.

A test of mean differences reveals statistically significant variations between migrants and non-migrants in terms of marriage type, household size, gender, age, marital status, age with married partner, ethnic affiliation, and educational attainment.

4.2.2 Farm-specific factors (socio-economics)

Figure 4.1 presents the findings on the crop combinations cultivated by farmers in the study area.

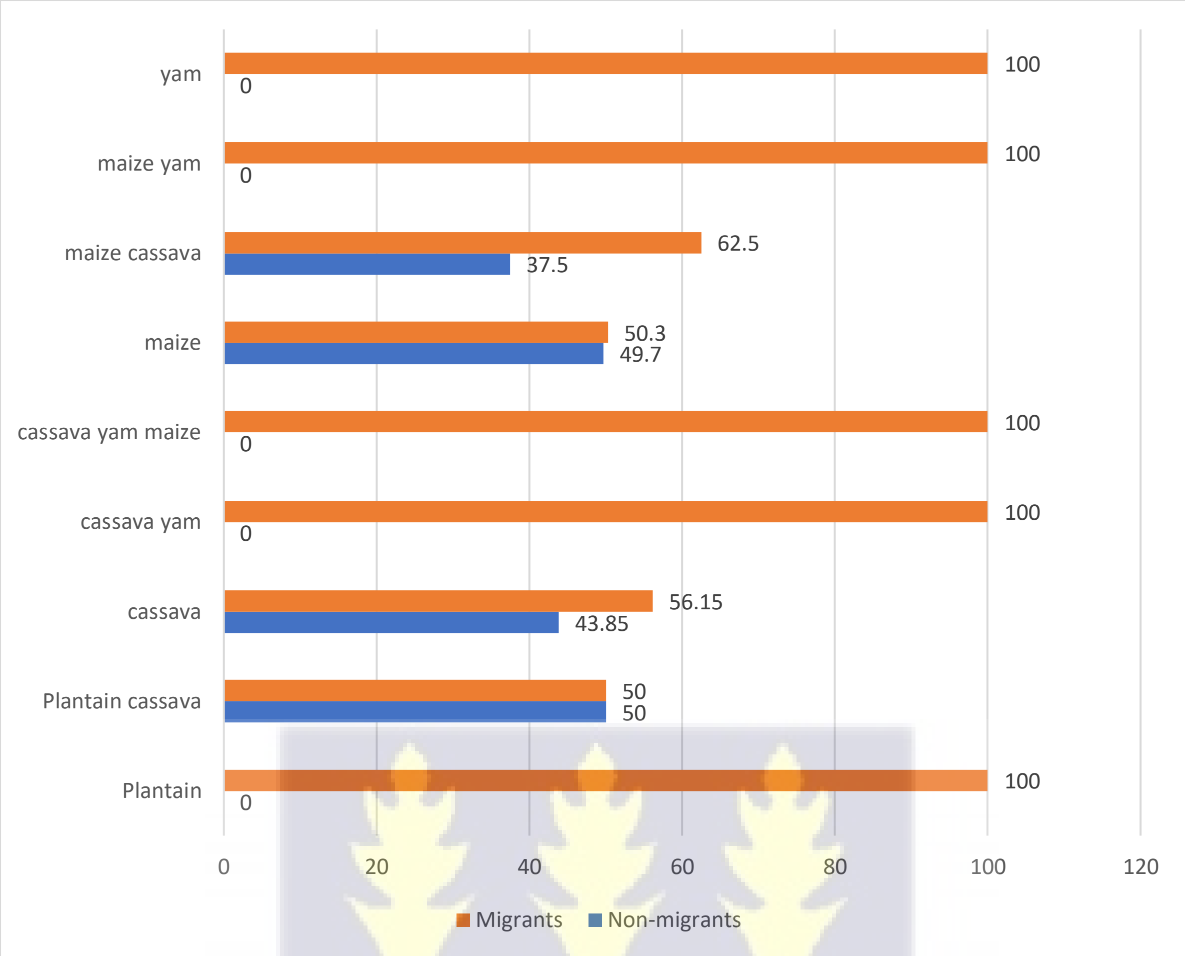

Figure 4.1: Distribution of Respondents who cultivate various crops by household type (%)

Source: Author, 2024.

The results indicate that approximately 56% of farmers who cultivate only cassava are migrants, while the remaining 44% are non-migrants. Similarly, maize production is evenly distributed between both groups, with 50% of maize-only growers being migrants and the other 50% non-migrants. Notably, all yam producers are from migrant communities, as this crop is not commonly cultivated among the non-migrant households. This pattern suggests that migrant farmers tend to have a more diverse crop portfolio.

Details on crop outputs, farm sizes, and input use are presented in Table 4.2.

Table 4.2: Summary statistics of farm-specific factors

	Migrants		Non-migrants			
Variable	Mean	Std. dev	Mean	Std. dev	Diff. in mean	P-value
Output (kg)						
Cassava production	2795.13	1608.71	2772.07	1358.62	-23.06	0.903
Maize production	1482.03	927.13	4217.15	2350.31	2735.12***	0.000
Yam production	763.89	577.47	N/A	N/A	N/A	N/A
Plantain production	1350.00	919.24	200.00	-	966.67	-
Land size (ha)						
Land size for cassava	6.50	3.71	6.28	3.23	-0.22	0.617
Land size for maize	6.26	4.04	5.49	2.97	-0.77	0.150
Land size for yam	3.78	2.80	N/A	N/A	N/A	N/A
Land size for plantain	3.50	2.12	1.00	-	2.67	-
Other composite inputs						
Seed (kg)	226.61	319.85	222.55	335.35	-4.06	0.897
Total labour (Man-days)	206.53	244.57	265.06	399.10	58.533*	0.059

Source: Author, 2024

Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively; N/A represents not applicable, Yam was not cultivated by non-migrant households; - stands for absence of results. Standard deviation and test statistics are not reported for plantain output and land due to lack of variation in the data.

Findings reveal that the mean cassava output among migrant households is 2,795.13 kg, while non-migrant households recorded a slightly lower mean output of 2,772.07 kg. However, the test statistic shows no significant difference in the mean output between both groups. For plantain, migrants harvested an average of 1,350 kg, compared to 200 kg among non-migrants, though this difference was also not statistically significant. Yam production was recorded exclusively among migrants; none of the non-migrant households reported cultivating yam during the study period.

In contrast, maize production revealed a significant difference between the groups. Non-migrants had a considerably higher mean output of 4,217.15 kg, while the migrant households averaged 1,482.03 kg. This disparity may be attributed to the disruption caused by flooding in migrant communities. Such losses typically stem from water-logged fields at harvest or from immature crops harvested early in anticipation of flood events.

With regard to land size, findings reveal an absence of significant statistical difference between the migrant and non-migrant groups for cassava, maize, or plantain cultivation. Similarly, seed usage is relatively comparable, with migrants planting an average of 226.61 kg compared to 222.55 kg by non-migrants.

Fertilizer usage is minimal across both groups, averaging 14.17 kg, with no significant difference. This is largely due to traditional soil fertility management practices such as fallowing, which is widely adopted among the farmers. Many respondents rated their land as either fertile or very fertile, indicating the effectiveness of this method in maintaining productivity.

Labour use (measured in man-days) differs significantly between the two groups. Non-migrant farmers recorded higher labour input (265.06 man-days) compared to migrant farmers (206.53 man-days). This gap is likely due to the displacement period experienced by migrants—typically lasting three to four months during annual flood episodes—which interrupts farm operations. Non-migrants, unaffected by such disruptions, remain active in their communities and are able to commit more labour to farming activities.

Using the conversion standards outlined in *Local Weights and Measures in Nigeria: A Handbook of Conversion Factors* by Kormawa and Ogundapo (2004), the outputs of the various crops were standardized into uniform weights expressed in kilograms, as presented in Table 4.2. The various crops were then converted into grain weight equivalents by adopting the work of Ojo, (1991) who used 0.96 conversion coefficient for maize and 0.26 for cassava, yam and plantain. The coefficients were used in multiplying the outputs and results computed as outputs in grain weights equivalents. These uniform grain weights were then used in estimating the various crops yields and lumped as yield. The various grain equivalents of the crops are shown in Table 4.3.

Table 4.3: Summary statistics of crops grown, in grain weight equivalents

	Migrants		Non-migrants			
Variable	Mean	Std. dev	Mean	Std. dev	Diff. in mean	P-value
Output (gr)						
Cassava production	726.735	418.265	720.739	353.241	-5.996	0.903
Maize production	1422.750	890.047	4048.465	2256.295	2625.715***	0.000
Yam production	198.611	150.142	N/A	N/A	N/A	N/A
Plantain production	351.000	239.002	52.000	35.081	-299.000	-
Yield (gr/ha)						
Cassava production	118.551	50.692	118.046	36.272	-0.505	0.929
Maize production	244.359	116.526	737.125	100.635	492.766***	0.000
Yam production	52.810	7.536	N/A	N/A	N/A	N/A
Plantain production	148.200	158.109	52.000	-	-96.200	-
Total Yield	172.234	111.277	394.577	318.559	222.343***	0.000

Source: Author, 2024

Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively; N/A represents not applicable, Yam was not cultivated by non-migrant households; - stands for absence of results. Standard deviation and test statistics are not reported for plantain output due to lack of variation in the data.

A significant difference is observed in the maize yield (productivity) of both categories of farmers in favour of the non-migrants. There is also a significant difference in the mean total yield (productivity) of both categories in favour of the non-migrants.

4.2.3 Trends in flooding episodes, migration and return migration of farming households

Figure 4.2 presents the mean values of key migration-related variables, including the number of household members who migrated during flooding episodes, the number who returned, the duration (in months) for which farm operations were suspended, and the average number of flooding episodes experienced between 2011 and 2022.

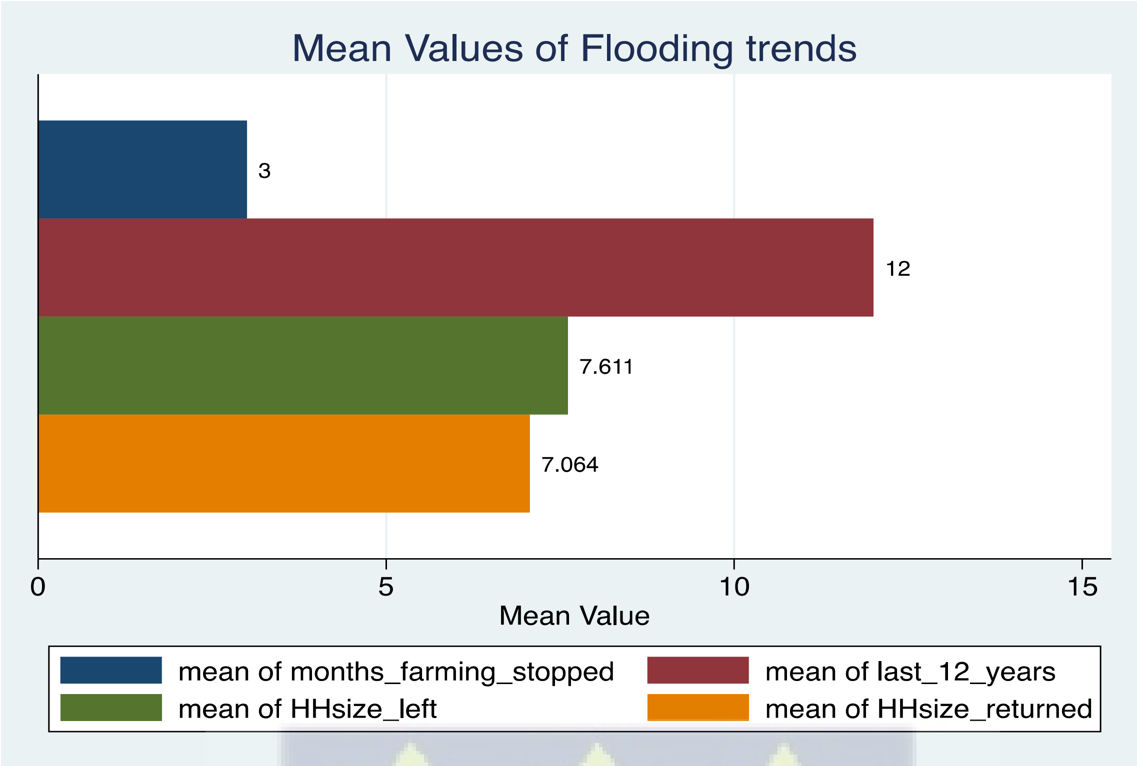

Figure 4.2: Mean values of flooding trends

Source: Author, 2024.

Figure 4.2 displays a bar chart illustrating the average values of key flooding-related indicators across the different local government areas (LGAs). The chart indicates that, on average, farming activities were halted for approximately three months annually during the 2011–2022 period. Additionally, the study area experienced flooding twelve times over the twelve years reviewed. On average, eight individuals from each household relocated during these flooding events, with seven typically returning afterward. Given that the mean household size among migrant families is eight, it implies that entire households in the affected areas migrate during each flooding episode.

This information was compiled for the different migrants across the three affected LGAs and is presented in Table 4.4.

Table 4.4: Summary of Flooding Trends by Local Government Areas

	Ahoada East	Ogba Egbema-Ndoni	Ahoada West					
	Mean	Mean	Mean	Total SS	Total df	Total MS	F-stat	P-value
No. of Months Farming Stopped	3.00	3.00	3.00	0.00	245.00	0.00	-	-
No. of Episodes (2011-2022)	12.00	12.00	12.00	15618.76	439.00	35.58	-	-
No. Migrated	7.00	8.00	8.00	2225.81	244.00	9.12	4.50**	0.012
No. Returned	6.00	7.00	7.00	2203.80	244.00	9.03	4.64**	0.011

Source: Author, 2024.

On average, the trend appears consistent across all the Local Government Areas (LGAs) with regard to the cessation of farming activities and the frequency of flooding episodes. However, variations exist in the number of migrants and returnees per household. In each affected LGA, there is at least one household member, on average, who did not return after displacement. Similarly, the mean number of migrants differs significantly across the LGAs; however, in all affected communities, every farming household experienced migration during flooding episodes, with no household left behind. This confirms that migration is not only widespread but universal among households in flood-prone areas. These findings underscore the compulsory and uniform nature of flooding-induced migration in the study area.

The observed uniformity in the cessation of farming activities and the frequency of flooding across all LGAs reflects the shared ecological and hydrological conditions of the study area. The affected LGAs are located along the same floodplain system and are influenced by the seasonal overflow of major rivers, resulting in similar flood timing, duration, and severity across communities. As documented in floodplain agriculture studies, when communities are exposed to the same river basin dynamics, flooding patterns tend to be spatially homogeneous, leading to synchronized disruptions in agricultural activities (Ayanlade & Radeny, 2020; Nkwunonwo *et al*., 2016).

Despite this uniform exposure, variations in the number of migrants and returnees per household across LGAs can be attributed to differences in household socio-economic characteristics, livelihood diversification options, access to social networks, and proximity to alternative settlement locations. Households with stronger kinship ties in urban or less flood-prone areas are more likely to experience permanent or semi-permanent out-migration of some members, while others return after floodwaters recede. This aligns with the new economics of labour migration theory, which posits that migration decisions are often household-based and shaped by risk management strategies rather than uniform responses to shocks (Stark & Bloom, 1985).

The finding that at least one household member, on average, did not return after displacement in each LGA suggests that repeated flooding acts as a catalyst for longer-term migration and gradual household fragmentation. Recurrent environmental shocks reduce the attractiveness of return, particularly for younger or economically active members who may secure alternative livelihoods elsewhere. Similar patterns have been observed in flood-prone regions of Nigeria and other developing countries, where repeated displacement leads to incremental permanent migration rather than full household return (Black et al., 2011; Warner et al., 2012; Ajibade *et al.*, 2019).

Overall, the universal experience of migration across all affected communities confirms that flooding-induced migration in the study area is not voluntary but compulsory. When floodwaters inundate farmlands and settlements, remaining in place becomes physically and economically untenable, leaving households with no viable alternative but to relocate temporarily or permanently. This finding supports existing evidence that environmental shocks such as flooding often trigger forced or distress migration rather than choice-based mobility, particularly in low-income, agriculture-dependent settings (IPCC, 2014; McLeman & Gemenne, 2018).

Furthermore, the data reveal that all surveyed households experienced migration during each of the twelve annual flooding episodes between 2011 and 2022, relocating to various forms of shelter. This consistent pattern indicates that migration was not occasional or selective but rather a recurring and compulsory response for every household in the flood-affected areas throughout the entire twelve-year period. For the most recent flood season in 2022, Figure 4.3 illustrates the distribution of migration destinations, highlighting the proportion of households that relocated to Internally Displaced Persons (IDP) camps, to the homes of family members in neighboring communities, or to urban areas.

For the difference in mean, atleast one group mean is statistically different from the others in terms of number of migrants and returnees per household.

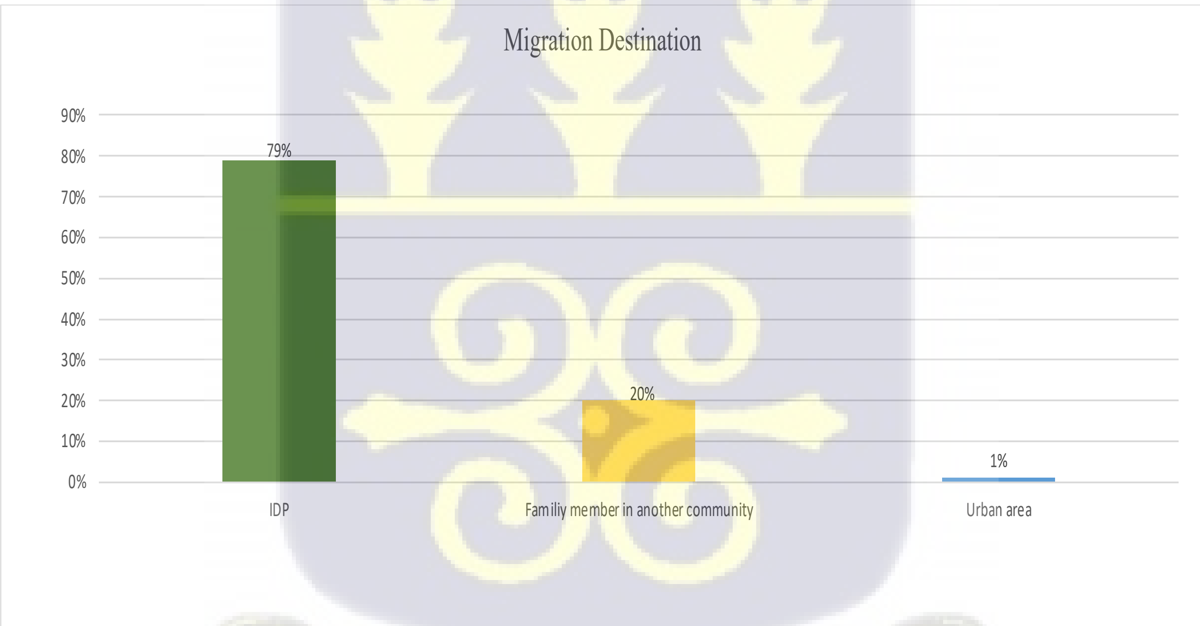

Figure 4.3: Migration destination of migrants in 2022

Author, 2024.

Out of the 246 migrant respondents, 79 percent (195 households) reported migrating to Internally Displaced Persons (IDP) camps during the 2022 flooding episode. This underscores that the majority of displaced farmers end up in formal shelter camps during flood events. This trend has persisted for decades, with no durable solution in place.

These findings align with those of Ajibade *et al.* (2019), who analyzed data from 240 smallholder rice farmers in Kwara State, Nigeria, an area similarly prone to recurring floods. As in the present study, Ajibade *et al.* found that farmers frequently sought refuge in IDP camps or relocated to other temporary shelters during annual flooding episodes.

All respondents in this study indicated that there were no opportunities for skill acquisition or engagement in alternative income-generating activities while in displacement camps. They noted that the only support received was food aid provided by the Federal Government of Nigeria. The annual nature of these migratory episodes has become a normalized response in the affected communities, particularly due to the overflow of the Orashi River, which borders the three Local Government Areas (LGAs) studied. This outcome reflects the emergency-oriented nature of displacement responses in the study area. Displacement camps established during flooding episodes are designed primarily to provide short-term humanitarian relief, rather than long-term livelihood support. As a result, government intervention is largely limited to food assistance, with little or no provision for skills training, livelihood diversification, or income-generating activities. The predictable, annual recurrence of flooding-driven by the seasonal overflow of the Orashi River, has led to displacement being treated as a temporary and routine event by both authorities and affected households. Consequently, displacement management focuses on immediate survival needs instead of sustainable recovery or economic empowerment. Over time, this has normalized migration as a survival strategy within the affected LGAs, reinforcing a cycle in which households repeatedly relocate without gaining access to opportunities that could enhance resilience, reduce dependence on aid, or improve post-flood livelihoods.

In essence, the absence of skill acquisition and alternative income opportunities in displacement camps is explained by the short-term relief focus of government responses, the temporary perception of displacement, and the recurrent nature of flooding, which together limit investments in longer-term livelihood interventions. Furthermore, the absence of post-flood recovery assistance beyond temporary relief in IDP camps corroborates findings by Etuonovbe (2011) and Adelekan (2016), who report that flood response in Nigeria remains largely short-term and relief-oriented, leaving affected households to rely on savings and stored food upon return.

Similar to Ajibade *et al.*'s findings, the flooding in these LGAs occurs yearly, typically lasting at least three months and uniformly disrupts agricultural activities across all communities. All households temporarily migrate during these episodes, ceasing farming operations until the floodwaters recede. Upon return, most household members resume life in the communities, while others choose to relocate permanently to less flood-prone areas or urban centres.

The findings highlight the urgent need for sustainable flood mitigation strategies to reduce the frequency and impact of displacement on farming households.

4.3 The coping strategies adopted by farming households, in mitigating the impacts of flooding

The results show that 97.2% (239) of the farmers affected by flooding have crop damage as their primary concern with flooding while 2.8% (7) stated infrastructural damage as their main concern. The result on the outputs and losses are represented in Table 4.5.

Table 4.5: Mean output and losses for crops due to flood

Variable	Migrants		Non-migrants	
	Mean	Std. dev.	Mean	Std. dev.
Output (Kg)				
Cassava	2795.134	1608.712	2772.07	1358.62
Maize	1482.031	927.133	4217.151	2350.307
Plantain	1350.0	919.239	200.00	-
Losses (Kg)				
Cassava loss	966.897	595.942	0	0
Maize loss	910.393	558.468	0	0
Plantain loss	400	141.421	0	0

Source: Author, 2024

Note: - stands for absence of result. Standard deviation is not reported for plantain output due to lack of variation in the data.

Result shows that the migrants which have a mean cassava output of 2795.13kg, have a mean loss of 966.90kg (34.60%) for the same crop due to flooding. Their non-migrant counterparts who have mean output of 2772.07kg have no recorded losses due to flood. The result shows that migrants on the average harvested more cassava than the non-migrants who are not in flooding areas. But a closer look at data showed the migrants harvest early before the flood comes and at those times, the cassava is considered immature. Such harvested cassava roots end up giving less quantity of the processed cassava (garri). This is because of the immature cassava harvested earlier than the maturity time due to flood. This type does not yield as much as the matured ones when harvested.

For maize with the mean output of 1482.03kg for migrants, there is a loss of 910.39kg (61.43%) due to flooding. Also, for non-migrant the mean for maize output is 4217.15kg with no recorded losses due to flood. For plantain with the mean harvest of 1350kg for migrants, there is a loss of 400kg (29.63%) due to flooding. Also, the non-migrants harvested on average 200kg with no recorded losses.

The coping strategies adopted by these farmers are identified as early planting and harvesting. The other coping strategies identified from literature like cultivation of crop-resistant varieties, elevated construction techniques, etc. were not adopted by the respondents. Table 4.6 shows these coping strategies and the ones adopted by migrants in the study area.

Table 4.6: Migrants coping strategies to flooding

Strategies	Used (%)	Not used (%)	Effectiveness
Early planting and harvesting	100.00	-	Not effective at all
Elevated construction techniques	-	100.00	Not used
Traditional knowledge	-	100.00	Not used
Cultivating flood-resistant crop varieties	-	100.00	Not used
Modern technologies	-	100.00	Not used
Adoption of innovative approaches to water management	-	100.00	Not used
Global initiatives related to flooding	-	100.00	Not used
Government assistance	-	100.00	Not used
NGO/Private sector assistance	-	100.00	Not used

Source: Author, 2024.

The results show that all the respondents (100%) from the migrant LGAs reported early planting and harvesting as a coping strategy to flooding episodes. This means that they did not use the other coping strategies listed in the survey. The reasons they gave for this ranges from climate variability to lack of information on the said strategies. It is worthy of note too that neither the government nor the private sector comes to their aid as regards coping after flooding episodes. They reported being fed in the IDPs for the number of months they migrated out of the communities and nothing more was received as help. When the water recedes, they return home without any assistance from any source, to face rebuilding and coping after every episode. Usually coping in this instance is merely by falling back on what they had saved up or stored before migrating out of the communities.

Similar results were found by Ajibade *et al.* (2019) who analyzed data from 240 smallholder rice farmers in Kwara state Nigeria, an area faced with flooding episodes. According to the survey, the majority of rice farmers (79.5%) planted early-maturing rice seedling varieties in order to secure an early harvest before the peak of rainfall, when floods are typically observed. The adoption of early maturing rice varieties which was harvested early in the planting season became the strategy used by these rice farmers in coping with flooding episodes.

The dominance of early planting and harvesting as a coping strategy among migrant households aligns with existing evidence from flood-prone regions of Nigeria. Studies have consistently shown that Nigerian farmers primarily adjust planting calendars to avoid peak flooding periods (Oladipo, 2010; Ajibade *et al.,* 2019).

The challenges faced by the farmers in the study area in utilizing the itemized coping strategies are shown in Table 4.7.

Table 4.7: Challenges of migrants in implementing the coping strategies

Challenges	**Respondents (%)**
Climate variability	0.40
Lack of resources	10.20
Limited access to information	89.0
Technical complexity	0.40
Total	100

Source: Author, 2024.

Eighty-nine percent of the migrants stated limited access to information as their impediment to utilizing the other listed strategies. About 10% said lack of resources hinder them from utilizing strategies like flood-resistant varieties. They plant early and harvest early. Early harvest of cassava gives less harvest and conversely less bags of garri (processed cassava). This affects the income of those who plant cassava. For maize and yams, they harvest as expected but sometimes the water comes even before the expected time and covers up the whole farm. In this case, there will be a total loss of crops. This has been the pattern and all they do is just adopt early planting and harvesting which clearly has proven as not an effective strategy in tackling the flooding issue. If it is effective, they will not have losses and also, they will have optimum output all things being equal. Data shows that all the farmers (migrants) harvest less than expected for cassava, maize, yam and plantain.

The limited use of alternative coping strategies reflects persistent information and extension gaps, as documented by Apata *et al.* (2009) and Onyeneke and Madukwe (2010).

4.4 Effects of flooding-induced migration and return on farm productivity (technical efficiency)

The Cobb-Douglas and Translog stochastic frontier models were fitted and analyzed using data from the 2022 crop production season. A Wald test was conducted to assess the joint significance of the additional squared and interaction terms included in the Translog specification. The null hypothesis of joint insignificance was rejected ($\chi^2(3)$ = 17.52, p = 0.0006), indicating that the Translog model provides a significantly better fit than the Cobb-Douglas specification. As a result, the Translog stochastic frontier was adopted for the analysis. The estimated coefficients of the production function, the technical inefficiency model, and the error components are presented in Table 4.8. Additionally, the mean technical efficiency scores were computed separately for migrant and non-migrant households, and these estimates are also reported in Table 4.8. The results of the Cobb-Douglas frontier are presented in appendix.

Table 4.8: Results of Translog Stochastic Frontier Analysis

	Coefficient	Std. Error	P-values
Translog Production Function			
LnSeed	0.0871*	0.0510	0.088
LnLabour	0.2094*	0.1227	0.088
LnSeed squared	-0.0455**	0.0180	0.012
LnLabour squared	-0.1456	0.1033	0.159
LnSeed x LnLabour	-0.0452	0.0288	0.116
Constant	0.6487	0.0920	0.000
Technical Inefficiency			
Migrants (RC = Non-migrants)	0.6679***	0.0541	0.000
Type of Family	0.0009	0.0728	0.990
Monogamous (RC = Polygamous	0.1809***	0.0506	0.000
Household Size	0.0389***	0.0080	0.000
Female (RC = Male)	-0.0010	0.1114	0.993
Age	-0.0018	0.0017	0.288
Primary (RC = No Education)	0.0397	0.0898	0.658
Secondary	-0.0226	0.0901	0.802
Polytechnic	0.4099***	0.1428	0.004
University	0.3820***	0.0985	0.000
Uni.(postgrad.)	1.8762***	0.3852	0.000
σ^2	0.2655	0.0191	
γ	0.9131	0.0228	
σ_{u2}	0.2424	0.0197	
σ_{v2}	0.0231	0.0059	
No. of Observation: 440; Wald Chi2(5): 23.24; P-value: 0.0003; Log Likelihood: -530.64			
Mean technical efficiency (TE) for migrants = 0.7117, non-migrants = 0.7463			

Source: Author, 2024.
Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively.
RC, reference category.

The results of the Stochastic Frontier Analysis provide critical insights into the production efficiency of farming households in the study area. The model is statistically significant, as indicated by a Wald chi-square value of 23.24 and a corresponding p-value of 0.0003. This suggests that the explanatory variables included in the model jointly have a significant effect on agricultural output.

In the production function estimates, the coefficient for seed input (LnSeed) is 0.0871 with a p-value of 0.088, indicating a positive and marginally significant relationship with output. This suggests that an increase in seed quantity is associated with higher output. Labour input (LnLabour) has a statistically significant coefficient of 0.2094, implying that a 1% increase in labour input leads to approximately a 0.21% increase in agricultural output.

The coefficient for the square of seed input (LnSeed squared) is -0.0455 and is statistically significant, indicating diminishing marginal returns to seed input—i.e., while increased seed use initially boosts output, the rate of increase declines as seed input continues to rise. Conversely, the squared term for labour (LnLabour squared) has a coefficient of -0.1456, but it is not statistically significant, suggesting no clear evidence of diminishing returns to labour input. The interaction term between seed and labour (LnSeed × LnLabour) has a coefficient of -0.0452 and is also statistically insignificant, implying no notable interaction effect between the two inputs on output.

Fertilizer input was excluded from the regression analysis due to its limited usage in the study area. The mean fertilizer application was recorded at only 14.17 kg per hectare, which is considered minimal. Consequently, its influence on output was assumed negligible for the purpose of this analysis.

There was no use of pesticide from data collected in the study area.

The second part of Table 4.8 presents the determinants of technical inefficiency in farm production. The coefficient for the variable "*migrants*" is positive and statistically significant (0.6679), indicating that migration is associated with increased technical inefficiency compared to non-migrants. This finding supports the hypothesis that repeated displacement due to annual flooding episodes negatively affects the efficient use of farm inputs. The result is consistent with previous studies by Ren et al. (2023) and Yang et al. (2016), who observed a decline in technical efficiency among migrant rice farmers in China.

Furthermore, being in a *monogamous marriage* (with polygamous marriage as the reference category) is positively associated with inefficiency. *Household size* is also positively associated with inefficiency and is statistically significant at the 1% level, suggesting that larger households may face more challenges in optimizing resource use. *Age* shows a negative but statistically insignificant relationship with inefficiency, implying that older farmers may be slightly more efficient. Interestingly, educational attainment at the *polytechnic, university*, and *postgraduate* levels shows positive and significant coefficients, suggesting that higher education is associated with greater inefficiency in this context. This counterintuitive result may reflect a shift in focus among highly educated individuals from direct farm management to off-farm or administrative activities.

Furthermore, being in a monogamous marriage is positively associated with technical inefficiency relative to polygamous households, which may benefit from greater labour pooling and task specialization (Becker, 1981). Household size also exhibits a positive and significant relationship with inefficiency, suggesting that larger households may face coordination challenges and increased dependency burdens that limit optimal resource use (Abdulai & Huffman, 2000; Rahman, 2003). Interestingly, higher educational attainment is positively associated with inefficiency. This counterintuitive result aligns with studies showing that educated individuals are more likely to engage in off-farm or administrative activities, reducing direct farm supervision and management intensity (Yang *et al*., 2016; Ren *et al*., 2023).

In the inefficiency component of the model, the estimated variance of the inefficiency term (*sigma_u2*) is 0.2424, while the variance of the random noise component (*sigma_v2*) is 0.0231, indicating that inefficiency accounts for a substantial portion of the total variability in output.

Finally, technical efficiency scores were computed for individual farmers. Using the "if" conditional statement in Stata, results were disaggregated by migration status. Migrant farmers operate at an average technical efficiency of 71.17%, while non-migrant farmers achieve a slightly higher efficiency of 74.63%. These results imply that both groups have substantial room for improvement: migrant farmers can increase efficiency by 28.83%, and non-migrants by 25.37%, to reach the optimal efficiency frontier. It is worth noting that annual migration due to flooding disrupts farm operations, but technical efficiency, defined as output given input levels is not inherently dependent on output volume alone. A farmer might be using more inputs than necessary to get that output while another farmer might achieve the same or more output using fewer or better-managed inputs, and thus be more efficient. Other factors such as managerial capacity, farming experience, and access to accurate information on input-output combinations, key elements that enhance production efficiency also play critical roles in determining technical efficiency (Yang et al., 2016). These factors are notably lacking among both migrant and non-migrant farming households in the study area, contributing to the generally moderate levels of technical efficiency observed. However, to isolate the portion of the efficiency gap that is directly attributable to migration, the Endogenous Treatment Effect model was employed. This approach accounts for selection bias and allows for a more robust estimation of the causal effect of migration on farm performance.

Furthermore, the distribution of technical efficiency scores differed significantly between migrant and non-migrant households, suggesting that migration status plays a notable role in shaping efficiency outcomes. The detailed results of these distributions are presented in Table 4.9.

Table 4.9: Distribution of technical efficiency scores by migration status

Percentile	Migrants	Non-migrants
10th	0.4950	0.6912
25th	0.7009	0.7043
50th	0.7412	0.7503
75th	0.7858	0.7959
90th	0.7973	0.8030
Mean	0.7117	0.7463

Source: Author's computations

The distribution of technical efficiency scores in table 4.9 further underscores the disparity between migrant and non-migrant farming households. Specifically, the 10th, 25th, 50th (median), 75th, and 90th percentile scores for non-migrant households were consistently higher than those of their migrant counterparts. This pattern reflects a leftward shift in the efficiency distribution among migrants, indicating overall lower technical efficiency. The difference in distributions was statistically significant, as confirmed by the Wilcoxon rank-sum test (p-value $= 0.0119 < 0.05$), reinforcing the conclusion that migration status is associated with reduced farm technical efficiency.

4.4.1 Logistic regression on the factors that affect migration

In constructing the propensity score model for estimating the treatment effect of migration, it is essential to include only pre-treatment covariates, those variables that influence both migration and the outcome of interest, but are not themselves influenced by the treatment. While flooding is the primary cause of migration in the study area, it is not a suitable covariate for the propensity score model because it is experienced only by the treated group (migrants) and not the control group (non-migrants). Including such a variable would violate the conditional independence assumption and compromise the balance between the treatment and control groups (Caliendo & Kopeinig, 2008). Moreover, flooding is an exogenous environmental shock that occurs before migration and directly triggers the treatment rather than characterizing the broader population. Therefore, it was excluded from the matching variables to maintain methodological rigor. Instead, socio-demographic characteristics such as age, education level, marital status, household size, and ethnicity are appropriate covariates, as they are pre-treatment factors that plausibly influence both migration and the associated outcomes (Rosenbaum & Rubin, 1985; Caliendo & Kopeinig, 2008).

The policy relevance of covariates included in the PSM model is explained as follows.

Family type (monogamous/polygamous): Family structure influences household resource allocation, dependency ratios, labour availability, and vulnerability to shocks. It is relevant for social protection design, livelihood support programmes, and targeting of vulnerable households in rural development and climate adaptation policies.

Household size: Household size affects consumption needs, labour supply, migration decisions, and food security outcomes. It is central to policies on poverty alleviation, food assistance, demographic targeting, and disaster response planning.

Age: Age captures life-cycle effects on migration propensity, productivity, and risk tolerance. It informs policies related to youth engagement, ageing farmers, labour mobility, and succession planning in agriculture.

Age with married partner (years spent married): This variable reflects household stability, land access, and cumulative farming experience, particularly in settings where land is allocated upon marriage. It is relevant to land tenure policies, rural settlement systems, and long-term livelihood planning.

Gender: Gender shapes access to land, credit, extension services, and adaptive capacity. It is critical for gender-responsive agricultural policies, migration governance, and equity-focused climate and development interventions.

Marital status: Marital status influences household responsibilities, mobility constraints, and decision-making autonomy. It is relevant for social welfare policies, migration support programmes, and household-level resilience planning.

Religion: Religion can shape social networks, norms, coping mechanisms, and access to informal support systems during shocks. It is relevant for culturally sensitive policy design, community-based interventions, and disaster response coordination.

Ethnic group: Ethnic affiliation reflects historical settlement patterns, land rights, and differential exposure to flooding risk. It is relevant for geographically targeted climate adaptation policies, conflict-sensitive development planning, and inclusive rural governance.

Education: Education captures human capital, information access, and adaptive capacity. It is central to policies on agricultural extension, skills development, migration outcomes, technology adoption, and long-term resilience building.

Table 4.10 presents the results of the logistic regression model estimated prior to the Propensity Score Matching procedure.

Table 4.10: Logistic Regression Estimates for Factors Influencing Migration

Variables	Coefficient	Std. Error	P-values
Family Type	-0.1109	0.5591	0.8430
Household Size	0.0745	0.0549	0.1750
Age	-0.0481***	0.0172	0.0050
Age with Married Partner	0.1279***	0.0406	0.0020
Gender	0.2304	0.7315	0.7530
Marital Status	0.2300	0.2083	0.2690
Religion	0.1407	0.1274	0.2700
Ethnic Group	0.0616***	0.0077	0.0000
Education	-0.5121***	0.1640	0.0020
Constant	-2.9190	1.8618	0.1170
No. of Obersernation	440		
LR Chi2	326.860		
P-value	0.000		
Log-Likelihood	-138.473		

Source: Author, 2024.

The chi-square value of 326.860 with a probability value of 0.000 indicates that the model is a good fit for analyzing the factors influencing migration. The estimation results reveal that *age* and *level of education* exert a negative influence on the likelihood of migration, while the *number of years spent married* and *ethnic group* have positive effects. The positive relationship between years of marriage and migration likely reflects the traditional land allocation system, where male farmers typically receive farmland upon marriage, thus linking marital duration with farming tenure. The positive effect of ethnic group on migration suggests that flooding is more prevalent in specific ancestral communities, making members of certain ethnic groups more vulnerable to displacement. Notably, the six local government areas included in this study correspond predominantly to distinct ethnic groups within Rivers State, with only a few cases of non-indigenous residents. The remaining covariates, though included in the model, did not exhibit statistically significant effects; their estimates are presented in the corresponding results table. Collectively, the findings suggest that migration in the study area is jointly determined by demographic factors and structurally embedded socio-cultural and environmental conditions, reinforcing the suitability of the logistic model for explaining migration behavior.

The table of the marginal effects of these factors that influence migration is placed in appendix.

4.4.2 Tests of matching quality

The test of matching quality was carried out after the match and the results are presented in this section. The graphs of the Propensity Score Matching for technical efficiency, average HFIAS, farm revenue and food availability are presented in figures 4.4, 4.5, 4.6 and 4.7 respectively. Figures 4.4, 4.5, 4.6 and 4.7 clearly show that estimating the p-score balanced the treated and untreated groups very well, a result which portrays the importance of the Propensity Score Matching approach.

Figure 4.4 shows the result of Nearest Neighbour Matching with 1(2) matching. The figure shows a good matching quality for technical efficiency matching of migrants and non-migrants.

Figure 4.5 shows the result of Nearest Neighbour Matching with 3(1) matching. The figure shows a good matching quality for average HFIAS matching of migrants and non-migrants. Figure 4.6 shows the result of Nearest Neighbour Matching with 1(1) matching with caliper. The figure shows a good matching quality for average farm revenue matching of migrants and non-migrants.

Lastly, Figure 4.7 shows the result of Nearest Neighbour Matching with 3(1) matching. The figure shows a good matching quality for food availability matching of migrants and non-migrants.

These results show that after applying the matching method, farmers who migrated and those who did not were made genuinely comparable. The matching successfully balanced their key characteristics, meaning the two groups were similar before outcomes were compared. As a result, any differences observed in technical efficiency, food insecurity, farm revenue, or food availability are more likely due to migration itself rather than pre-existing differences between the farmers.

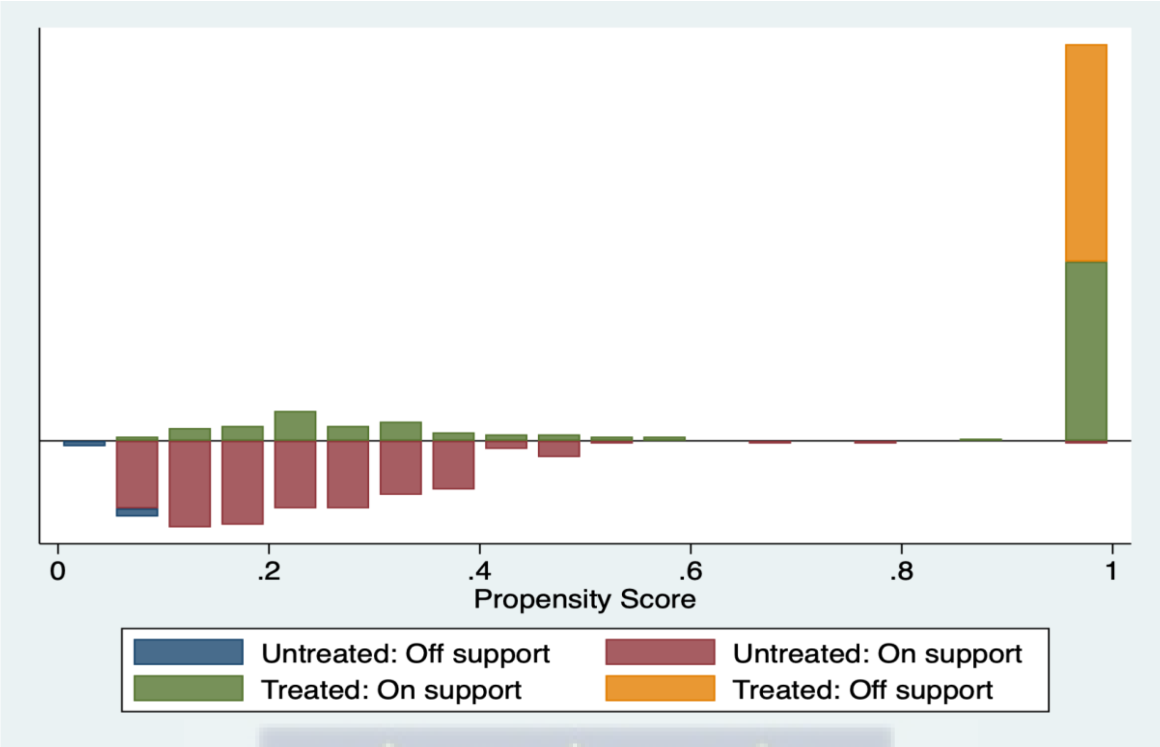

Figure 4.4: Matching for Technical efficiency

Source: Author, 2024.

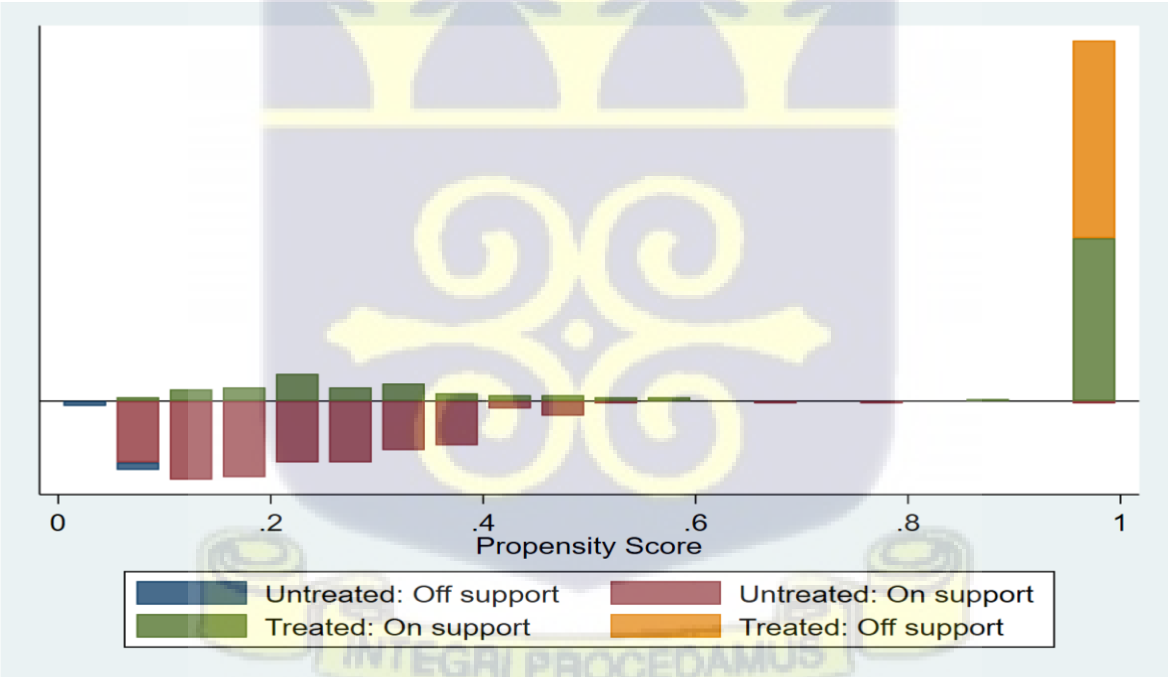

Figure 4.5: Matching for Household Food Insecurity Access Score

Source: Author, 2024

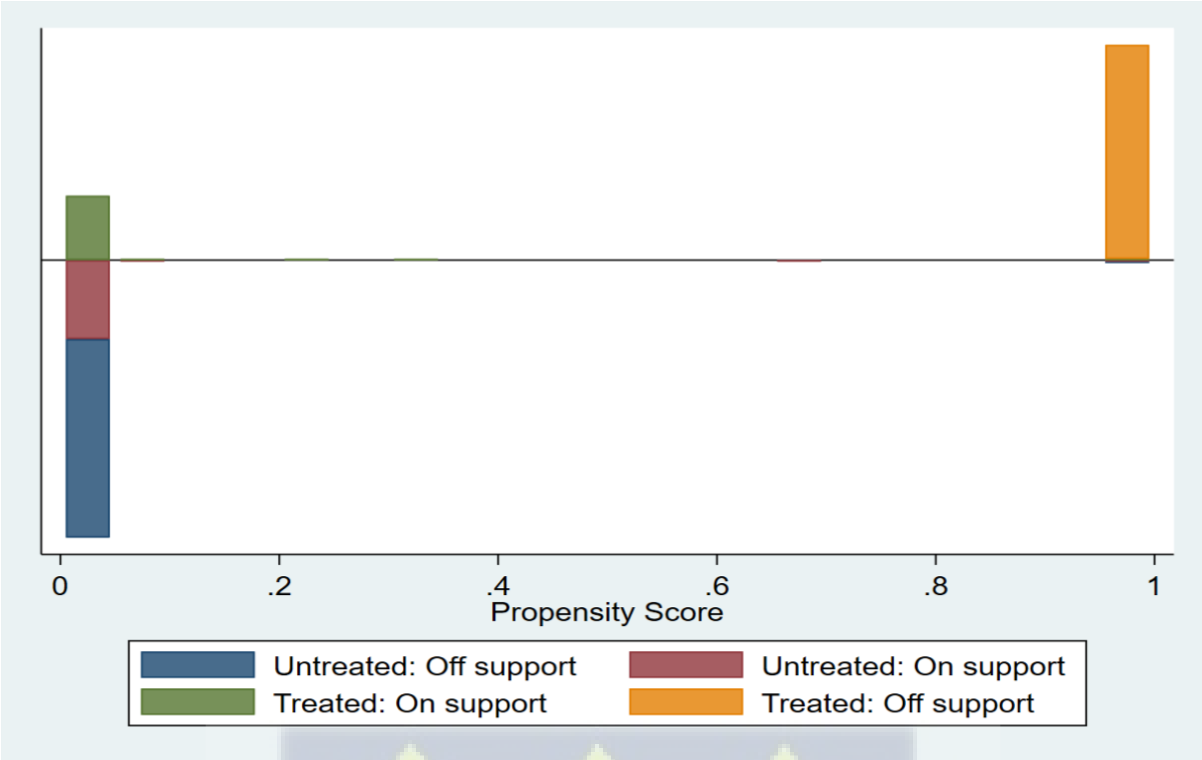

Figure 4.6: Matching for Farm revenue

Source: Author, 2024.

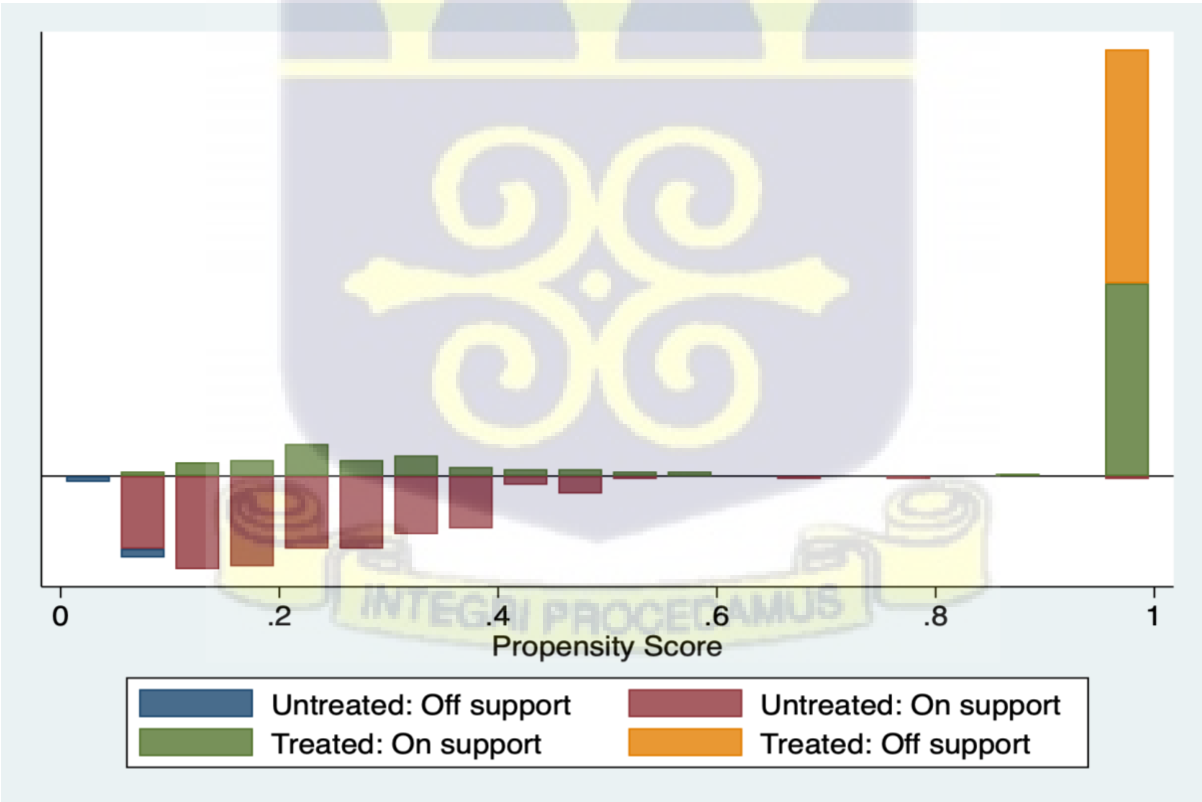

Figure 4.7: Matching for Food availability

Source: Author, 2024.

4.4.3 Treatment effects of migration on farm's technical efficiency (TE)

The endogeneity test using the two-stage residual inclusion method revealed that the coefficient on the residual term was highly statistically significant ($p = 0.000$). This indicates that migration is endogenous and correlated with unobserved factors affecting technical efficiency. As a result, treating migration as exogenous would bias the estimated effect. Therefore, the subsequent model accounts for this endogeneity using an endogenous treatment effect framework.

To compare the technical efficiencies between the treatment and control groups, a logit model of migration participation was first estimated as part of the Endogenous Switching Regression (ESR) framework. The technical efficiency (TE) scores obtained from the stochastic frontier analysis were incorporated into the ESR model as the outcome variable. Following this, treatment effects were computed. The resulting estimates, Average Treatment Effect on the Treated (ATT), Average Treatment Effect on the Untreated (ATU), and Average Treatment Effect (ATE) are presented in Table 4.11.

Table 4.11: Treatment effects of migration on technical efficiency

	ESR			PSM		
	ATT	ATU	ATE	ATT	ATU	ATE
Technical Efficiency (%)	-3.85 ***	2.01***	-0.39 *	-3.73	0.19	-1.72
	(0.0024)	(0.0028)	(0.0022)	(0.0358)	(0.0107)	(0.0171)

Source: Author's computations
Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively. Figures in parenthesis are std. errors. ESR; Endogenous switching Regression, PSM; Propensity Score Matching

The comparison of technical efficiency between migrants and non-migrants using a two-sample t-test with equal variances reveals statistically significant differences between the two groups. The Average Treatment Effect on the Treated (ATT) is negative 3.85%, indicating that migration reduces the technical efficiency of migrant farmers by approximately 3.85%. Similarly, the ATU is 2.01%, suggesting that, had migrants not been exposed to flooding and forced migration, their technical efficiency could have improved by this margin. These findings underscore the detrimental impact of migration on farm-level technical efficiency. Additionally, the ATE is negative 0.39% and statistically significant, further confirming that migration negatively influences the overall technical efficiency of farming households.

This result aligns with the findings of several studies like Ren *et al*. (2023), and Yang *et. al*. (2016) who examined the impact of migration on farm-level technical efficiency. For instance, migration has been shown to reduce both technical and fertilizer use efficiency among rice farmers in China, where households engaged in migration exhibited significantly lower technical efficiency than non-migrant households. Similar outcomes have been reported in Kosovo, Lesotho, and Burkina Faso by Sauer *et al*., 2015; Mochebelele, 2000; and Wouterse, 2010 respectively, where migrant households demonstrated lower technical efficiency in agricultural production. In these contexts, migration was identified as a contributing factor to inefficiency on farms.

For the robustness check of the treatment effect estimates, a Logit model of migration participation was first estimated to obtain the propensity scores. This included estimating the influencing factors of migration participation. The Nearest Neighbour Matching (NNM) method was employed, using a 1(2) match and bootstrapped standard errors to estimate the treatment effects. The resulting estimates, presented in Table 4.11, show statistically insignificant coefficients for the ATT, ATU, and the ATE, indicating that the results derived from the PSM approach are not as robust as those obtained from the ESR model.

The ESR estimates proved to be more robust and statistically reliable than those derived from the PSM method, even though both techniques utilized an identical dataset for analysis. This difference is anticipated due to the structural strengths of the ESR model. While PSM adjusts only for observable variables and is sensitive to issues such as sample trimming and the quality of matches, the ESR method addresses both observed and unobserved factors that influence the likelihood of treatment and the resulting outcome. By jointly estimating the selection and outcome equations and accounting for the potential correlation between their error terms, the ESR model effectively mitigates problems of endogeneity and self-selection bias. This leads to more consistent and accurate results, particularly in cases like this study, where treatment—migration—is not randomly assigned but influenced by external environmental shocks such as repeated flooding. These shocks often vary in intensity and geographic distribution, introducing heterogeneity that may not be captured by observable data. Consequently, the ESR approach offers a more dependable foundation for assessing the true causal effect of migration on farm technical efficiency, and as such, this study relies primarily on the ESR estimates for interpretation.

4.5 Effects of migration on the food security status of farming households in Rivers State following flooding

4.5.0 Mean HFIAS, Farm revenue and food availability

The food security dimension measured in the study area is food accessibility and availability. The accessibility aspect was measured with Household Food Insecurity Access Scale (HFIAS) and farm revenue. HFIAS measured the level of food insecurity in the study area while farm revenue was a proxy that measured economic access to food. Availability was measured with Daily Per Capita Dietary Energy Supply. The results obtained after analysis showed the migrants' average HFIAS as 13.4675 while that of the non-migrants is 2.1598. This shows that the migrants are more food insecure when compared with the non-migrant group. The exact difference in their average HFIAS was estimated using endogenous treatment effect.

However, as a categorical variable, households are classified into four groups: food secure, mildly food insecure, moderately food insecure, or severely food insecure. The categorizations of the food security status of farming households in the study area is shown in Table 4.12.

Table 4.12: Food security status of farming households in Rivers state, Nigeria

HFIAS Categorisations	Household type	
	Non-migrants (%)	Migrants (%)
Food Secure	70.60	0.00
Mildly food insecure	5.70	0.00
Moderately food insecure	10.80	50.00
Severely food insecure	12.30	50.00
Total	100.00	100.00

Source: Author, 2024.

The table shows that 50 percent of the migrants are categorized as moderately food insecure while the other 50 percent are severely food insecure. This shows that the migrants indeed are not food secure and a look at their non-migrant counterparts shows otherwise. The result shows that 70.60 percent of the non-migrants are food secure, 5.70 percent are mildly food insecure, 10.80 percent moderately food insecure with the remaining 12.30 percent severely food insecure. The disparity in food security categorizations is also as a result of the differences in the average HFIAS for both groups.

In the aspect of food accessibility proxied by farm revenue, the average farm revenue of migrant households per head is ₦54,509.34 while that of non-migrants is ₦183,153.6 (USD 128.90 and USD 433 respectively for the 2022 planting season). This shows that households who are not faced with flooding problems and who also do not migrate due to same, have more revenue. With more revenue, these non-migrants can access more food than their migrant counterparts who earn less revenue. The difference in farm revenue attributable to migration was estimated using endogenous treatment effect.

For food availability measured with Daily Per Capita Dietary Energy Supply, the total energy supply from the various crops grown by the households was calculated. The energy supply from the foods purchased was also calculated. These were used in estimating the per capita per day DES of households for the migrants and non-migrants. The results are shown in Table 4.13.

Table 4.13: Household crop energy supply

	Migrants			Non-migrants				
Variable	Mean (kg)	Mean (Kcal)	Std. dev	Mean (kg)	Mean(Kcal)	Std. dev	Diff. in mean	P-value
Cassava	819.09	2088669	3332774	779.65	1988110	2465083	-100558.9	0.820
Maize	374.38	1332802	2110725	709.19	2524721	3259745	1191918***	0.008
Yam	300.00	303000	429695.4	N/A	N/A	N/A	N/A	N/A
Plantain	100.00	120000	-	50.00	60000	-	-60000	-
Total Food Purchased	292.32	949731.4	705772	360.56	1128231	674832.9	178499.1***	0.008
DES in kcal/person/day		850.94	876.88		1207.50	874.53	356.56***	0.000

Source: Author, 2024

Note: *** represents 1% significance level; N/A represents not applicable, Yam was not cultivated by non-migrant households; - stands for absence of results. Standard deviation and test statistics are not reported for plantain due to lack of variation in the data.

Result shows the migrants are only able to supply 850.94kcal/person/day of their daily energy requirement. The non-migrants supply 1207.50kcal/person/day of their daily energy requirement. The average dietary energy requirement (ADER) for Nigeria is 2160kcal/person/day. This means that the migrants' food available ratio when computed with this requirement stands at 0.394 (39.4 percent) while that of non-migrants is 0.559 (55.9 percent).

The results also indicate a statistically significant difference in per capita dietary energy supply in kilocalories between migrants and non-migrant households. Those who migrated due to flood supply only about 39 percent of their daily food energy requirement from own food production and foods purchased, while their counterparts who did not encounter flood, who also did not migrate, supply about 56 percent. This shows the migrants have less food energy available when compared with their non-migrant counterparts. The difference in per capita food availability ratio for both groups attributable to migration was estimated using endogenous treatment effect.

4.5.1 Treatment effects of migration on HFIAS, farm revenue and food availability

An objective of this study is to determine the effect of flooding-induced migration on food security. The application of the endogenous switching regression methodology allows us to obtain the expected outcomes of food security, contingent upon migration. The difference between the outcome of migrants who actually migrated and the expected outcomes if they (migrants) had not migrated, is called average treatment effect on the treated (ATT). The results of the estimated ATT are presented in Table 4.14.

Table 4.14: Treatment effects of migration on HFIAS, Farm revenue and food availability

	ESR			PSM		
	ATT	ATU	ATE	ATT	ATU	ATE
Food Security (HFIAS)	9.17***	-11.59***	-2.14***	10.93***	-11.55***	11.28***
	(0.1868)	(0.1907)	(0.2306)	(1.2575)	(0.6167)	(0.6917)
Farm Revenue (Naira)	-290.45	114439.5***	128353.8***	-118065.33***	145499.54***	-131430.71***
	(20575.09)	(4878.95)	(23542.74)	(14265.97)	(22454.03)	(16721.62)
Food availability (%)	38.31***	-1.19	54.81***	9.42	3.32	2.19
	(0.0463)	(0.0157)	(0.0516)	(0.0946)	(0.0719)	(0.0656)

Source: Author's computations
Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively. Figures in parenthesis are std. errors. ₦423 = USD 1 (2022).

The results from the endogenous treatment effect analysis of food security reveal significant differences between migrant and non-migrant households. The average treatment effect on the treated (ATT) shows a mean difference of 9.17 with a statistical significance of 1 percent. This means that flooding problems and conversely migrating out of the affected communities increases food insecurity. The average treatment effect on the untreated (ATU) shows a mean difference of negative 11.59 which is also statistically significant. This means that if the migrants were not faced with flooding issues which led to migration, their food insecurity would have reduced by 11. 59. HFIAS score ranges from 0 to 27 and having an expected scale reduction of 11.59 will mean moving towards food security. Indeed, there is a significant difference in the average HFIAS of the migrants and non-migrants. While the migrant household tend towards food insecurity, their non-migrant counterparts tend towards food security.

Issahaku, (2019) also reported similar findings that households who adopted climate smart practices improved their food security. However, in the present case, migration serving as a negative treatment has the opposite effect, diminishing food security and contributing to increased food insecurity.

The average treatment effect is statistically significant with an estimated value of negative 2.14 and also means a reduction in food insecurity for the entire sample.

To verify the robustness of the estimates, the Nearest Neighbor Matching (NNM) approach was applied using a 3-to-1 match and bootstrapped standard errors. This analysis explored the impact of migration on the average HFIAS scores for both migrants and non-migrants. As presented in Table 4.14, the results indicate significantly positive coefficients for the ATT and the ATE, while the ATU is significantly negative. However, these estimates were less robust compared to those obtained from the ESR model, and as such, the ESR results were used for interpretation.

The results from the endogenous treatment effect analysis of farm revenue in Table 4.14 indicated that the ATT has a mean difference of negative ₦290.45 (USD 0.69) which is not statistically significant. The average treatment effect on the untreated (ATU) has a mean difference of ₦114,439.5 (USD 270.54) which is statistically significant at 1 percent level. This means that if the migrants are not faced with flooding issues and eventual migration, their expected farm revenue will increase by ₦114,439.5 per head. This result is quite similar to the findings of Issahaku (2019). He found that adopting climate smart practises improved farm income, although in this case migration is a negative treatment which reduced farm revenue. In this case, farm revenue reduced by ₦290.45 per head if there is migration and increased by ₦114,439.5 per head if there is no migration. Indeed, flooding and migration reduce farm revenue generatable by migrants and if there is no flooding and migration, revenue will increase. The average treatment effect (ATE) is statistically significant with a value of ₦128,353.8 (USD 303.44) and means on an average farmers earn ₦128,353.8 per head.

As a robustness check, the Nearest Neighbor Matching (NNM) technique was employed, using a 1-to-1 match and bootstrapped standard errors. This method was used to estimate the treatment effects of migration on farm revenue among both migrants and non-migrants. The outcomes, displayed in Table 4.14, reveal that the ATT and the ATE were both significantly negative, while the ATU was significantly positive. However, these estimates were found to be less robust compared to those obtained from the ESR model. Therefore, the ESR results were used for interpretation.

The results from the endogenous treatment effect analysis of Daily Per Capita Dietary Energy Supply in Table 4.14 shows the ATT had a mean difference of 38.31 percent which is significant and an insignificant mean of negative 1.19 percent for the ATU. This analysis revealed mixed outcomes of flooding-induced migration on household food security. Specifically, the Average Treatment Effect on the Treated (ATT) for dietary energy supply (DES) was positive and statistically significant, indicating that, on average, households that migrated due to flooding had higher caloric availability than they would have had if they remained in flood-prone areas. However, this improvement in caloric supply did not translate into broader food security benefits. ATT estimates for both the Household Food Insecurity Access Scale (HFIAS) and farm revenue — proxies for food access and economic access respectively — were negative, suggesting that displaced households experienced greater food insecurity and lower income from agriculture following flooding and migration. These findings point to the multidimensional nature of food security (FAO, 2008; 2012), where improvement in one domain (availability) may coexist with deterioration in others (access and stability). Similar patterns have been documented in previous empirical work, such as Hidrobo *et al.*

(2014), who found that increases in food availability or caloric intake do not necessarily correspond with improvements in perceived food security (HFIAS). Thus, while migration may mitigate some of the immediate effects of environmental shocks, such as food shortages, it also introduces new vulnerabilities that weaken households' economic resilience and subjective food access. This complexity underscores the need for integrated policy responses that address not only food supply, but also income restoration and access mechanisms for displaced populations.

This study's use of multiple indicators aligns with the multidimensional food security frameworks advanced by the FAO (2008, 2012) and supported in empirical literature (Misselhorn, 2005; Tadesse *et al*., 2020; Hidrobo *et al.,* 2014). The observed divergence between the ATT for dietary energy supply and the ATT for HFIAS and farm revenue is not contradictory but rather highlights the complexity of food security in displacement contexts, where increased caloric availability may coincide with decreased economic and perceived access to food. As Hidrobo *et al.* (2014) demonstrate, interventions that improve food availability or caloric intake do not necessarily lead to improvements in subjective food security, emphasizing the need to distinguish between food quantity and food access in impact evaluations.

To verify the robustness of the estimates, the Nearest Neighbor Matching (NNM) approach was applied. Specifically, a 3-to-1 matching was used, and standard errors were bootstrapped to improve reliability. This analysis aimed to assess the effect of migration on farm revenue for both migrant and non-migrant groups. The outcomes, shown in Table 4.14, indicate that the ATT, the ATU, and the ATE were all statistically insignificant. As these findings were not as strong as those obtained from the ESR model, interpretation of results relied primarily on the ESR estimates.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1. Introduction

This chapter provides the summary of the research findings and the conclusions derived from the principal findings. It also articulates the policy suggestions derived from the key findings of the study. Section 5.2 presents the summary of the findings from the research. Section 5.3 presents the conclusions drawn from the findings. In section 5.4, the policy recommendations emanating from the conclusions drawn are presented. The last section 5.5, presents and discusses the suggestions made for further research. The contributions to knowledge and limitations of the study are included here also.

5.2 Summary of findings from the study

5.2.1 Trend in flooding episodes, migration and return migration of farming households

The findings of the study revealed that flooding episodes occurred twelve times over the twelve-year period under review in the study area. On average, eight individuals per household migrated during each flooding episode, while approximately seven returned afterward. All respondents reported migrating during each of the twelve annual flooding events, relocating to various forms of shelter.

The hypothesis of this objective, flooding episodes have no influence on the livelihood of farming households in the study area is rejected by the findings. The findings confirm that flooding occurs annually, typically between July and October, and causes severe disruptions to farming operations, including displacement of households, delayed planting, crop destruction, and loss of stored produce. Migration patterns indicate that household members often return only after floodwaters recede, leading to interruptions in farming cycles. Respondents reported significant losses in farm output and income, indicating a negative influence of flooding on household livelihoods. This finding is consistent with existing literature that links environmental shocks to decreased agricultural productivity and income insecurity. The qualitative narratives and quantitative patterns observed across the sampled households provide no support for this hypothesis.

5.2.2 Coping strategies adopted by farming households

The result from the study shows that 97.2% (239) of the farmers in the study area affected by flooding have crop damage as their primary concern with flooding while 2.8% (7) stated infrastructural damage as their main concern.

The coping strategies adopted by these farmers as gathered from the data collected are identified as early planting and harvesting. The reasons they gave for not using other strategies identified in literature ranges from climate variability, lack of resources, lack of information on the said strategies, to technical complexity.

The hypothesis, farmers' coping strategies are not characterized by crop diversification, community support networks, adaptive capacities and government interventions is supported by the evidence. Contrary to expectations and existing adaptive frameworks, farmers in the study area overwhelmingly reported reliance on a single coping strategy: early planting and early harvesting. This strategy is employed to avoid crop losses ahead of peak flood periods and was cited by 100% of the respondents, underscoring its dominance.

Other commonly proposed strategies such as crop diversification, government intervention, or organized community networks were largely absent. This limited portfolio of coping mechanisms suggests a low level of adaptive capacity and resilience in the region, with significant implications for long-term vulnerability. Consequently, this hypothesis is supported by the findings. Instead, the findings highlight the need for broader institutional and community-based interventions to diversify and strengthen local adaptation strategies.

5.2.3 Effects of flooding-induced migration and return on farm productivity (technical efficiency)

The results from the Translog stochastic frontier analysis indicate that the coefficient for seed is positive and statistically significant, suggesting that increased seed usage leads to higher output levels. Similarly, labour input has a positive and significant effect on output, implying a proportional relationship between labour use and output.

In the inefficiency model, the migration variable has a positive and significant coefficient, indicating that migration contributes to higher technical inefficiency relative to non-migrants. The yearly displacement caused by flooding is thus associated with reduced efficiency in farm production. The calculated mean technical efficiency scores reveal that migrant farmers operate at 71.17% efficiency, while non-migrants operate at 74.63%, suggesting room for improvement among both groups.

Further analysis using the endogenous treatment effect model confirms that migration negatively affects technical efficiency. The Average Treatment Effect on the Treated (ATT) is statistically significant, with a mean difference of negative 3.85%, indicating that migrants would have 3.85% higher efficiency if they had not migrated. The Average Treatment Effect on the Untreated (ATU) is also significant at 2.01%, implying that non-migrants would experience a 2.01% decrease in efficiency if they were to migrate. These findings confirm that migration, driven by recurring flood episodes, adversely impacts farm-level technical efficiency.

These results provide no empirical support for the hypothesis of this objective, which posits that flooding-induced migration and return have no effect on the productivity (technical efficiency) of farms in the study area. They suggest that migration, while often a necessary coping mechanism in response to environmental stress, is associated with significant declines in productive efficiency among affected farming households. Therefore, flooding-induced migration and return have a negative effect on the productivity (technical efficiency) of farms in the study area. Policy interventions should therefore focus on minimizing displacement disruptions and enhancing adaptive capacities to support continued productivity during and after migration episodes.

5.2.4 Effects of migration on the food security status of farming households

The average HFIAS, farm revenue and Daily Per Capita Dietary Energy Supply were analysed and result showed that migrants' average HFIAS was 13.4675 while that of the non-migrants was 2.1598. This shows that the migrants are more food insecure when compared with the non-migrant group. The exact difference in their average HFIAS was estimated using endogenous treatment effect.

However, it was found that as categorical variable the categorizations of the food security status of farming households in the study area showed 50 percent of the migrants are categorized as moderately food insecure while the other 50 percent are severely food insecure. This shows that the migrants indeed are not food secure and a look at their non-migrant counterparts shows otherwise. The result showed that 70.60 percent of the non-migrants are food secure, 5.70 percent are mildly food insecure, 10.80 percent moderately food insecure with the remaining 12.30 percent severely food insecure. The disparity in food security categorizations is also as a result of the differences in the average HFIAS for both groups.

The result of this analysis showed that the average treatment effect on the treated (ATT) had a mean difference of 9.17 with a statistical significance of 1 percent. This means that flooding problems and conversely migrating out of the affected communities increases food insecurity. The average treatment effect on the untreated (ATU) showed a mean difference of negative 11.59 which is also statistically significant. This means that if the migrants were not faced with flooding issues which led to migration, their food insecurity would have reduced by 11. 59.

Worthy of note is the fact that HFIAS score ranges from 0 to 27 and having an expected scale reduction of 11.59 will mean moving towards food security. Indeed, there is a significant difference in the average HFIAS of the migrants and non-migrants.

The result on average farm revenue showed a mean value of migrant household's farm revenue per head was ₦54,509.34 while that of non-migrants was ₦183,153.6 (USD 128.90 and USD 433 respectively). This shows that households who are not faced with flooding problems and who also do not migrate due to same, have more revenue. With more revenue, these non-migrants can access more food than their migrant counterparts who earn less revenue. A farmer who has little money can only access food worth his money while a farmer who has more can access more food equivalent to his income. The exact difference in their farm revenue was estimated using endogenous treatment effect.

The result from the endogenous treatment effect analysis of farm revenue showed that the average treatment effect on the treated (ATT) had a mean difference of negative ₦290.45 (USD 0.69) which is not statistically significant. The average treatment effect on the untreated (ATU) had a mean difference of ₦114,439.5 (USD 270.54) which is statistically significant at 1 percent level. This means that if the migrants are not faced with flooding issues and eventual migration, their expected farm revenue will increase by ₦114,439.5 per head. Migration indeed reduces farm revenue as the result depicts a reduction of ₦290.45 Naira per head if there is migration. Therefore, flooding and migration reduce farm revenue generatable by migrants and if there is no flooding and migration, revenue will increase.

Finally, the result from the estimation of per capita food availability using Daily Per Capita Dietary Energy Supply showed the migrants supply 850.94kcal/person/day out of the 2160kcal required for an adult Nigerian. The non-migrants supply 1207.50kcal/person/day of the required daily food energy. This means that the migrants only meet about 39 percent of their daily food energy while the non-migrants meet 56 percent. These results were compared using endogenous treatment effect.

The result from the endogenous treatment analysis showed ATT had a mean difference of 38.31 percent and an insignificant mean difference of negative 1.19 for the ATU. The endogenous treatment effect analysis revealed mixed outcomes of flooding-induced migration on household food security. Specifically, the Average Treatment Effect on the Treated (ATT) for dietary energy supply (DES) was positive and statistically significant, indicating that, on average, households that migrated due to flooding had higher caloric availability than they would have had if they remained in flood-prone areas. However, this improvement in caloric supply did not translate into broader food security benefits. ATT estimates for both the Household Food Insecurity Access Scale (HFIAS) and farm revenue — proxies for food access and economic access respectively — were negative, suggesting that displaced households experienced greater food insecurity and lower income from agriculture following flooding and migration. These findings point to the multidimensional nature of food security (FAO, 2008; 2012), where improvement in one domain (availability) may coexist with deterioration in others (access and stability).

This study's use of multiple indicators aligns with the multidimensional food security frameworks advanced by the FAO (2008, 2012) and supported in empirical literature (Misselhorn, 2005; Tadesse *et al.*, 2020; Hidrobo *et al.,* 2014). The observed divergence between the ATT for dietary energy supply and the ATT for HFIAS and farm revenue is not contradictory but rather highlights the complexity of food security in displacement contexts, where increased caloric availability may coincide with decreased economic and perceived access to food. As Hidrobo *et al.* (2014) demonstrate, interventions that improve food availability or caloric intake do not necessarily lead to improvements in subjective food security, emphasizing the need to distinguish between food quantity and food access in impact evaluations.

The hypothesis that migration has no effect on the food security status of migrant households was tested and the ESR estimates indicated a statistically significant negative effect of migration on farm revenue and HFIAS. These findings demonstrate that flooding-induced migration compromises both economic access to food and households' food security, thus opposing the hypothesis. Flooding-induced migration therefore, has a negative effect on the food security status of migrant households. However, results for food availability, proxied by per capita dietary energy supply, did not show a consistent negative effect. This divergence reflects the multidimensional nature of food security, where availability can be influenced by broader market and household-level factors that may not immediately respond to displacement or migration patterns. Despite this, the combined evidence from HFIAS and farm revenue confirms that migration exacerbates food insecurity, particularly in terms of access and affordability.

5.3 Conclusions

Based on the findings from this study, the following conclusions are drawn:

Firstly, the recurrent flooding episodes have a significant negative impact on the livelihoods of farming households, particularly those who depend primarily on crop production for income. The frequent displacement caused by flooding disrupts farm operations, reduces output, and diminishes household income. These findings highlight the urgent need for effective flood mitigation strategies and interventions to reduce the frequency and severity of flood events in the study area.

Secondly, coping strategies has to be adopted by farmers in the study area. The identified coping strategies from literature should be implemented either in part or as a whole in mitigating the effect of persistent flood in the study area. It is clear from the results that early planting and harvesting is not effective in the study area as a coping mechanism to flood disasters.

Thirdly, there is a critical need to improve the technical efficiency of both migrant and non-migrant farming households in the study area. The current levels of efficiency indicate considerable room for improvement. Contributing factors to these inefficiencies include limited managerial capacity, suboptimal crop combination practices, and inadequate use of fertilizer and labour inputs. Addressing these issues could significantly enhance farm productivity and resilience.

Finally on the level of food insecurity, the average HFIAS showed migrants are food insecure while non-migrants are more food secure. Migration makes it worse for the migrant farmers since it affects their output and conversely revenue generatable from their farms.

For economic access to food, farm revenue reduces for migrants who face flooding issues with imminent migration and returns. They have losses in output due to flood disasters and this cuts down on their revenue. Their counterparts who do not face flooding challenges are better off. This also explains why they are more food secure. With more revenue per head, the non-migrants access more food in comparison with the migrants.

In the aspect of per capita food availability, the improvement in caloric supply did not translate into broader food security benefits. The Household Food Insecurity Access Scale (HFIAS) and farm revenue — proxies for food access and economic access respectively — suggested that displaced households experienced greater food insecurity and lower income from agriculture following flooding and migration.

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5.4 Policy recommendations

Based on the conclusions drawn, the study recommends the following.

It is imperative that the government (through the Federal Ministry of Works) and relevant stakeholders proactively initiate and implement targeted interventions aimed at mitigating the impact of flooding in the affected communities. One viable approach is the construction of embankments along vulnerable riverbanks to prevent seasonal overflows. Similar infrastructural and environmental management practices have proven effective in other flood-prone regions globally. The Federal Government of Nigeria is therefore encouraged to adopt and adapt such best practices to the local context, particularly in Rivers State and other areas where recurrent flooding continues to disrupt agricultural livelihoods.

Also, the government (through the Federal Ministry of Agriculture and Food Security) can give these farmers grants and credits to assist with coping after flooding episodes. These farmers have lands that are fertile and if assisted during rebuilding times after flooding episodes, they can have more output. This is because most times after floods, they depend on savings for rebuilding and end up with little to nothing left for the next year planting season. Therefore, grants and credit from the government can help them cope in such times. With effective coping strategies, farmers output and conversely revenue will improve. This will in turn improve their food security.

In addition, the Federal Ministry of Agriculture and Food Security, through the Agricultural Development Programme (ADP) offices, should actively engage farmers in targeted extension and educational initiatives. These should focus on improving farm management practices, effective crop combination strategies, and the optimal use of fertilizer and labour. Such capacity-building efforts are essential for enhancing farmers' technical efficiency and overall productivity, especially in flood-prone areas where resources are limited and farming systems are vulnerable.

Private sector and the government should engage in projects in these rural areas which will lead to income generation through non-farm activities. Industries can be built in these areas to assist the farmers in diversifying their sources of income. When the farmers earn more income, they will be empowered to access more food. When they access more food, their Household Food Insecurity Access Scale will equally improve. Accessing more food will also mean an improvement on their food availability.

5.5 Suggestions for further research

Before making suggestions for further research, it's worthy of note to mention the contributions this study has made to knowledge. This study makes several significant contributions to the existing body of knowledge on climate-induced migration, farm productivity, and food security in Nigeria. First, it provides one of the earliest empirical analyses that jointly examines flooding-induced migration and farm technical efficiency using both Stochastic Frontier Analysis (SFA) and the Endogenous Switching Regression (ESR) framework. In contrast to earlier studies that focused mainly on descriptive accounts of flood impacts, this work establishes causal links between recurrent migration and technical efficiency losses among farming households. Secondly, the study advances food security research by simultaneously analysing three complementary indicators—HFIAS, farm revenue, and Dietary Energy Supply. This multidimensional approach offers a more holistic assessment of the food security consequences of migration, an area that has been largely neglected in Nigerian and Niger Delta-focused literature. Thirdly, by compiling twelve years of flooding and migration history (2011–2022), the study provides rare documentation of recurrent full-household migration, patterns of return, and associated livelihood disruptions. Existing studies often rely on single-event shock analyses and therefore miss the cyclical nature of displacement experienced in flood-prone communities. Finally, the findings generate direct evidence to guide climate adaptation and agricultural policy. The study empirically demonstrates that: migration reduces farm technical efficiency, migration increases food insecurity, and recurrent flooding undermines agricultural productivity and household income. These insights strengthen the case for improved flood control, adoption of climate-resilient agricultural practices, and promotion of diversified livelihood strategies. Overall, the study fills a major research gap for Rivers State and the wider Niger Delta, where rigorous econometric evidence on flooding, agricultural efficiency, and food security has been scarce.

Indeed, the study has made contributions to knowledge however, there are areas that could be improved upon through further research. This study was limited to Rivers State, a region severely affected by flooding. While the findings offer valuable insights, they may not fully reflect the experiences of all flood-prone communities in Nigeria or across West Africa. Future research should replicate this study in other flood-prone states and across different ecological zones in West Africa to enable broader regional comparisons and improve the generalisability of results.

Farm production and technical efficiency were estimated using data from a single production year (2022). This restricts the ability to capture inter-annual variations in productivity that may arise from changes in weather patterns, input availability, or market conditions. Subsequent studies should adopt panel or longitudinal data to better capture the long-term impacts of flooding-induced migration on agricultural performance and food security.

The study focused primarily on economic and food security dimensions, with limited exploration of the psychological, educational, and social consequences of repeated displacement on household well-being. Future research should examine the mental health impacts, educational disruptions, community cohesion, and social stability implications associated with recurrent flooding and displacement.

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APPENDICES

Appendix A: Survey Questionnaire

DEPARTMENT OF AGRICULTURAL ECONOMICS AND AGRIBUSINESS
COLLEGE OF BASIC AND APPLIED SCIENCES
UNIVERSITY OF GHANA, LEGON

HOUSEHOLD QUESTIONNAIRE ON THE STUDY "RETURN MIGRATION, COPING STRATEGIES AND FOOD SECURITY STATUS OF AGRICULTURAL HOUSEHOLDS IN TIMES OF FLOODING IN RIVERS STATE, NIGERIA"

CONSENT STATEMENT

The aim of this research is to analyze return migration, coping strategies and food security status of agricultural households in Rivers State, faced with flooding challenges. The study aims to understand how and to what extent flooding affects you, the farmer and how you cope each time you return after migrating for safety during flood disasters.

Benefits of the study

This study will help to understand how you try to cope over time, with several years of repeated flooding, and how that affects your food safety. This will help inform policy makers on interventions that will help alleviate your pains and also improve your food security.

Risk of the study

This study does not have any physical, social or psychological risks for you the farmer.

Confidentiality

The data collected from you is only for my academic work. They will only be used for scientific analysis. So, any personal data provided through this study is highly confidential. Myself the researcher, supervisory team and the sponsors of this research (PASET-RSIF) will have access to the records.

Compensation

At the end of the interview, you shall be presented with a small incentive offered as a sign of thanks in the form of washing soaps, for your time and response to this interview.

I affirm that I have read, or have had the information in this study explained to me, and I have had the chance to ask questions and receive satisfactory answers. I freely consent to take part in this study, or for my child/ward to participate. I understand that by signing this form, I am not waiving any of my legal rights. A signed copy of this consent form will be given to me for my personal records.

Name:

Signature or mark:

Date:

SURVEY INFORMATION

Zone: ……………………………………
1-Ahoada.
2-Eleme

LGA………………………………………
If Zone 1, select LGA
1-Ahoada East.
2-Ogba Egbema-Ndoni.
3-Ahoada West.
4-Emohua.

If Zone 2, select LGA
5-Eleme
6-Oyigbo
7-Gokana
8-Tai

Community name……………………………… ☐☐☐ Community ID: ……….. ☐

HOUSEHOLD: ……………☐☐ ☐

Phone Contact(s): 1…………………………………….. 2……………………………………………

Supervisor: ………………………………………………………………………..

Enumerator: ………………………………………………………………………

Date of interview: ……………………………………………………………...

What is your primary occupation:
1- crop
2- livestock production
3- Crop and livestock production?

Household type: ……………………………………………………………………
1-Non-migrant
2-Migrant:
(If non-migrant, skip Section A22-33 and move to section B)

SECTION A: Socio-economic characteristics

	A4 Sex 0=Female 1=Male	A6 How old is the household head?	ONLY 18 YEARS OR OLDER		A9 What is your religious denomination? **Code C**	A10 To which ethnic group do you belong? **Code D**	A12 What is your highest educational qualification? **Code E**	A14 What is your main secondary occupation? **Code G**
			A7 What is your present marital status? **Code B**	A8 At what age did you first get married or start living with a partner?				

Code B	**Code C**	**Codes D**	**Code E**	**Code G**
1 I am married	1 No religion	1 Ekpeye people	0 None	0 None
2 I am in a consensual union	2 Catholic	2 Ikwerre	1 Primary	1 Casual farm labourer
3 I am separated	3 Protestant	3 Ogoni	2 Secondary	2 Casual nonfarm labourer
4 I am divorced	4 Pentecostal/Ch'matic	4 Igbo	3 Polytechnic	3 Agricultural trader
5 I am widowed	5 Islam	5 Ijaw	4 University	4 Artisan
6 I have never been married	6 Traditionalist	6 Ogba	5 Uni. (postgrad.)	5 Security service
	7 Other (specify)	7 Ntoro	6 Voc/Tech	6 Store operator
		8 Ibani	7 Other (specify)	7 Housekeeping
		9 Eleme 10 Saro		8 Other (specify)
		11 Boma. 12 Defaka		9 Don't know
		13 Others (spe.cify)		

SECTION A: Socio-economic characteristics (continued)

A17 In what Nigerian language can you read a phrase or sentence? **Code I**	A19 In what Nigerian language can you write a sentence? **Code I**	A20 Can you do written calculatio ns? 0=No 1=Yes	A21 Have you ever attended a literacy course? 0=No 1=Yes	A22 During the 2022 season did you encounter flooded farms? 0= No 1= yes If no, skip to part C	A23 Did you have to stop the farm activities because of this? 0=No 1=Yes	A24 For how many months did you stop operation on the farm in the 2022 season?	A25 How many times during the last 12 seasons (2011-2022) did you suffer from the flooding episodes?	A26 Did you migrate out of the community all those years during flooding? 0=No 1=Yes	A27 If yes, to where? Code **Code J**	A28 How many household members left?	A29 How many household members returned?
A30 Did you acquire any new skill while away? 0-No 1-Yes	A31 If yes, in what area? 1-Farming activity 2-Trade 3-Skill acquisition 4-Others (Specify)	A32 Have you ever insured the farm for flood? **Code K**	A33 If yes, are you currently covered? 0=No 1=Yes								

Code I	**Code J**	**Code K**
0 None 4 Kalabari 9 Ijaw 1 Igbo 5 Ogoni. 10 Other (specify) 2 Hausa. 6 Ogba 3 Yoruba 7 Abua 4 Ikwerre 8 Emohua	1 IDP 2 Family member in another community 3 Urban area 4 Others (specify)	0 No 1 Yes, registered presently 2 Yes, registered some years back

SECTION B: Coping strategies adopted by farming households during flooding

Part 1: Farmer's coping strategies

B01 Have you encountered flooding on your farm before? 0-No 1- Yes	B02 If yes, select the primary impact of flooding on your farm **Code L**	B03 Do you employ crop diversification (e.g., early-maturing varieties) to cope with flooding? 0-No 1-Yes	B04 If yes, what crops do you diversify into during flooding? **Code M1**	B05 What other crop diversification methods do you use? **Code M2**	B06 How do you manage water during flooding on your farm? **Code N**
Code L 1 Crop damage 2 Soil erosion 3 Infrastructure damage 4 Contamination of water sources	**Code M1** 1-Taro (cocoyam) 2-Cassava 3-Vegetables 4-Rice. 7-Sorghum	**Code M2** 1-Inter-cropping 2-Mixed-farming 3-Crop rotation 4-Upland cropping	**Code N** 1-Improved drainage system 2-Raised beds 3-Terracing 4-Water pumps		

5 Others (specify)	5-Millet 8-Others (specify) 6-S/potatoes 7		5-Sand bag barriers 6-Others (specify)		

B07 Have you used elevated construction techniques before to protect your structures from flooding? 0-NO 1-Yes	B08 If yes, what primary method of elevated construction did you use? **Code O (multiple selection allowed)**	B09 Do you rely on traditional knowledge or practices passed down through generations to cope with flooding? 0-No 1-Yes	B10 If yes, what traditional knowledge did you apply? **Code P**	B11 Do you cultivate crop varieties known for their resistance to flooding? 0-No 1-Yes
B12 If yes, what flood-resistant crops do you cultivate? **Code Q**	B13 Are you utilizing modern technologies to cope with flooding on your farm? 0-No 1-Yes	B14 If yes, what technologies did you use? **Code R**	B15 Have you adopted new or innovative approaches to water management during flooding? 0-No 1-Yes	B16 If yes, what innovative approaches did you use? **Code S**
Code O 1-Raised platforms 5-Stilts 2-Raised embarkments 6-Levees 3-Bamboo rafts. 7-Others (specify) 4-Flooting gardens	**Code P** 1-Traditional planting calendars 2-Rituals for soil fertility 3-Indigenous flood forecasting 4-Crop rotation 5-Others (specify)	**Code Q** 1-Maize 2-Rice 3-Sorghum 4-Others (specify)	**Code R** 1-Precision farming technologies 5-Others (specify) 2-Automated irrigation systems 3- Satellite-based flood monitoring 4-Sensor-based flood alert systems	**Code S** 1-Rainwater harvesting 5-Others (specify) 2-Sustainable drainage systems 3-Floating gardens 4-Subsurface irrigation

B17 Are you aware of and implementing any global initiatives related to flood mitigation that are locally relevant? 0-No 1-Yes	B18 If yes, what global initiatives have you implemented? Code T	B19 How effective do you consider the coping strategies you've implemented in mitigating the impacts of flooding on your farm? **Code U**	B20 What challenges, if any, have you faced in implementing these coping strategies, especially during flooding events? **Code V**
Code T 1-Climate-smart agriculture 2-Sustainable Development Goals related to agriculture 3-Participating in international flood awareness campaigns 4-Collaborating with NGOs working on flood resilience	**Code U** 1-Very Effective 2-Somewhat Effective 3-Neutral 4-Not Very Effective	**Code V** 1-Lack of resources 2-Limited access to information 3-Climate variability 4-Technical complexity	

5-Other (please specify)	5- Not Effective at All	5-Other (please specify)	

Part 2: Government and donor agencies interventions

B21 Did you receive any form of government support or assistance to enable you cope with the flooding impact? 0-No 1-Yes	B22 Did you receive any assistance from any NGO or private sector to enable you cope with the flooding impact? 0-No 1-Yes	B23 Was this assistance received before the flooding? 0-No 1-Yes	B24 If no, was the assistance received when you returned? 0-No 1-Yes	B25 What form of assistance did you receive? **Code W**	
B26 If cash/credit, how much in naira value did you receive? Government- NGO - Private sector-	B27 What did you put the money into? 1-Farming activity 2-New skill acquired 3-Feeding 4-Others (specify)	B28 If extension advice/visit, how many times did you receive a visit from an extension officer?	B29 Please specify the type of service you received from the extension officer? **Code AH (used below)**	**Code AH (repeated)** 1 Use of seeds 4 Mechanization 7 Animal husbandry 10 Other (spec.) 2 Planting 5 Credit facilities 8 Use of chemicals 3 Use of fertilizer 6 Irrigation 9 Post harvest services	**Code W** 1-Farm inputs (seeds, fertilizer, agrochemicals etc) 2-Cash/credit 3-Extension advice/visit

SECTION C: Farm household's production activities

Part 1: Production

C101 How much agriculture land is owned by the household now? Area	Unit **Code X**	C102 What is the number of years engaged in farming (in general up to 2021/22 farming season)?		C103 For how many years have you independently engaged in (crop) farming up to 2021/2022 season??	C104 What type of (CROP) variety did you plant? **Code Y**	C105 What was the quantity of seed used for planting? (kg)?	C106 If you planted flood-resistant seeds, how many years have you been cultivating it?	C107 Have you been consistent in your use of flood-resistant seeds since you started using them? 0=No 1=Yes	C108 What quantity of seeds were purchased (kg)? If no purchase >> B110
			Cassava						
			Maize						
			Yam						
			Rice						

Code X	**Code Y**
1 Acre 2 Hectare 3 Other (specify)	1 Local variety 2 Improved variety 3 Flood-resistant varieties 4 Improved and local varieties

Crop	C109 How much was spent in purchasing the seeds? (Naira)	C110 Why did you not cultivate flood-resistant seeds? **Code Z**	C111 Did you apply any fertilizer to your (CROP) plot? 0= No >> B115 1= Yes	C112 What type did you use? **Code AA**	C113 How much was applied? (Kg)	C114 How much did it cost per unit? (Naira)	C115 Did you apply pesticides? 0=No >> C116 1=Yes			C116 Did you apply weedicides? 0=No >> C117 1=Yes			C117 Was green manure used? 0=No 1=Yes
							C115a Which type did you apply? **Code AB**	C115b How much was applied on farm (litres)	C115c How much did you spend in total on pesticides (Naira)	C116a Please specify the type you applied **Code AB**	C116b What quantity? (litres)	C116c What amount was spent? (Naira)	
Cassava													
Maize													
Yam													
Rice													

	C118 Did you use animal dung on your farm? 0=No 1=Yes	C119 Did you use compost manure on your farm? 0=No 1=Yes	C120 What type of cropping did you adopt in the 2021/2022 cropping season? 0=Mono 1=Multi	C121 What is your view of the natural fertility of the land cultivated? **Code AC**	C122 How would you rate the level of flooding on your plot, in comparison with others in your area? 1=less flooded 2=same as others 3=more flooded	C123 What is the slope of your plot? 1=Plain 2=Gentle 3=Hilly	C124 Do you irrigate this land using any source other than rain? 0=No >> B126 1=Yes	C125 Please specify your main source of watering **Code AD**	C126 Are you engaged in conserving soil and water? 0=No >> B129 1=Yes	C127 If you do, what types are they? **Code AE**
Cassava										
Maize										
Yam										
Rice										

Code Z			**Code AA**		**Codes AB**
1 Cannot get seed at all	6 Requires more money	11 Requires high skills	1 NPK (15-15-15)	6 Commercial organic (including Fertisoil, cocopeat)	1 Powder/condemn
2 Lack of cash to buy seed	7 Don't know how to use it	12 Seeds are expensive	2 Ammonium sulphate (SA)	7 Phosphorus	2 Sarosate
3 Susceptible to field pests/diseases	8 Low yielding	13 Cannot get credit	3 23-10-5 (Actyva)	8 Sulfan	3 Insecticide
4 Susceptible to storage pests	9 Poor market price	14 Need for other crops	4 Other types of fertilizer	9 Inoculant	4 Fungicide
5 Poor taste	10 No market	15 Other specify)	5 Urea	10 Other (specify)	5 Tintani
					6 Other (specify)

Code AC	Code AD	Code AE	
1 Fertile 3 Less fertile 2 Moderately fertile 4 Infertile	1 Well 5 Other (spec.) 2 Borehole 3 Pond/tank 4 River/stream	1 Crop rotation 3 Legumes 5 Minimal tillage 7 Agroforestry 2 Land enriching cover crops 4 Zero tillage 6 Composting 8 Other (spec.)	

C138 Did you have any contact with extension agent? 0=No >> C142 1=Yes	C139 How many times did the extension officer(s) visit you for farm-related support?	C140 What kind of support or services did the extension officer provide? **Code AH**	C141 What is your orientation towards farming? **Code AI**
Code AH 1 Use of seeds 3 Use of fertilizer 2 Planting 4 Mechanization 5 Credit facilities 6 Irrigation 7 Animal husbandry 8 Use of chemicals. 10 Other (spec.) 9 Post harvest services	**Code AI** 1 Primarily for consumption 2 Primarily for market 3 Both, but more 4 Both, but more market consumption 5 Other (spec.)		

Activity	Family						Hired						Communal			
	C142 Was family labour utilized? 0=No >> C149 1=Yes						C143 Was hired labour utilized? 0=No >> C144 1=Yes						C144 Did you use communal labour? 0=No >> Part 2 1=Yes			
	Male		Female		Children		Male			Female			Male		Female	
	No.	Time period	No.	Time period	No.	Time period	No.	Time period	Rate/day (Naira)	No.	Time period	Rate/day (Naira)	No.	Time period	No..	Time period
Clearing																
Ploughing																
Planting																
Chem. Application																
Weeding																
Harvesting																

Part 2: Harvest, sales and purchases of crops

Crop	C245 What quantity did the household harvest from all farm areas in the 2021/22 season?		C246 Size of all farm areas? (Size of farmland cultivated)		C247 Was any quantity lost during harvest? 0=No >> B249 1=Yes	C248 What quantity of the crop was lost during harvest?		C249 How was the crop harvested? 0=Hand 1=Machine 2=Both 3=Other (spec.)	C250 How did you store the harvest? **Code AK** If none >> B252	C251 Was your output treated with chemicals while in storage? 0=No 1=Yes	C252 Were any of your crops sold? 0=No >> next crop 1=Yes	C253 How did you sell most of the harvest? **Code AL**
	Q'TY	UNIT **Code AJ**	AREA	UNIT **Code X**		Q'TY	UNIT **Code AJ**					
Cassava												
Maize												
Yam												
Rice												

Code AJ	Code AK	Code AL
1 Mini bag	0 I did not store	1 I sold right after harvest
2 Maxi bag	1 I used local silo in my house/farm	2 I sold before cultivation started
3 Kilogram	2 I stored in bags in my house/farm	3 I sold when my family was cash constrained
4 Painter	3 I stored with private aggregator	4 I sold when I realized I had enough to consume
5 Margarin tin	4 I used a cooperative facility	5 I sold when I noticed an increase in output price
6 Other (spec.)	5 I used a communal storage unit	6 I sold when I foresaw a decrease in the near future
	6 Other (spec.)	7 Other (spec.)

Crop	C254 Quantity sold during and after harvest(s) in 2021/22		C255 What was the unit price of first quantity you sold? (Naira)	C256 For crops sold at the market, what's the distance to the market? (Km)	C257 How much did you pay to transport a unit quantity? (Naira)	C258 Are there other marketing costs you incurred? **Code AM**	C259 How much was spent on these costs? (Naira)	C260 What is the major reason for selling? **Code AN**
	Q'TY	UNIT **Code AJ**						
Cassava								
Maize								
Yam								
Rice								

Codes AM	Code AN
0 None	1 Flooding devastation
1 Market toll	2 I sold to Meet basic family needs/necessities
2 Loading/offloading	3 I had excess
3 Comm.: search & negotiation	4 Took advantage of favorable market conditions
4 Packaging	5 To make profit
5 Other (spec.)	6 Other (specify)

C261 Yearly earnings from the sale of other crops (Naira)	C262 Income from aid (NGO/Gov't/Remittance) (Naira)	C263 Others not classified (Naira)	C264 What is your average monthly expenditure on other routine non-food items? (Naira)	C265 What amount did you spend on occasional expenses (such as funerals, remittances, gifts, weddings, etc.) in the past 12 months? (Naira)	C266 Other expenditure (Naira)

PART 3: Other Assets

Item	C367 Do you own any functional …...? 0=No >> next asset 1=Yes	C368 How many items in all?	C369 Average age of items (years)	C370 How many at the beginning of the 2021/2022 season?	C371 Number purchased in 2021/22 season?	C372 Did you sell any item? 0=No >> c8 1=Yes	C373 Value of sale (Naira)	C374 Price if you were to sell now (Naira)
Radio								
Computer (desk/laptop)								
Television								
Bicycle								
Motor cycle								
Tricycle								
Car								
Mobile phone								
Tractor								
Combine harvester								
Bullock								
Donkey cart								
Cutlass								
Hoe								
Knapsack								
Thresher								
Mechanized sheller								
Irrigation kit								
Other (specify)								

E05 Do you have an insurance policy for any of your agricultural activities? 0=No >> E08 1=Yes	E06 What type of agric. insurance policy do you have? **Code AO**	E07 How much did you spend on this policy in 2021/22 season? (Naira)	E08 Are you willing to acquire weather insurance if you have access? 0=No 1=Yes
	Code AO 1 Protection against crop failure 2 Protection against fire burning produce 3 Protection against price fluctuation 4 Others (spec.)		

PART 4: Nonfarm Activities and Remittances

F01 Did any member of the household engage in any activity outside agriculture in the 2021/2022 season? 0=No >> F06 1=Yes	F02 How many members were engaged?	Members engaged	F03 How many nonfarm activities were you engaged in during the season?	F04 In which specific nonfarm activity were you engaged in? **Code AP**	F05 How much in total was gained in the engagement in the nonfarm activity(ies)? (Naira)	F06 Did you receive remittance in the 2021/22 season? 0=No >> section D 1=Yes	F07 Were these remittances made on a regular basis? **Code AQ**	F08 What was the total amount of cash sent?
		1						
		2						
		3						
		4						
		5						

F09 What were the 3 main uses of cash sent? **Code AR**			F10 What was the proportion of remittance invested in your farm operations?	F20 If remittance was sent in-kind/goods, what was the value of other goods (non-food items) sent? (Naira)	F21 Were the goods converted to cash for use? 0=No >> Next Section 1=Yes	F22 How much was realized? (Naira)	F23 What was the proportion of remittance invested in your farm operations?
1st	2nd	3rd					

Code AP		Code AQ		Code AR		
1 Casual farm labourer	5 Security service	0 No	3 Yes, on a quarterly basis	1 Daily consumption	6 Education	
2 Casual nonfarm labourer	6 Store operator	1 Yes, on a weekly basis	4 Yes, on an annual basis	2 Agric investment	7 Health	
3 Agricultural trader	7 Mining	2 Yes, on a monthly basis	5 Yes, other (specify)	3 Housing	8 Funerals	
4 Artisan	8 Other (specify)			4 Nonfarm business	9 Other ceremonies	
				5 Savings	10 Other (spec.)	

SECTION D: Effects of migration on the Food Security status of farming households

Part 1: Household Food Insecurity Access Scale (HFIAS) Module

Q No.	Question	Response Code
H301	During the last four weeks (30 days), were you ever concerned that your household might not have sufficient food to eat?	0 = No (Skip to H302) 1 = Yes
H301a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H302	During the preceding 30 days, were you or anyone in your household unable to consume favoured food items due to insufficient resources?	0 = No (Skip to H303) 1 = Yes
H302a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H303	In the preceding 30 days, was there any instance where you or someone in your household had to consume a restricted variety of foods due to insufficient resources?	0 = No (Skip to H304) 1 = Yes
H303a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H304	In the preceding four weeks (30 days), was there any instance where you or anyone in your household had to consume meals that you preferred to avoid due to insufficient finances to acquire alternative options?	0 = No (Skip to H305) 1 = Yes
H304a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H305	In the preceding 30 days, was there any instance where you or anyone in your household consumed a smaller meal than necessary due to insufficient food availability?	0 = No (Skip to H306) 1 = Yes
H305a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)

H306	In the preceding four weeks (30 days), did you or any member of your household have to reduce the number of meals consumed daily due to insufficient food availability?	0 = No (Skip to H307) 1 = Yes
H306a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H307	During the preceding 30 days, was there ever a time when there was no food of any type available in your household due to insufficient finances to procure food?	0 = No (Skip to H308) 1 = Yes
H307a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H308	In the preceding four weeks (30 days), did you or any member of your household retire for the night feeling hungry due to insufficient food availability?	0 = No (Skip to H309) 1 = Yes
H308a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)
H309	In the preceding 30 days, did you or any member of your household go a full day and night without consuming food due to insufficient provisions?	0 = No (Skip to Part 4) 1 = Yes
H309a	What was the frequency of this occurrence?	1 = Infrequently 2 = Occasionally 3 = Frequently (greater than ten)

Part 2: Food Insecurity Experience Scale (FIES) Module

During the last 12 MONTHS:		**Code** 0=For the answer, no 1=For the answer, yes 8=For the answer "don't know" 9=For the answer refused
H101	Have you or any members of your household ever experienced concerns regarding insufficient food due to financial constraints or resource scarcity?	
H102	Reflecting on the past 12 months, was there a period when you or other members of your household were unable to access appropriate and nutritious food due to financial constraints or insufficient resources?	
H103	Have you or any members of your household ever consumed a reduced diversity of foods due to financial constraints or other resource deficiencies?	
H104	Have you or any members of your household ever had to forgo a meal due to insufficient financial resources or lack of access to food?	

H105	Reflecting on the past 12 months, was there a period when you or other members of your household consumed less food than was necessary due to financial constraints or insufficient resources?	
H106	Has there been an instance when your household experienced food scarcity due to insufficient financial means or other resources?	
H107	Have you or any members of your household ever experienced hunger without the means to procure food due to insufficient financial resources or other constraints?	
H108	Have you or any members of your household ever experienced a full day without food due to financial constraints or resource scarcity?	

Part 3: Consumption of food groups

No.	Food item	H401 Did your household consume this in the last 7 days? 0=No >> H404 1=Yes	H402 How many times in the last 7 days?	H403 What amount of money goes into this in a month? (Naira)	H404 Why did you not consume this in the last 7 days? **Code AS**
1	Cereals and grains				
2	Roots and tubers				
3	Vegetables				
4	Fruits				
5	Meat and Poultry				
6	Eggs				
7	Fish and Seafood				
8	Legumes and nuts				
9	Milk and milk products				
10	Oil, fat and butter				
11	Sugar and sweet/Honey				
12	Condiments and spices				

Code AS
1 Run out of money 5 Not our delicacy
2 It was too expensive. 6 Other (spec.)
3 It wasn't physically available
4 Don't like it

END OF QUESTIONNAIR

Appendix B: Result of Cobb-Douglas Stochastic Frontier Analysis

	Coefficient	Std. Error	P-values
Cobb-Douglas Production Function			
LnSeed	0.0269**	0.0112	0.016
LnLabour	-0.0391*	0.0227	0.084
Constant	0.4115	0.0453	0.000
Technical Inefficiency			
Migrants (RC = Non-migrants)	1.3070***	0.1736	0.000
Type of Family	-0.2012**	0.0981	0.040
Monogamous (RC = Polygamous	0.1116*	0.0584	0.056
Household Size	0.0364***	0.0090	0.000
Female (RC = Male)	-0.3436*	0.1901	0.071
Age	-0.0100***	0.0027	0.000
Primary (RC = No Education)	-0.1162	0.0971	0.231
Secondary	-0.4032***	0.1217	0.001
Polytechnic	0.3235**	0.1522	0.034
University	0.0596	0.1254	0.635
Uni.(postgrad.)	2.3017***	0.3743	0.000
σ^2	0.3947	0.0397	
γ	0.8097	0 .0260	
σ_{u2}	0.3196	0.0406	
σ_{v2}	0.0751	0.0065	

No. of Observation: 440 ; Wald Chi2(2): 11.55 ; P-value: 0.0031; Log Likelihood: -1081.91
Mean technical efficiency (TE) for migrants = 0.4332, non-migrants = 0.4360

Source: Field survey, 2024

Appendix C: Average Partial Effects After Logistic Regression Estimation (Partial effects of factors that influence migration)

Variables	Marginal Effect (dy/dx)	Std. Error	P-values
Age	-0.0048	0.0010	0.0000
HHSize	0.0074	0.0031	0.0180
Education	-0.0511	0.0091	0.0000
Gender	0.0230	0.0421	0.5860
Marital Status	0.0230	0.0119	0.0540
Family Type	-0.0111	0.0322	0.7310
Age with Married Partner	0.0128	0.0022	0.0000
Religion	0.0140	0.0073	0.0540
Ethnic Group	0.0061	0.0003	0.0000

Source: Field survey, 2024

Appendix D: Test of Mean Difference Before Matching for Matching Quality

Variables	Migrants (N= 246)	Non-Migrants (N = 194)	Difference	% Bias	V(T) / V(C)
Age	62.8820	60.0410	2.8410	27.10	0.75*
Gender	1.0244	1.0670	-0.0426	-20.50	0.38*
Education	1.4837	2.0103	-0.5266	-49.30	0.52*
HHSize	7.7114	6.8402	0.8712	31.10	1.20
Family Type	1.0854	1.0825	0.0029	1.00	1.03
Age with Married Partner	31.8210	30.9120	0.9090	21.70	1.00
Marital Status	1.1504	1.1186	0.0318	4.60	1.65*
Religion	3.0528	2.9175	0.1353	11.20	0.99
Ethnic Group	75.5080	3.7680	71.7400	238.80	36.41*

Source: Field survey, 2024

Appendix E: Test of Mean Difference After Matching for Matching Quality

Variables	Migrants (N= 246)	Non-Migrants (N = 194)	Difference	% Bias reduction	V(T) / V(C)
Age	58.8330	57.8460	0.9870	65.30	0.83
Gender	1.0667	1.0769	-0.0102	75.90	0.86
Education	1.5667	1.2308	0.3359	36.20	1.03
HHSize	6.8833	6.6154	0.2679	69.20	1.42
Family Type	1.0833	1.0385	0.0448	-45.80	1.02
Age with Married Partner	32.3330	32.7690	-0.4360	52.00	0.95
Marital Status	1.2000	1.2308	-0.0308	3.40	1.04
Religion	3.1000	3.1923	-0.0923	31.80	0.47*
Ethnic Group	2.6833	7.1923	-4.5090	93.70	0.46*

Source: Field survey, 2024

Appendix F: Matching Quality

Sample	PS R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.543	328.01	0.0000	45	21.7	246.4*	8.59*	56
Matched	0.098	10.33	0.3240	12.1	9.6	76.9*	1.43	44

Source: Field survey, 2024

Appendix G: Published Article: Effects of flooding-induced migration on farm technical efficiency in Rivers State, Nigeria.

This article was published in *Journal of Agriculture and Food Research,* Volume 23, 2025, 102189. https://doi.org/10.1016/j.jafr.2025.102189.
The article is attached.

Appendix H: Article undergoing review: Effects of flooding-induced migration on the food security status of farming households in Rivers State, Nigeria.

This article is undergoing review with Scientific African Journal and is attached.

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Effects of flooding-induced migration on farm technical efficiency in Rivers State, Nigeria

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ABSTRACT

This study assessed the effects of flooding-induced migration on farm technical efficiency in Rivers State. Data were collected on episodes that occurred between 2011 and 2022 to estimate the trend of flooding in the study area and also farm technical efficiency (TE), specifically from 2022 production activities. Translog Stochastic frontier was estimated and TE generated. The effect of migration on farm's TE was analyzed using endogenous treatment effect model and the average treatment effects were estimated. Results obtained showed that flooding episodes occurred yearly in the twelve years under review. The Stochastic frontier analysis showed that migration has a positive and significant coefficient in the inefficiency model, thus depicting that migration increases technical inefficiency. The TE results showed that migrants operate at 71.17 % efficiency and non-migrants at 74.63 %. This shows that both groups of farmers have room for improvement to achieve efficient production. The result of average treatment effect on the treated (ATT) is significant, with a mean difference of negative 3.85 % and also significant for the untreated (ATU) with 2.01 % value of mean difference. This means that the TE of migrants reduced by 3.85 percent and their expected TE will increase by 2.01 percent if they are not faced with flooding problems and did not migrate. This shows that migration indeed, as seen in the technical inefficiency model, affects TE. It is recommended that government and stakeholders should initiate and execute projects meant to curb flooding in these communities. The ministry of agriculture should engage the Famers in educational activities on how to manage their farms, combine crops, and proper fertilizer and labour usage for optimum output. These will improve their farm technical efficiency.

1. Introduction

Globally, environmental disasters such as floods are increasingly affecting food production, rural livelihoods, and migration patterns [1,2]. Floods now account for a significant share of global disaster-related losses, with the United Nations estimating annual economic losses from disasters at $250–300 billion [3]. These impacts are especially severe in developing regions like West Africa, where high population growth and rapid urbanization heighten exposure to climate risks [4,5].

In Nigeria, the frequency and severity of flooding events have grown over the past two decades, transforming what were once sporadic occurrences into regular, destructive episodes. The 2012 flood remains one of the most catastrophic, affecting 32 of Nigeria's 36 states including Rivers State and damaging over 1.9 million hectares of farmland. The agricultural sector suffered deeply: rice output fell by 22.4 %, maize by 14.6 %, and cassava by 11.2 % [6,7]. Coastal states like Rivers are now particularly vulnerable, not only due to their geography but also due to increased tidal surges and rising sea levels [8–11].

Within Rivers State, recurrent flooding has displaced thousands of farming households seasonally, triggering an annual cycle of short-term migration. These households are often relocated into temporary shelters for up to 3–4 months before returning to resume farming activities. Despite multiple studies addressing the causes and impacts of flooding in Rivers State (e.g., risk, mitigation, and disaster preparedness), few have explored the link between flood-induced migration and agricultural productivity [12–15].

Meanwhile, international evidence suggests a complex relationship between migration and farm performance. For instance, Ren et al. [16] found that migration positively influenced technical and fertilizer use efficiency in rice farming in China. Similarly, Nonthakot and Villano

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[17], reported that migration and remittance characteristics enhanced maize productivity in Thailand. However, in Ghana, Adaku [18], found that temporary migration reduced farm production, while permanent migration had no significant effect. These mixed findings suggest that the migration–agriculture link is context-specific.

Studies carried out before now on the recurrent floods in Rivers State [12–15,19,20], focused on the causes, impact, panacea and risk reduction. None looked into how the yearly migratory movement affects farm's technical efficiency. While the impact of flooding on agriculture is known, a substantial research gap exists in comprehending the intricate dynamics of migration and the effect this particular migration due to environmental vulnerability has on farm's technical efficiency in Rivers State.

Therefore, this study seeks to contribute to the empirical literature by examining how seasonal migration due to recurrent flooding affects farm technical efficiency in Rivers State, Nigeria. This is a critical gap, given the increasing frequency of climate-induced displacement and its implications for agricultural development in flood-prone areas.

Flooding in Rivers State and its impact on farmers is explained in details below.

One of the most catastrophic floods to ever hit Nigeria happened between July and October of 2012. Rivers State was among those affected. The government of Nigeria was cautioned by Nigerian Meteorological Agency (NIMET) that above-average rainfall would cause floods in 12 important states, but the government disregarded the caution. Together with the water released from the Lagdo dam in Cameroon, this caused the Niger and Benue rivers to overrun their banks, causing enormous floods [21]. The effects of the flood were terrible. Fatalities were documented, individuals were rendered homeless, agricultural lands were compromised, there was contamination of water, and economic operations were entirely suspended. The cost of transporting individuals increased because there were limited transportation options available to the affected communities, which were solely local canoes and speedboats. In numerous locations nationwide, there was the incursion of reptiles, including snakes and crocodiles, due to the flood. Agricultural producers nationwide incurred substantial financial deficits. Challenges were posed by food production, food marketing, and food storage. Prices of goods increased, and there was also a sudden closure of schools. The floods decreased food production along flood plains and damaged about 1.9 million hectares of agriculture. These areas saw a reduction in rice output of 22.4 %, a reduction in maize production of 14.6 %, and reductions in the production of cowpea (6.3 %), soyabean (11.2 %) and cassava [21]. The 2012 floods claimed the lives of 136 cattle, 3 million chickens, and 12 million goats. According to estimates from the National Emergency Management Agency (NEMA), the floods incurred an aggregate expenditure of 2.29 trillion-naira, equivalent to 2.83 % of the adjusted Gross Domestic Product of 81 million naira for 2013. The nation's food security was put in jeopardy as hundreds of farmers were forced out of their places of residence and agricultural products were destroyed, making the floods dubbed the worst in recent memory. Major staples in the localities, such as yam, maize, plantain, cassava and pawpaw, were among the crops most adversely affected by the flood [22]. Out of the 36 states in Nigeria, 32 were hit by this devastation; Rivers State was one of the worst-hit states [21]. The relief materials to the affected people were not enough, yet the affected states' governors ordered that the flood victims evict their homes and put-up temporary shelters for them. Due to the fear of thieves breaking into their homes, several flood victims refused to leave their towns. Prior to this time, there had been a flooding episode in 2013 but it was not as devastating as the 2012 episode. There is indeed an understatement of 50 % in the estimation of the losses from the 2012 episode.

About 2.5 trillion US dollars are lost in the world economy due to this devastation in West Africa that includes Nigeria. [21]. West Africa's population growth and urbanisation patterns since the turn of the century suggest that an increasing number of people may be impacted by flooding episodes in the coming years. According to the United Nations Office for Disaster Risk Reduction (UNISDR), the 2015 Global Assessment Report on Disaster Risk Reduction (GAR 15), indicates an average of between $250 billion and $300 billion of yearly economic losses resulting from catastrophes [23]. The Nigeria Hydrological Services Agency's director general in 2015 issued a warning in the capital city of Abuja at the annual flood outlook presentation. The nation's danger areas were split into three categories: lowland flood areas, medium risk, and high risk. The river basins of Niger-Benue, Sokoto-Rima, and Anambra had predictions for high flooding; Biase, Munya, Chikum, Shinkafi, and Etiosa, among others, had predictions for localised flooding; while Rivers, Lagos, Bayelsa and Delta states had predictions for coastal due to rising sea levels and tidal surge. As a result of this recent warning, it is necessary to examine the methods farmers currently employ to prepare for flooding, the steps taken by organisations and government agencies to lessen flooding, and the steps the government has taken to manage flood disasters.

2. Methodology

The study area, research design (data source, type and data collection tools, sample size, sampling procedure), and analytical tools used in the study are enumerated in this section.

2.1. Study area

One of Nigeria's 36 states, Rivers State is centred in the country's South-South geopolitical zone with its capital, Port Harcourt. It is bordered to the east by the states of Abia and Akwa Ibom, to the west by the states of Bayelsa and Delta, to the north by the states of Anambra and Imo, and to the south by the Atlantic Ocean. The population was 5,198,716 in the 2006 census, and was projected as 7,492,366 in 2023. Its coordinates are Latitude 4.75°N and longitude 6.50°E, and it encompasses an area of 11,077 km^2 (4,277 m^2). The Ijaw, Ikwere, Etche, Ogoni, and Ogba/Egbema are the predominant ethnic groupings. The primary means of subsistence for the populace is agriculture, and food production serves as the cornerstone of state agriculture policy.

Nigeria's seventh most populous state is Rivers State. The linguistic diversity of the state is especially well-known; it is estimated that 28 indigenous languages, including Ikwerre, Ogba, the Etche, Abua, Ogoni, Igbo, and Ijaw languages among others, are spoken in Rivers State. Rivers State is the 26th largest state in Nigeria by geographical area, and is traversed by numerous rivers, including the Bonny River. These rivers shape the topography of the state.

2.2. Research design

2.2.1. Data source, type and data collection tools

Primary and secondary data were used for the study. Primary data were collected from rural farmers in one of the three Agricultural Zones in Rivers State where the flooding episodes are prevalent and farmers engage in crop production. The households included in the sample were interviewed using a structured questionnaire coded into KoboCollect software. The questionnaire gathered a variety of data regarding households' socioeconomic circumstances, their production activities and also the coping strategies adopted in mitigating the impact of flood in their farms. Information was also collected from households in communities that do not experience flooding and migration to serve as our control group. Crop farmers were included in the study while those who rear livestock alone were excluded. Household heads who are eighteen years and above were also included, whether male or female. Secondary data were collected from National Emergency Management Agency (NEMA) on the flooding episodes in the study area over the period 2011–2022.

2.2.2. Sample size determination

This study included a sample size of 440 farmers. Using the mathematical method developed by Miller and Brewer [24] the study's sample size was determined from the sample frame. The following is the formula;

$$n = \frac{N}{1 + N(\alpha)2} \quad (1)$$

Where;

N = Sample frame

n = Sample Size

α = Confidence Interval.

A 95 % confidence interval and 5 % margin of error were used in this study. The reason behind this was that in contrast to other physical sciences, the study included human subjects, whose accuracy of information is prone to biases. So, α used is 0.05. Also, 70 % of the population of the area under study form the farming population, so the sample frame is 1258670.

Consequently,

$n = 399.87$ (approx. 400)

Considering the specified confidence level and margin of error, the sample size of 400 farmers was calculated by applying the formula above. Consequently, 400 with an additional 10 percent farmers was included in the study's sample (440). This information is shown in Table 1.

2.2.3. Sampling procedure

A sample of 440 households from one out of the three agricultural zones of Rivers state—Ahoada, Degema, and Eleme—were used for this study. Every agricultural zone has vast, rich farmlands and produces a multitude of products, including vegetables, plantains, rice, cassava, yam, and cocoyam. Nevertheless, some regions are more naturally fertile than others, which means they produce more food, while other regions are more conducive to fishing. There is a total of 23 Local Government Areas (LGAs): 7 in the Ahoada Agricultural Zone, 8 in the Degema Agricultural Zone, and 8 in the Eleme Agricultural Zone. Degema is primarily for fish farmers while Eleme does not experience flooding episodes, therefore both zones were excluded for the research and only Ahoada zone included.

Multi-stage random sampling technique was used to guarantee accurate representation.

Using simple random sample technique, the first stage involved clustering the farming households into migrants and non-migrants. Three LGAs were chosen for each cluster from the 7 LGAs in this Agricultural Zone that produce primarily crops (3 LGAs experience flooding and 4 do not). There were six LGAs chosen in all, three LGAs for the treatment group in cluster one (migrants) and three for the control group in cluster two (non-migrants).

Table 1
Sampling procedure.

Captured LGAs (Migrant group)	Farming Population (70 %)	Sample size	Captured LGAs (Non-migrant group)[a]	Farming Population (70 %)	Sample Size
Ahoada East	167,440	58	Emohua	202,440	71
Ahoada West	250,880	88	Omuma	101,080	35
Ogba-Egbema-Ndoni	285,180	100	Etche	251,650	88
Total	**703,500**	**246**		**555,170**	**194**

[a] Control group.
Source: Author's computation.

Using simple random sample technique, two communities were selected at random from each of the Local Government Areas in stage two. Sampling of 12 communities were done in all, six from areas affected by flooding that experiences migration and six from areas without flooding and forced migration issues.

The third stage involves employing a systematic random sample technique to select 440 households in total, from the 12 communities. Sample size of 246 was selected for the treatment group and 194 for the control group based on their population sizes. The information on how this was done is also presented in Table 1.

The sampling frame for this study comprised exclusively of crop farmers residing in flood-prone agricultural communities across selected Local Government Areas (LGAs) of Rivers State, Nigeria. Animal farmers were excluded, as the research focused solely on crop production systems and their relationship with flood-induced migration and farm technical efficiency. A multistage sampling technique was adopted. First, three LGAs with high exposure to seasonal flooding, Ahoada East, Ahoada West, and Ogba/Egbema/Ndoni were purposively selected. Within each LGA, communities were randomly selected, followed by random sampling of farming households. The sample size of 440 crop-farming households was proportionally distributed across the selected LGAs to ensure representation of the flood-affected agricultural population. The assumption of homogeneity within the crop farming population was considered valid due to similarities in environmental exposure, cropping systems, and socioeconomic conditions across the study area. Furthermore, the adequacy of the sample size allows for the application of inferential statistical techniques, supported by the Central Limit Theorem (CLT), which states that the sampling distribution of the mean will approximate normality as the sample size increases, regardless of the population's underlying distribution [25].

2.3. Analytical tools

The first objective of this study was to describe the trend in flooding episodes, migration and return migration of farming households in the study area. To achieve this, descriptive statistical tools such as tables, graphs, mean differences and percentages were used.

The second objective was to examine the effect of flooding-induced migration and return on farm productivity (technical efficiency). This study adopted and amended the approach of Ren et al. [16], to examine the effect of flooding-induced migration on farm technical efficiency. To estimate these effects, Endogenous Switching Regression (ESR) model was used. Additionally, Propensity Score Matching (PSM) was incorporated to complement the ESR approach so as to provide more robust estimates of the effects of migration on technical efficiency.

To examine the effect of flooding-induced migration and return on farm productivity (technical efficiency) in Rivers State, the Cobb Douglas and Translog Stochastic Frontiers were used to run two production functions and the one that gave the best fit was chosen. Endogenous switching regression analyses was then done to estimate the effect of migration on farm's technical efficiency. PSM analysis was also carried out for robustness check. Technical efficiency reflects the economic performance of farms, quantifiable by their capacity to reduce input usage relative to output levels. To measure technical efficiency, the production function was firstly defined. The Translog production function is stated as follows;

$$\ln Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{n}\sum_{s=1}^{n} \beta_{js} \ln X_{ij} \ln X_{is} + \sum_{k=1}^{n} \alpha_k D_{k+} V_i - Ui \quad (2)$$

Where;

Y represents the farm output (in kilograms/ha) (Yield);

X1 represents the total quantity of seeds (in kilogrammes);

X2 denotes the total area cultivated (in hectares);

X3 represents the fertiliser (composed of nitrogen, phosphorus, and potassium), (measured in kilogrammes)

X4 denotes the quantity of insecticide administered (in litres);

X5 represents the cumulative labour utilised before and throughout the harvesting process (man-days);

Employing a dummy variable to account for the occurrence of zero observations allows for the unbiased estimation of the parameters in Cobb-Douglas production functions [26].

D1 is the dummy variable for fertiliser, assigned a value of 1 when X3 = 0 and 0 when X3 > 0;

D2 serves as the dummy variable for pesticide, assigned a value of 1 when X4 equals 0 and 0 when X4 exceeds 0;

D3 is the dummy variable representing soil fertility, assigned a value of 1 if fertile and 0 if otherwise.

D4 is the dummy variable for extension contact with a value of 1 if the respondent had access to an extension agent and 0 otherwise;

D5 serves as the dummy variable for migration, assigned a value of 1 when the household undergoes migration and 0 when it does not.

The subscripts j, i, and k denote the j-th input (j = 1, 2, …, 5), i-th farmer (i = 1, 2, …, 440), and k-th control variable (k = 1, …, 5), respectively.

The αs and βs are parameters to be evaluated;

V_i represents the noise component;

U_i is the non-negative technical inefficiency component.

The technical efficiency (TE) of the i-th farm is defined as follows:

$$\mathrm{TE_i} = \exp(-\mathrm{u_i}) \tag{3}$$

The technical efficiency index (TE_i) equals 1 when the farm operates at optimal efficiency and equals zero when it is completely inefficient.

The next step in the empirical analysis involves assessing the effect of migration on technical efficiency. The variable of interest is technical efficiency, which assesses the economic performance of farms. The treatment variable is migration (Mi). The treatment variable, migration (Mi), is defined as one if the household migrated during the most recent flood disaster and zero otherwise. Nevertheless, households' migration decisions are influenced by multiple circumstances; so, the choice to migrate is not arbitrary. Consequently, to assess the causal impact of migration on agricultural production, the Endogenous Switching Regression (ESR) method is employed to address the self-selection bias associated with migration. The selection equation in the first stage of the switching regression is specified as:

$$\boldsymbol{G_i^*} = \boldsymbol{\alpha X_i} + \varepsilon_i$$

where

$$\boldsymbol{G_i} = \left\{ \begin{matrix} 1, if\ \boldsymbol{G_i^*} > 0, and \\ 0, if \quad otherwise \end{matrix} \right\} \tag{4}$$

Where;

$\boldsymbol{G_i^*}$ = vector of the binary unobservable or latent variable for the utility of migration to the farmer.

$\boldsymbol{G_i}$ = vector of the binary dummy (1 = migrate, 0 = 0therwise) for the migration equation where the farmer either migrated or did not.

$\boldsymbol{X_i}$ = vector of exogenous variables including the farm and household characteristics.

$\boldsymbol{\alpha}$ = vector of parameters to be estimated.

ε_i = the error terms.

The two regimes for the technical efficiency outcomes are specified as:

$$\mathrm{TE}_{1i} = \beta_1 Z_{1i} + \mu_{1i}, \text{if G} = 1 \text{ and} \tag{5}$$

$$\mathrm{TE}_{0i} = \beta_0 Z_{1i} + \mu_{0i}, \text{if G} = 0 \tag{6}$$

Where;

TE_{1i} and TE_{0i} = the technical efficiency outcomes for migrants and non-migrants respectively.

$\boldsymbol{Z_i}$ = represents a vector of exogenous variables considered to influence TE_{1i} and TE_{0i} At least one variable in X_i is excluded from Z_i.

The endogeneity test was conducted using the two-stage residual inclusion (2SRI) method. This approach, also known as the control function approach, accounts for unobserved factors that may simultaneously influence both the treatment (migration) and the outcome (technical efficiency). The procedure involved first estimating a logit model of migration using theoretically valid instruments, and then including the first-stage residual as an additional regressor in the second-stage technical efficiency equation. A statistically significant coefficient on the residual term would indicate that migration is endogenous and correlated with unobserved determinants of technical efficiency. In such a case, treating migration as exogenous would result in biased estimates. Therefore, the subsequent analysis addresses this endogeneity by applying an endogenous treatment effect model.

2.3.1. The endogenous treatment effects

To model the effects of migration on technical efficiency, we estimate the endogenous treatment effect model. In Stata, this is modelled simultaneously in two stages and also accounts for selection bias. First, it is assumed that a farmer chooses any one of the migration statuses that maximize their utility. The first stage estimates a logit model with the outcome equation using sub-samples, while the second stage estimates the selection equation (eqn. (4)) using the full sample.

The outcome equation for the individual migration statuses is specified as;

$$E(\mathrm{TE}_i = 1 | d_{ik}, z_i, \bar{z}_i, \varepsilon_i) = z_i\beta + \sum\nolimits_{k=1}^{k} Y_k d_{ik} + \sum\nolimits_{k=1}^{k} \lambda_k \xi_{ik} + \varepsilon_i \tag{7}$$

Where;

TE_i = technical efficiency.

z_i = is a set of exogenous covariates with associated parameter vector β.

d_{ik} = binary variables for observed treatment choice.

Y_k = is the treatment effects relative to non-migrants.

ξ_{ik} = is a set of latent factors.

$E(\mathrm{TE}_i = 1 | d_{ik}, z_i, \bar{z}_i, \varepsilon_i)$ = is a function of each of the latent factors ξ_{ik}.

The resultant model was analyzed with Stata tool using a Maximum Likelihood technique.

2.3.2. Propensity score matching

The final phase in the empirical analysis involves employing the propensity score matching method as a robustness check for the Maximum likelihood estimates of treatment effects for the ATT. This was used because it's mostly used in migration related studies. Ren et al. [16] and Sauer et al. [27] all used PSM in their studies on migration and effects on farm's technical efficiency. PSM establishes an artificial control group to assess a program's counterfactual [28]. PSM enables the formation of a comparable treatment and control group based on observable exogenous factors influencing migration, facilitating the assessment of causal effects through the comparison of outcome variable disparities between the constructed treated and non-treated groups. Households in the treatment group (migrant households, Mi = 1) or the control group (non-migrant households, Mi = 0) have potential outcomes Z0i if untreated and Z1i if treated. The effect of migration on the outcome variable for migrant and non-migrant groups can be expressed as follows;

$$\mathrm{E}(\mathrm{Z_{1i}} \big| \mathrm{M_i} = 1) - \mathrm{E}(\mathrm{Z_{0i}} \big| \mathrm{M_i} = 1), \text{for the migrant group} \tag{8}$$

$$\mathrm{E}(\mathrm{Z_{1i}} \big| \mathrm{M_i} = 0) - \mathrm{E}(\mathrm{Z_{0i}} \big| \mathrm{M_i} = 0), \text{for the non} - \text{migrant group} \tag{9}$$

In empirical estimation, we employ the most often utilised Nearest Neighbour (NN) matching for PSM. Specifically, we apply NN with two matching partners and restrict the matching within the common support.

3. Results

The results of the estimation of the trend in flooding episodes and the effects of flooding on farm technical efficiency are presented in this section.

3.1. Descriptive statistics

3.1.1. Farmer characteristics

The results for the socio-economic characteristics of farmers in the study area are presented in Table 2.

Findings reveal that majority of the farmers are assigned lands in the community once married and thereafter go into farming. 96 % of the migrants are married while 96 % also of the non-migrants are married. Monogamy is prevalent in the study area with migrants having a 71 % figure and non-migrants, 78 %. The mean age with married partner for migrants is approximately 32 years, while that of non-migrants is approximately 31 years. The mean age of migrant farmers is approximately 63 years while that of non-migrant farmers is 60 years. The males dominate in all the two groups of farmers under study. Result shows that 98 % are males in migrant group while 93 % are males in non-migrant groups respectively. For females, 2 % exist in migrant group while non-migrants have 7 %.

The average years of farming experience for the migrant group is approximately 29, that of non-migrants is 28 years. The mean household size for the migrant farmers is approximately 8 people per household while the mean household size for non-migrants is approximately 7 persons per household. Migrant farmers were also found to be educated to several levels, with only 6 % having no formal education. For the non-migrants, only 2 % lack formal education while the rest are educated to several levels.

The test of mean difference shows a significant difference exists between the migrants and non-migrants' type of marriage, household size, gender, age, age with married partner, ethnic group and level of education.

3.1.2. Farm-specific factors (socio-economics)

The results on crop combinations grown by farmers in the study area, are shown in Fig. 1.

The results show that about 56 percent of the farmers who plant cassava only, are migrants while the remaining 44 percent are non-migrants. Fifty percent of those who grow maize only, are migrants and the other 50 percent are non-migrants. All the yam and plantain producers fall under the migrant communities as the result showed yam and plantain are not key crops grown among the non-migrants.

Table 2
Socio-economic statistics of farmers in the study area.

Variable	Migrants (Treatment)		Non-migrants (Control)		Diff. in mean	P-value
	Mean	Std. dev.	Mean	Std. dev.		
Family type					−0.003	0.914
Nuclear	0.915	0.280	0.918	0.276		
Extended	0.085	0.280	0.082	0.276		
Marriage type					0.072*	0.086
Polygamous	0.290	0.454	0.220	0.413		
Monogamous	0.711	0.454	0.784	0.413		
HHSize	7.711	2.929	6.840	2.676	−0.871***	0.001
Gender					0.043**	0.029
Male	0.976	0.155	0.933	0.251		
Female	0.024	0.155	0.067	0.251		
Age	62.882	9.720	60.041	11.210	−2.841***	0.005
Marital status					−0.032	0.638
Married	0.963	0.188	0.959	0.199		
Separated	–	–	0.021	0.142		
Divorced	–	–	0.005	0.072		
Widowed	0.033	0.178	0.015	0.124		
Never married	0.004	0.064	–	–		
Age with married partner	31.821	4.180	30.912	4.186	−0.909**	0.024
Years of farming experience	28.780	9.520	28.170	9.646	−0.616	0.504
Religion					−0.135	0.245
No religion	0.024	0.155	0.046	0.211		
Catholic	0.374	0.485	0.418	0.494		
Protestant	0.297	0.458	0.258	0.439		
Ch'matic	0.215	0.412	0.201	0.402		
Islam	0.008	0.090	0.005	0.072		
Traditionalist	0.081	0.274	0.072	0.259		
Ethnic groups					−71.740***	0.000
Ekpeye people	0.236	0.425	0.005	0.072		
Ikwerre	–	–	0.361	0.481		
Igbo	0.004	0.064	0.619	0.487		
Ijaw	–	–	0.005	0.072		
Ogba	–	–	0.005	0.072		
Other	0.760	0.428	0.005	0.072		
Education					0.527***	0.000
None	0.057	0.232	0.015	0.124		
Primary	0.549	0.499	0.454	0.499		
Secondary	0.309	0.463	0.273	0.447		
Polytechnic	0.024	0.155	0.026	0.159		
University	0.061	0.240	0.227	0.420		
Uni. (postgraduate)	–	–	0.005	0.072		

Source: Field survey, 2024

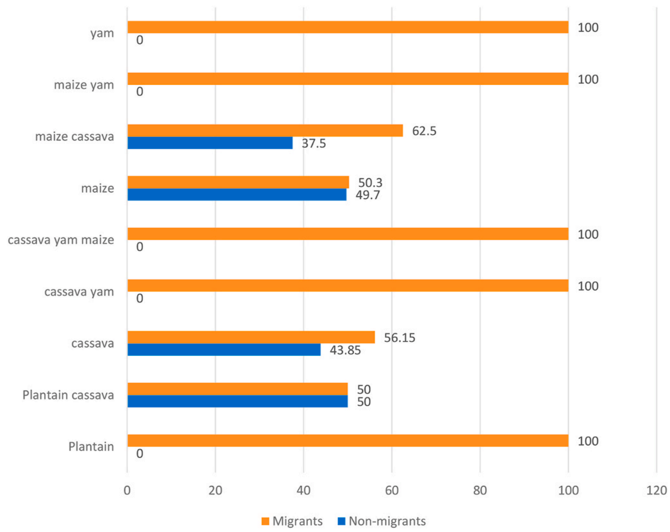

Fig. 1. Distribution of Respondents who cultivate various crops by household type (%).
Source: Field Survey, 2024.

The various crop outputs, land sizes where these crops are grown and farm input use information are shown in Table 3.

Findings reveal that the mean cassava output of migrants is more than that of non-migrants (2795.13 kg and 2772.07 kg respectively). Migrants also harvest more plantain (1350 kg as against 200 kg). There is no recorded yam production by the respondents in the non-migrant communities who were a part of this research. Only the migrants recorded yam production. The mean output from maize is 4217.15 kg for the non-migrants while that of migrants is 1482.03 kg. This shows that the non-migrants have more maize output than their migrant counterparts who encounter flood. The losses experienced by the migrants due to flooding explains the reason for this difference. Losses come from flooded farms during harvest or from immature harvested outputs in early harvest.

The mean of seeds in kg planted by the migrants (226.61) is more than the mean for non-migrants (222.55). Result also shows no mean difference in the amount of fertilizer used by both categories of farmers. This result of fertilizer use (14.17 kg) shows minimal usage for all the respondents. This is because the lands are left to fallow over time and allowed to regain its soil fertility. Responses to the question on how fertile the land is shows that some farmers have their lands fertile and others as very fertile. All the farmers also practice fallowing. Therefore, the farmers apply fertilizers minimally.

Result also shows that the non-migrants use more labour in man-days than the migrants who encounter flooding (265.06 and 206.53 respectively). This difference could be explained by the number of months spent outside the community away from the farm and farming activities during the flooding episodes. The farmers migrate out of their communities for three-four months every year and return when the waters recede. The non-migrants do not experience these flooding episodes and so remain in their communities engaging in farming activities which utilize labour.

3.2. *Trends in flooding episodes, migration and return migration of farming households*

The mean values of household members that migrated during flooding episodes, number that returned, number of months they stopped farm operations, and the mean value of flooding episodes between 2011 and 2022 is represented in Fig. 2.

The bar chart shows the mean values for various flooding-related metrics across the local government areas (LGAs). Each bar represents the mean value of a specific metric, with corresponding values labelled on the bars. It can be seen that farm operations stopped for three months each year between 2011 and 2022. The flooding episodes also can be seen to have occurred twelve times in the twelve years under review, in the study area. On the average, eight persons migrated from each household and seven persons returned home after the flooding episodes. This number that migrated represents the average household size for the migrants, thus all household members for the affected communities

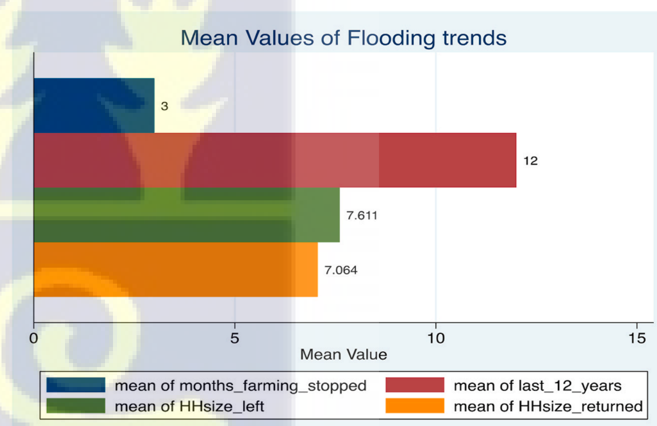

Fig. 2. Mean values of flooding trends.
Source: Field survey, 2024

Table 3
Summary statistics of farm-specific factors.

Variable	Migrants		Non-migrants		Diff. in mean	P-value
	Mean	Std. dev	Mean	Std. dev		
Output (kg)						
Cassava production	2795.134	1608.712	2772.072	1358.620	−23.062	0.903
Maize production	1482.031	927.133	4217.151	2350.307	2735.12***	0.000
Yam production	763.889	577.471	0	0	–	–
Plantain production	1350.000	919.239	200.000	–	966.667	–
Land size (ha)						
Land size for cassava	6.500	3.709	6.279	3.227	−0.221	0.617
Land size for maize	6.255	4.039	5.488	2.969	−0.767	0.150
Land size for yam	3.778	2.803	0	0	–	–
Land size for plantain	3.500	2.121	1.000	–	2.667	–
Other composite inputs						
Seed (kg)	226.610	319.851	222.546	335.350	−4.063	0.897
Fertilizer (kg)	14.167	0.913	14.167	0	$3.88x10^{-8}$	1.000
Total labour (Man-days)	206.528	244.565	265.062	399.102	58.533*	0.059

Source: Field survey, 2024

migrate each episode.

The results also show that all the respondents migrated during the flooding episodes in the twelve years under review, to several shelters. For the 2022 season, Fig. 3 gives a description of the percentage migrations to Internally displaced persons' camps (IDP), family members houses and urban areas.

Out of 246 migrants, 79 % (195) migrated to IDPs, 20 % (48) migrated to family members houses in other communities and 1 % (3) migrated to urban areas during the 2022 flooding episode. This goes to show that majority of the migrants end up in IDPs during the flooding episodes. Data was also collected and analyzed on the number of migrants that left during this time and those that returned home after the floods.

This information was tabulated for the various migrants across the three LGAs affected and is represented in Table 4.

On the average, the trend is the same for all the LGA as regards stoppage of farming operations and number of flooding episodes. There is at least one person on an average per household, from each of the affected local government areas who did not return. This goes to show that migration cuts across all the affected areas and no farmer is left out. This is the trend of episodes which has lasted for decades, with no solution. These findings are in line with the work of Ajibade et al. [29], who analyzed data from 240 smallholder rice farmers in Kwara state Nigeria, an area faced with recurring flooding episodes. With each flooding episodes, these farmers also move into IDPs, family members houses and urban areas.

Data collected showed that households who identified as migrating to other family members houses and urban areas are mostly those who do not return. All the respondents stated that while in the shelter camps, there is no opportunity for new skill acquisition and there is also no opportunity to non-farm activities so as to earn income. The federal government of Nigeria feeds them while in the camps and that is all they get as relief. As regards how often this happens, this trend has persisted as long as they have known and been members of these communities. The river bordering on these four LGAs (Orashi River) is the reason this happens and has continued to happen.

Also, like the work of Ajibade et al. [29], who analyzed data from smallholder rice farmers in Kwara state Nigeria, the experience is the same. They too are bordered by a river which overflows its banks at certain times of the year and the episode occurs yearly.

The trend of flooding across the affected LGAs covered in this study is yearly, with a minimum of three months in a year and cuts across all the areas. All farmers migrate at these times, stop farming and are away until the water recedes. When the flood goes away, most members of households return while others change location to other unaffected communities and some to the city. There is indeed the need to curb the flood or reduce it to the barest minimum.

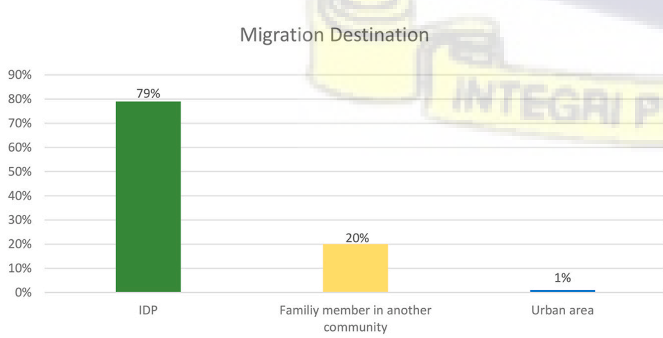

Fig. 3. Migration destination of migrants.
Source: Field survey, 2024

Table 4
Summary of flooding trends by local government areas.

	Ahoada East		Ogba Egbema-Ndoni		Ahoada West	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
No. of Months Farming Stopped	3.00	0.00	3.00	0.00	3.00	0.00
No. of Episodes (2011–2022)	12.00	0.00	12.00	0.00	12.00	0.00
No. Migrated	7.00	3.50	8.00	2.35	8.00	3.22
No. Returned	6.00	2.87	7.00	2.70	7.00	3.29

Source: Field Survey, 2024.

3.3. *Effects of flooding-induced migration and return on farm technical efficiency*

Data were collected on farmer's crop production activities for the 2022 planting season and analyzed. Cobb-Douglas and Translog stochastic frontiers were fitted and analyzed using the crop production activities. Based on a Wald test of the additional squared and interaction terms, the null hypothesis of joint insignificance was rejected ($X^2(3) = 17.52$, $p = 0.0006$), indicating that the Translog model provides a statistically better fit than the Cobb Douglas specification. The Translog model was therefore chosen. The results of the production function, technical inefficiency and error terms are presented in Table 5. Finally, the mean technical efficiencies were calculated for the migrant and non-migrant groups respectively. These results are also presented in Table 5.

The results of the stochastic frontier analysis provide insights into the efficiency of agricultural production in the study area. The model is statistically significant with a Wald chi-square value of 23.24 and a probability value of 0.0003, indicating that the factors included in the model significantly affect agricultural output. The log likelihood value of −530.64 further supports model convergence and fit. The gamma parameter (γ) which is 0.9131 also confirms that a large proportion of the total error is attributable to inefficiency rather than random noise,

Table 5
Results of stochastic frontier analysis.

	Coefficient	Std. Error	P-values
Translog Production Function			
LnSeed	0.0871*	0.0510	0.088
LnLabour	0.2094*	0.1227	0.088
LnSeed squared	−0.0455**	0.0180	0.012
LnLabour squared	−0.1456	0.1033	0.159
LnSeed x LnLabour	−0.0452	0.0288	0.116
Constant	0.6487	0.0920	0.000
Technical Inefficiency			
Migrants (RC = Non-migrants)	0.6679***	0.0541	0.000
Type of Family	0.0009	0.0728	0.990
Monogamous (RC = Polygamous)	0.1809***	0.0506	0.000
Household Size	0.0389***	0.0080	0.000
Female (RC = Male)	−0.0010	0.1114	0.993
Age	−0.0018	0.0017	0.288
Primary (RC = No Education)	0.0397	0.0898	0.658
Secondary	−0.0226	0.0901	0.802
Polytechnic	0.4099***	0.1428	0.004
University	0.3820***	0.0985	0.000
Uni.(postgrad.)	1.8762***	0.3852	0.000
σ^2	0.2655	0.0191	
γ	0.9131	0.0228	
σ_{u2}	0.2424	0.0197	
σ_{v2}	0.0231	0.0059	

No. of Observation: 440; Wald Chi2(5): 23.24; P-value: 0.0003; Log Likelihood: −530.64.
Mean technical efficiency (TE) for migrants = 0.7117, non-migrants = 0.7463.
Note: ***, **, * represent 1 %, 5 % and 10 % significance levels, respectively. RC, reference category. TE: 0 score = inefficient, score 1 = efficient.
Source: Field survey, 2024.

which validates the appropriateness of the model specification.

In the production function section, the coefficient for seed (LnSeed) is 0.0871 with a p-value of 0.088 suggesting a significant positive impact on output. This implies that increasing seed usage increases the output level. The coefficient of Labour (LnLabour) is significant with a value of 0.2094. This implies that a unit input of seed will result in a 0.2094 percent increase in output level. The coefficient for the square of seed (LnSeed squared) is −0.0455 which is significant. This result means that as additional units of seed is added, the output level increases at a decreasing rate. That is, the input seed has diminishing marginal returns on the output. The coefficient for the square of labour (LnLabour squared) is −0.1456 which is not significant. The interaction coefficient of seed and labour (LnSeed x LnLabour) is −0.0452 which is not significant.

Fertilizer input was excluded from the regression because result showed minimal fertilizer use in the study area. The mean fertilizer use recorded is 14.17 kg per hectare which is very minimal and therefore, was excluded in the regression.

The next section technical inefficiency, shows the impact of various factors on the technical inefficiency of production. The variable migrants have a positive and significant coefficient of 0.6679. This shows that migration increases technical inefficiency when compared to their non-migrant counterparts. Indeed, the movement yearly due to flooding episode is associated with increased inefficiency. This result is in line with the findings of several researchers who carried out studies on the effect of migration on farm's technical efficiency. Migration was found to have led to lower technical and fertilizer use efficiency among rice farmers in China [16,30].

The variables monogamous marriage with reference category polygamous has positive influence on technical inefficiency. Household size also is statistically significant at 1 percent level and influences inefficiency positively. Age has a negative and insignificant influence on technical inefficiency. The variables polytechnic, University and postgraduate are all positive and significant. This means they contribute to technical inefficiency but the result from the socioeconomics of the farmers shows only few respondents in these categories of education.

In the last section, the sigma_u2 (variance of inefficiency) is 0.2424 and sigma_v2 (variance of the error term) is 0.0231. The technical efficiencies of farms were then calculated for the individual farmers. The "if" condition was used to separate this result for migrants and non-migrants and result shows that migrants operate at a mean of 71.17 percent efficiency and non-migrants at 74.63 percent. This goes to show that both groups of farmers have room for improvement on their TE score. The migrants have 28.83 percent improvement to make while the migrants have 25.37 percent improvement to makes so as to achieve 100 percent technical efficiency in their farms. Of a truth migration happens yearly but, operating at an efficient level given inputs is not a function of output levels. Other factors like managerial skills, farming experience, proper information on input-output combinations that can enhance efficient production etc. all contribute to higher technical efficiency. These are lacking for both migrants and non-migrants alike. The exact difference in the technical efficiency of these two groups was estimated using endogenous treatment effect.

3.3.1. *Technical efficiency distribution*

The distribution of technical efficiency scores was analyzed and the results are shown in Table 6.

The distribution of technical efficiency scores differed significantly between migrants and non-migrant households. The 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} technical efficiency scores for non-migrant households were consistently higher than those for migrant households, suggesting a leftward shift in the efficiency distribution among migrants. The difference was statistically significant (Wilcoxon p-value of $0.0119 < 0.05$). This indicates that migration status is associated with lower farm technical efficiency.

Density distribution of the technical efficiency scores was also analyzed. This gives a visual of how the technical efficiency scores are spread across both groups. The result is shown in Fig. 4.

Table 6
Distribution of technical efficiency scores by migration status.

Percentile	Migrants	Non-migrants
10th	0.4950	0.6912
25th	0.7009	0.7043
50th	0.7412	0.7503
75th	0.7858	0.7959
90th	0.7973	0.8030
Mean	0.7117	0.7463

Source: Author's computations

Kernel density estimation was employed to visually compare the distribution of technical efficiency scores between migrant and non-migrant households. This non-parametric technique allows for the assessment of differences in the shape, spread, and central tendencies of efficiency distributions across the two groups. The technical efficiency scores were derived from the stochastic frontier analysis, and the kernel density plots were generated using Stata 17.0. Specifically, the kdensity command was used with group overlay based on migration status, allowing for a smooth comparison of efficiency score patterns. The figure provides insight into the relative performance and variability in technical efficiency among the two household categories.

3.3.2. *Logistic regression on the factors that affect migration*

The results of the estimates for logistic regression carried out before Propensity Score Matching is presented in Table 7.

The chi-square value of 326,86 and a probability value of 0.000 shows the model has a good fit for modelling the factors that influence migration. The result of the estimates shows that age and education of respondents has negative influence on migration while the number of years spent married and ethnic group has positive effect. The number of years spent with married partner also connotes how long the farmer has been farming and this goes for most of the male respondents as they are given plots of land as soon as they are married, for farming operations. Ethnic group has positive effect because the flooding problems are domiciled in certain communities which are ancestral heritage of such ethnic groups. This is to say that the four local governments areas covered in this study belong to separate ethnic groups in Rivers state, with very few exceptions of foreigners. The rest of the estimates which do not show statistical significance are also depicted in the table.

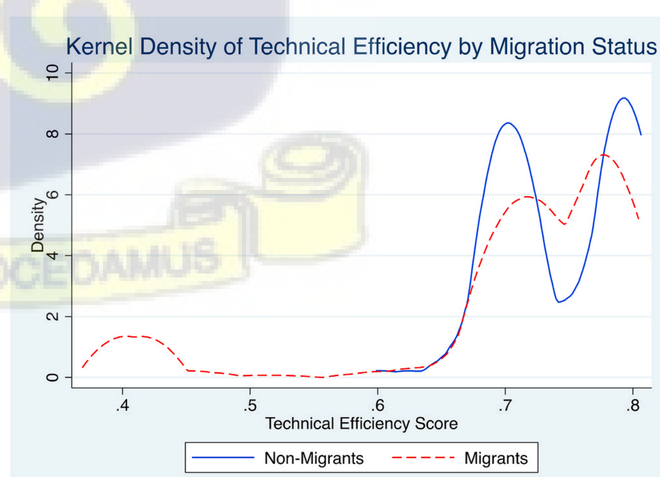

Fig. 4. Density distribution of technical efficiency scores.
Source: Author's computations

Table 7
Logistic regression estimates for factors influencing migration.

Variables	Coefficient	Std. Error	P-values
Family Type	−0.1109	0.5591	0.8430
Household Size	0.0745	0.0549	0.1750
Age	−0.0481***	0.0172	0.0050
Age with Married Partner	0.1279***	0.0406	0.0020
Gender	0.2304	0.7315	0.7530
Marital Status	0.2300	0.2083	0.2690
Religion	0.1407	0.1274	0.2700
Ethnic Group	0.0616***	0.0077	0.0000
Education	−0.5121***	0.1640	0.0020
Constant	−2.9190	1.8618	0.1170
No. of Obersernation	440		
LR Chi2	326.860		
P-value	0.000		
Log-Likelihood	−138.473		

Source: Field survey, 2024.

3.3.3. Treatment effects of migration on farm's technical efficiency (TE)

The treatment effect analysis using endogenous switching regression started with a test to confirm the presence of endogeneity. To test for potential endogeneity of the migration variable in the technical efficiency model, the control function approach was applied. A first-stage logit regression was estimated using distance to market and ethnic group as instruments, both of which were statistically significant predictors of migration ($\chi^2(2) = 42.37$, $p < 0.001$). The residual from this model was included in the technical efficiency regression. The coefficient of the residual term was statistically significant ($p = 0.000$), indicating that migration is endogenous. Consequently, the relationship between migration and technical efficiency was estimated using an endogenous treatment effect model to address selection bias.

To compare the technical efficiencies of the treatment and control groups, the Logit model of migration participation was first estimated for an endogenous switching regression. The TE results from the stochastic frontier analysis were built into the model and analyzed with TE as outcome variable. The treatment effects were then generated. The results showed the average treatment effect on the treated (ATT), average treatment effect on the untreated (ATU) and the average treatment effect (ATE). These results are presented in Table 8.

The comparison of the technical efficiency of migrants and non-migrants using two-sample t-tests with equal variances, reveals significant differences between the two groups.

The ATT is significant, with a mean difference of negative 3.85 % and also significant for the ATU with 2.01 % value of mean difference. This means that migration indeed, as seen in the technical inefficiency model, affects TE. In essence, due to migration, the TE of migrants reduced by 3.85 percent and their expected TE will increase by 2.01 % if they are not faced with flooding problems and did not migrate. This goes to show that migration affects TE of farms. It also shows that the TE of migrants is lower than that of non-migrants. The ATE is statistically significant with a value of negative 0.39 %.

These results align with a growing body of literature suggesting that migration—especially when environmentally induced—can disrupt agricultural efficiency. For example, Ren et al. [16] reported that rural-urban migration significantly reduced both technical and fertilizer use efficiency among rice farmers in China. Likewise, in Kosovo, Lesotho, and Burkina Faso, Sauer et al. [27], Mochebelele [31] and Wouterse [32] respectively found that households with migrant labor experienced lower farm efficiency due to reduced on-farm labor, delayed cultivation, and weakened farm management structures. In the Nigerian context, Ayuba et al. [33] confirmed that rural migration adversely influenced household-level crop productivity, particularly in climate-stressed zones, due to temporary abandonment of plots and resource depletion.

Similar patterns are seen across climate-vulnerable regions. Mueller et al. [34] observed that prolonged environmental stress in Pakistan led to increases in long-term migration, which disrupted labor availability and contributed to lower agricultural productivity. Kumasi et al. [35], in a study on small-holder farmers' climate change adaptation practices in Ghana, further concluded that environmentally driven migration often constrains farm capacity and food availability at origin communities. These findings reinforce the notion that recurrent displacement, such as the seasonal migration observed in Rivers State, can negatively impact farm efficiency, not simply due to loss of labor but also due to interruption of production cycles.

For the robustness check of estimates, the Logit model of migration participation was first estimated to obtain the propensity score. The influencing factors of participation in migration were also estimated. The Nearest Neighbour Matching (NN) method was used. The treatment effects estimation using the Nearest Neighbour Matching method with a 1(2) match and bootstrapped standard errors was done. The result provides an insight into the impact of migration on the TE of the farms of treated group versus control group. These results are also presented in Table 7 and show insignificant coefficients for ATT, ATU and ATE. These are not as robust as the ESR estimates.

The estimates obtained from the Endogenous Switching Regression (ESR) model were found to be more robust and statistically significant than those derived from the Propensity Score Matching (PSM) approach, despite both methods being applied to the same dataset. This difference is expected due to the structural advantages of the ESR framework. Unlike PSM, which adjusts only for observable characteristics and is sensitive to sample trimming and matching quality, the ESR model accounts for both observable and unobservable factors that influence treatment assignment and outcome simultaneously. By explicitly modeling the selection process and incorporating the correlation between the error terms of the selection and outcome equations, ESR effectively corrects for endogeneity and self-selection bias. This leads to more efficient estimates, especially in contexts such as this study, where treatment assignment (migration) is driven by exogenous environmental shocks such as flooding, and where differences in exposure severity, geographic vulnerability, or damage extent may not be fully captured by observed covariates. Thus, the ESR estimates are more reliable in identifying the true causal effect of migration on farm technical efficiency. Therefore, interpretation was done with ESR estimates.

4. Summary of findings

The result of the study showed that flooding episodes occurred twelve times in the twelve years under review, in the study area. On the average, eight persons migrated from each household and seven persons

Table 8
Treatment effects of migration on technical efficiency.

	ESR			PSM		
	ATT	ATU	ATE	ATT	ATU	ATE
Technical Efficiency (%)	−3.85 ***	2.01***	−0.39 *	−3.73	0.19	−1.72
	(0.0024)	(0.0028)	(0.0022)	(0.0358)	(0.0107)	(0.0171)

Note: ***, **, * represent 1 %, 5 % and 10 % significance levels, respectively. Figures in parenthesis are std. errors. ESR, Endogenous Switching Regression; PSM, propensity score matching.
Source: Author's computations.

returned home after the flooding episodes. All the respondents migrated during the flooding episodes in the twelve years under review, to several shelters. For the 2022 season, the result showed that out of 246 migrants, 79 % (195) migrated to IDPs, 20 % (48) migrated to family members houses in other communities and 1 % (3) migrated to urban areas. The result of the Translog stochastic frontier analysis showed that the coefficient for seed has a significant positive impact on output. This implies that increasing seed usage increases the output level. The coefficient for labour is also positive and significant. This means that additional use of labour will increase the output level proportionally. The variable for the squared terms showed seed as negative and significant meaning that seed has diminishing marginal returns on output. Squared labour is not significant, so also the interaction between seed and labour. Minimal fertilizer use was recorded in the study area; therefore, it was excluded in the regression.

In the inefficiency model, the variable migrants have a positive and significant coefficient thus showing that migration increases technical inefficiency when compared to their non-migrant counterparts. Indeed, the movement yearly due to flooding episode is associated with increased inefficiency.

The technical efficiencies of farms were calculated from the error terms and result shows that migrants operate at 71.17 % efficiency and non-migrants at 74.63 %. This goes to show that both groups of farmers have room for improvement to achieve efficient production.

The results of the technical efficiency for both groups were compared using endogenous treatment effect and result showed that the average treatment effect on the treated (ATT) is significant, with a mean difference of negative 3.85 % and also significant for the ATU with 2.01 % value of mean difference. This means that migration indeed, as seen in the technical inefficiency model, affects TE. In essence, the TE of migrants reduced by 3.85 % due to migration. Their expected TE will increase by 2.01 % if they are not faced with flooding problems and did not migrate. This goes to show that the TE of migrants is lower than the TE of non-migrants and also, that migration affects TE of farms.

5. Conclusions

Based on the findings from this study, the following conclusions are drawn.

First, the incessant flooding episodes impact negatively on the livelihood of the farmers who earn income majorly from crop production. There is need for this frequent occurrence to be curbed or brought to minimal. Secondly, technical efficiency for both categories of farmers has to be improved upon so as to operate at an efficient level. Part of the reason for these inefficiencies is lack of managerial skills, proper crop combinations and optimum fertilizer and labour use.

Therefore, the study recommends the following.

The government and stakeholder alike should endeavor to initiate and equally execute projects meant to curb flood in these communities affected by flood. The government can build embarkments around the river banks to stop the overflow which occurs at certain times of the year. There are practices that have worked in this regard in other parts of the world where flood is an issue. The federal government of Nigeria can emulate this in curbing the menace of flood in Rivers State and other parts of Nigeria where farmers are affected by flooding episodes.

The ministry of agriculture through the Agricultural Development Programmes offices should engage the famers in educational activities on how to manage their farms, how to combine crops and how to utilize fertilizer and labour for optimum output. These will help improve on farm's technical efficiency.

CRediT authorship contribution statement

Jacinta Nmutaka Umechukwu: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Daniel Bruce Sarpong:** Writing – review & editing, Validation, Supervision. **Akwasi Mensah-Bonsu:** Writing – review & editing, Validation, Supervision. **Ama Ahene-Codjoe:** Writing – review & editing, Validation, Supervision. **Taeyoon Kim:** Writing – review & editing, Validation, Supervision.

Ethical declaration

Ethical clearance, with number ECBAS 065/23–24, was obtained from the Ethics Committee for Basic and Applied Sciences (ECBAS), University of Ghana for the collection of primary data. All participants signed a consent to participate, form indicating their willingness to be interviewed.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Effects of flooding-induced migration on the food security status of farming households in Rivers State, Nigeria

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ABSTRACT

This study assessed the effects of flooding-induced migration on the food security status of farming households in Nigeria. Data were collected on the episodes that occurred between 2011-2022 to estimate the coping strategies of the farmers. The farm revenue specifically from 2022 production activities was also computed. This was used in estimating the effect of migration on food security (economic access to food). Farmers Household Food Insecurity Access Scale (HFIAS) was also computed and used to estimate the effect of migration on the farmers' level of food security. Endogenous treatment effect models were then estimated to identify the average treatment effects of migration on the treated (ATT) and untreated (ATU). Result showed that migrants' mean HFIAS was 13.4675 while that of the non-migrants was 2.1598, depicting that migrants are more food insecure when compared with the non-migrants. The ATT result showed a significant mean difference of 9.17 while the ATU showed a significant and negative value of 11.59. This means that flooding problems and conversely migration, increases food insecurity. It also means that if the migrants were not faced with flooding issues which led to migration, their food insecurity would have reduced by 11.59. Finally, the result on average farm revenue showed the migrant's mean farm revenue per head was 54509.34 naira while that of non-migrants was 183153.6 naira (USD 128.9 and USD 433 respectively). This shows that households who are not faced with flooding who also do not migrate, have more revenue. It is recommended that government and stakeholder should initiate and execute projects meant to curb flood in these communities. Farmers can be given grants and credits to assist with coping after flooding episodes. Non-farm income generating activities is also advised for income diversification. With more income, they will be empowered to access more food and this will improve their HFIAS.

1. Introduction

The impact of flooding on agriculture transcends mere disruption of fields; it permeates the very framework of livelihoods, food security, and the broader economy. Understanding the multifaceted repercussions requires a comprehensive exploration that delves into the direct and indirect consequences of flooding on the agricultural landscape. By incorporating specific examples and studies, a vivid picture emerges, portraying the severity of these impacts and underscoring the intricate interconnections between agriculture and the well-being of the region [1,2]. At its core, flooding manifests as a formidable adversary to agricultural activities. The inundation of fields during flooding events inflicts immediate damage to crops, compromising yields and diminishing the economic viability of farming endeavours. The direct impact on crop production is a pivotal aspect, as staple crops that form the backbone of local agriculture may face substantial losses, thereby threatening food security [3,4]. Beyond the visible devastation, the alteration of soil conditions due to flooding introduces a layer of complexity to the challenges faced by agricultural communities. Soil erosion, sediment deposition, and changes in nutrient composition become pronounced issues, affecting the long-term fertility and productivity of arable land [5,6]. The repercussions extend beyond the immediate aftermath of flooding, posing enduring challenges to sustainable agriculture in the region.
The consequences of flooding on agriculture reverberate through the socio-economic framework of an area. Livelihoods dependent on agriculture experience a sudden and profound disruption, as farmers grapple with the loss of crops and the diminished capacity to generate income. Smallholder farmers, constituting a significant portion of the agricultural landscape, are particularly vulnerable, facing heightened economic uncertainty and potential impoverishment [5,7].

Food security, a critical concern for any region, becomes increasingly precarious in the wake of flooding. The disruption of agricultural activities contributes to a decline in local food production, necessitating external sources to meet the nutritional needs of the population. This dependence on external food supplies not only strains resources but also leaves communities susceptible to fluctuations in market prices, exacerbating the vulnerability of already marginalized households [5,8]. The economic ramifications extend to the broader economy of Rivers state. Agriculture serves as a mainstay, and any upheaval in this sector ripples through related industries and markets. Reduced agricultural output translates to diminished income for farming households, influencing their purchasing power and, consequently, impacting local businesses.

Agriculture is foundational to Rivers State's economy, supporting livelihoods through diverse activities including crop cultivation, livestock rearing, and fishing. Fertile riverbank soils historically sustain crops such as cassava and yams, while proximity to the Gulf of Guinea fuels a thriving fishing industry, vital for both nutrition and economic prosperity. Despite its importance, agriculture faces challenges, with flooding being a major concern [4]. The waterways nurturing agriculture become sources of disruption, impacting farmlands and threatening sustainability.

The flooding problem has persisted over the years and affects farmers who major in production of cassava, rice, maize and other crops [2]. Both their farms and houses end up being submerged with each incidence of flood and in these cases, the families affected migrate to Internally Displaced People's camps (IDPs) until the waters recede and they can return home. This in most cases can take about one month to several months outside their farming communities. This research focuses on the nexus of temporary migration and coping strategies employed by agricultural households after flooding in Rivers State and their effects on their food security (accessibility).

The agricultural landscape in Rivers State, Nigeria, faces a critical challenge—simultaneous increases in flooding and return migration. The historical narrative of flooding in Rivers State reveals a transformation from sporadic occurrences to a pervasive and recurrent menace. This shift is attributed to accelerated urbanisation, climate change, and alterations in land use patterns [2, 4]. These factors, now driving the escalating challenge of flooding, necessitate comprehensive understanding for the development of effective strategies to mitigate its consequences.

Rivers State was not spared the devastation caused by the floods in Nigeria in 2022. The Federal Government's data indicates that the flood brought about the relocation of more than 1.4 million people, loss of lives of over 603 individuals, with more than 2,400 people injured. Furthermore, homes and hectares of land were damaged numbering about 82,035 and 332,327 respectively [1]. Nigeria experiences frequent flooding, but the most recent flood of 2022 is the worst since the floods of 2012 [1]. The floods resulted from intense rainfall, climate change, and the release of water from the Lagdo Dam in adjacent country Cameroon, that started in 2022 September 13. Then, flooding began in the early summer of 2022 and continued until the second week of November 2022. Alert was issued by National Emergency Management Agency (NEMA) and households were asked to evacuate to IDP camps in the various States of Nigeria affected. Farmlands and crops were lost and several families affected. The government over the years feeds the displaced persons in the camps and also, humanitarian organisations come in to assist. After the floods, the households return to their homes to navigate the challenges posed by the flood, without assistance.

Studies carried out before now on the recurrent floods in Rivers state [1,2,4], focused on the causes, impact, panacea and risk reduction. None looked into how the farmers cope each year given the yearly migratory movements and how it affects their food security.

While the impact of flooding on agriculture is known, a substantial research gap exists in comprehending the intricate dynamics of return migration and the strategies of coping employed by agricultural households amid escalating flooding and their effects on households' food security status. This study seeks to fill this gap by evaluating the intricate relationships among flooding-induced migration, coping mechanisms and food security status, specific to Rivers State, Nigeria.

2. Review of literature

2.1 Coping Mechanisms in Response to Flooding

The coping strategies during flooding can take the form of traditional measures taken by farmers or innovative adaptive measures. These are extensively discussed as follows.

2.1.1 Traditional Coping Mechanisms

In the face of recurrent flooding challenges, farming households have demonstrated resilience by relying on time-tested coping mechanisms, with a particular emphasis on crop diversification and water management [9]. These traditional strategies, deeply rooted in local agricultural practices, serve as adaptive measures to mitigate the impact of flooding and sustain agricultural productivity.

Crop Diversification: Crop diversification emerges as a cornerstone of traditional coping strategies employed by farming communities. The practice involves cultivating a variety of crops with different growth cycles, resistance to flooding, and nutritional profiles [10]. By diversifying their crop portfolio, farmers aim to spread the risk associated with flooding, ensuring that a single catastrophic event does not lead to the complete loss of their agricultural output. Notably, this strategy not only enhances resilience but also contributes to maintaining local food security.

Water Management: Water management stands out as another vital traditional coping mechanism in places where flooding poses a persistent threat [11]. Farmers engage in meticulous water control practices to regulate the impact of inundation on their fields. Techniques such as constructing raised beds, contour ploughing, and utilizing irrigation systems allow farmers to exert a degree of control over water flow [11]. This not only minimizes immediate damage to crops during flooding events but also contributes to soil conservation and fertility in the long run.

Elevated Construction: Elevated construction is a traditional coping mechanism employed by people in flood-affected regions like Rivers State to mitigate the impact of rising floodwaters on homes and infrastructure [12]. This architectural adaptation involves building houses on elevated platforms or stilts, a practice widely observed in regions vulnerable to flooding. By elevating structures above the potential flood level, communities aim to protect their homes and possessions during inundation. This strategy not only reduces the risk of flood damage but also provides a practical solution for shelter and refuge during extreme flooding events [12].
The use of elevated construction is deeply rooted in the local knowledge of flood dynamics and has evolved over generations as a response to the recurring threat posed by seasonal floods in Rivers State.

Use of Traditional Knowledge: The utilization of traditional knowledge is integral to coping with flooding. Local communities rely on indigenous wisdom passed down through

generations to anticipate, understand, and adapt to weather patterns and flooding events. This traditional knowledge encompasses observations of natural indicators, such as animal behaviour, changes in atmospheric conditions, and river water levels, which communities interpret to forecast potential flooding [13,14].
This grassroot approach to early warning systems, grounded in traditional knowledge, enables communities to take timely preventive measures, such as evacuation or safeguarding essential assets, contributing to their overall resilience in the face of flooding challenges [13]

Flood-Resistant Crop Varieties: Flood-resistant crop varieties are a traditional coping strategy in agricultural communities, aiming to ensure food security in the aftermath of flooding events. Farmers selectively cultivate crop varieties known for their resilience to waterlogged conditions and inundation [15,16]. These flood-resistant varieties exhibit traits such as tolerance to submersion, ability to recover after flooding, and adaptation to the local agro-climatic conditions.
The cultivation of flood-resistant crop varieties represents a dynamic interplay between traditional agricultural practices and local environmental challenges. This traditional knowledge of selecting and cultivating resilient crop varieties contributes significantly to sustaining agricultural productivity despite the recurrent threat of flooding in flood-prone areas.

2.1.2 Innovative Adaptive Measures

As the challenges posed by flooding continue to evolve, the agricultural communities have begun to explore innovative adaptive measures, incorporating technological advancements and new approaches to enhance resilience [17]. In response to the changing dynamics of flooding, the integration of forward-looking strategies becomes imperative, requiring a detailed exploration of global initiatives and their potential applicability to the unique agricultural landscape of an area.

Technological Advancements: The infusion of technology into agricultural practices offers a promising avenue for innovative adaptive measures in the face of flooding. Precision agriculture, for instance, utilises satellite photos, sensors, and data analytics to enhance agricultural practices [18,19]. In the context of flooding, current information on soil moisture levels and weather patterns can equip farmers to make intelligent decisions, allowing for timely adjustments to mitigate the impact of flooding.
Remote sensing technologies are essential in monitoring flood-prone areas [20]. Drones outfitted with high-quality sensors and cameras offer an aerial perspective of fields, aiding farmers in assessing the extent of flooding and planning targeted interventions. These technological tools empower farmers to proactively manage the risks associated with flooding, marking a departure from reactive strategies.

New Approaches to Water Management: Innovative approaches to water management complement traditional strategies, offering sustainable solutions to cope with flooding. Water-sensitive urban design, for example, integrates urban planning and water management to minimize the adverse impacts of flooding in rural and urban areas [21]. The principles of this approach, if tailored to the agricultural context, could contribute to more resilient farming practices.

Additionally, bioengineering techniques, such as the use of flood-resistant crop varieties or eco-friendly soil stabilization methods, showcase a modern approach to addressing the consequences of flooding on agriculture. Genetic modifications that enhance crops' resilience to waterlogged conditions and the use of environmentally friendly soil amendments represent a departure from conventional methods, offering novel avenues for safeguarding agricultural productivity [22,23].

Global Initiatives and Local Relevance: Examining global initiatives and projects that have successfully implemented innovative adaptive measures provides valuable insights for Rivers State. For instance, initiatives in flood-prone regions of Asia or other parts of Africa may offer lessons applicable to the local context. By adapting successful strategies to the specific environmental and socio-economic conditions, agricultural communities can draw inspiration from global best practices.

It is crucial to consider the scalability and affordability of these innovative measures in the local setting [24]. While cutting-edge technologies may offer effective solutions, their widespread adoption hinges on factors such as cost, accessibility, and the capacity of local communities to implement and maintain them. Balancing technological sophistication with practical feasibility is essential to ensure the relevance and sustainability of these adaptive measures.

The exploration of innovative adaptive measures in response to flooding goes beyond the traditional coping mechanisms. By embracing technological advancements and drawing inspiration from global initiatives, agricultural communities can forge a path toward resilience that aligns with the evolving nature of environmental challenges. The integration of these innovative measures not only enhances the capacity to withstand flooding but also contributes to the sustainable development of agriculture.

2.2 Food security

Food security is widely recognised to be founded on six critical pillars: availability, access, utilisation, stability, agency and sustainability.

Accessibility: The food security (FS) component access, measures the ability of a household to obtain food by taking into account both the household's ability to buy food to meet their basic needs and the accessibility of food commodities on the local market [25]. Access to food is influenced by a variety of factors, including the range of food alternatives available to households based on their income, market price, accessibility, employment, income disparities, and structured or unstructured safety net systems [26, 27]. Wineman claims that the demand side of food production is represented by FS accessibility, which really leads to an uneven distribution of food among and within households.

The availability and access to food and energy in a region depend on a number of factors, including quantity, quality, safety, and cultural acceptance and choices [28]. According to HLPE [29], a few of the issues affecting food access include a lack of readily available, healthful food at an affordable price; reliance on imported food; poverty and unstable livelihoods; disparities in the standard of food environments; plus, access within households, by gender, class, age, and other categories. Small-scale producers also face barriers to market access and distribution because of a lack of infrastructure. Per capita food expenditure is typically used to measure this component [30]. Experience-based indicators, such as the household food security scale module (HFSSM), household dietary diversity score (HDDS), food consumption score (FCS), and many others, can also be used to measure this component [Leroy *et al.* 2015]. Two indicators, Household Food Insecurity Access Scale (HFIAS) and farm revenue as proxy are discussed below:

HFIAS: The Household Food Insecurity Access Scale is a tool designed to capture the level of food insecurity in households, specifically focusing on the "access" dimension of food security. Specifically, HFIAS measures the perceptions and experiences of food insecurity due to insufficient access to food, typically over the past 30 days. HFIAS focuses on three key domains; Anxiety and uncertainty about household food availability, inadequate quality (including diversity and preferences of food types), and inadequate food intake together with its physiological consequences.

It consists of 9 questions that assess increasing levels of severity of food insecurity. These questions help identify whether households have experienced problems like; worrying about not having enough food, eating fewer meals than needed, eating foods they did not prefer, going to bed hungry, and going for an entire day and night without eating [31].

Farm revenue: This mainly measures the economic access dimension of food security. Economic access refers to people's ability to afford food, based on their income levels relative to food prices. When farmers earn higher revenues, they are better able to access sufficient and nutritious food for themselves and their households, either by producing it directly or purchasing it from markets. Farm revenue also affects the local food economy — profitable farms can invest more in production, contributing to food availability and stability over time.

According to the Food and Agriculture Organization (FAO), food security exists when all individuals, at all times, possess physical, social, and economic access to adequate, safe, and nutritious food. [32]. Economic access is the ability of individuals and households to afford food, which is closely tied to income.

Farm revenue reflects the income farmers earn from selling agricultural products. Higher farm revenue generally increases farmers' ability to purchase food, invest in farm improvements, and build resilience against shocks, thus strengthening their economic access to food [33, 34].

In research by Barrett [35], farm incomes are discussed as a core determinant of household food security, particularly in rural areas where farming is the primary livelihood. Barrett emphasized that increased income from farm revenue improves the affordability of a diverse and sufficient diet. Therefore, farm revenue primarily captures the economic access aspect of food security.

Smith *et al.* [36] show that income growth, particularly from agriculture, has been historically significant for enhancing household food security, specifically through improving the ability to buy food.

3. Methodology

The study area, research design (data source, type and data collection tools, sample size, sampling procedure), conceptual framework and analytical tools used in the study are enumerated in this section.

3.1 Study Area

One of Nigeria's 36 states, Rivers State is centred in the country's South-South geopolitical zone with its capital, Port Harcourt. It is bordered to the east by the states of Abia and Akwa Ibom, to the west by the states of Bayelsa and Delta, to the north by the states of Anambra and Imo, and to the south by the Atlantic Ocean. The population was 5,198,716 in the 2006 census, and was projected as 7,492,366 in 2023. Its coordinates are Latitude 4.75°N and longitude 6.50°E, and it encompasses an area of 11,077 km^2 (4,277m^2). The Ijaw, Ikwere, Etche, Ogoni, and Ogba/Egbema are the predominant ethnic groupings. The primary means of subsistence for the populace is agriculture, and food production serves as the cornerstone of state agriculture policy.

Nigeria's seventh most populous state is Rivers State. The linguistic diversity of the state is especially well-known; it is estimated that 28 indigenous languages, including Ikwerre, Ogba, the Etche, Abua, Ogoni, Igbo, and Ijaw languages among others, are spoken in Rivers State. Rivers State is the 26th largest state in Nigeria by geographical area, and is traversed by numerous rivers, including the Bonny River. These rivers shape the topography of the state.

3.2 Research design

3.2.1 Data source, type and data collection tools

Primary and secondary data were used for the study. Primary data were collected from rural farmers in one of the three Agricultural Zones in Rivers State where the flooding episodes are prevalent and farmers engage in crop production. The households included in the sample were given a structured questionnaire. The questionnaire gathered a variety of data regarding households' socioeconomic circumstances, their production activities and also the coping strategies they adopt in mitigating the impact of flood in their farms. Information was also collected from households in communities that do not experience flooding and migration to serve as our control group. Crop farmers were included in the study while those who rear livestock alone were excluded. Household heads who are eighteen years and above were also included, whether male or female. Secondary data were collected from National Emergency Management Agency (NEMA) on the flooding episodes in the study area over the period 2011-2022.

3.2.2 Sample size determination

This study included a sample size of 440 farmers. Using the mathematical method developed by Miller and Brewer [37], the study's sample size was determined from the sample frame. The following is the formula; $n = \frac{\mathrm{N}}{1+N(\alpha)2}$ .... (1)

Where;
N= Sample frame
n = Sample Size
α = Confidence Interval
A 95% confidence interval and 5% margin of error were used in this study. The reason behind this was that in contrast to other physical sciences, the study included human subjects, whose accuracy of information is prone to biases. So, α used is 0.05. Also, 70% of the population of the area under study form the farming population, so the sample frame is 1258670.
Consequently,
n = 399.87 (approx. 400)
Considering the specified confidence level and margin of error, the sample size of 400 farmers was calculated by applying the formula above. Consequently, 400 with an additional 10 percent farmers was included in the study's sample (440). This information is shown in Table1.

3.2.3 Sampling procedure

A sample of 440 households from one out of the three agricultural zones of Rivers State, Ahoada, Degema, and Eleme, were used for this study. Every agricultural zone has vast, rich farmlands and produces a multitude of products, including vegetables, plantains, rice, cassava, yam, and cocoyam. Nevertheless, some regions are more naturally fertile than others, which means they produce more food, while other regions are more conducive to fishing. There is a total of 23 Local Government Areas (LGAs): 7 in the Ahoada Agricultural Zone, 8 in the Degema Agricultural Zone, and 8 in the Eleme Agricultural Zone. Degema is primarily for fish farmers while Eleme does not experience flooding episodes, therefore both zones were excluded for the research and only Ahoada zone included.
Multi-stage random sampling technique was used to guarantee accurate representation.
Using simple random sample technique, the first stage involved clustering the farming households into migrants and non-migrants. Three LGAs were chosen for each cluster from the 7 LGAs in this Agricultural Zone that produce primarily crops (3 LGAs experience flooding and 4 do not). There were six LGAs chosen in all, three LGAs for the treatment group in cluster one (migrants) and three for the control group in cluster two (non-migrants).
Using simple random sample technique, two communities were selected at random from each of the Local Government Areas in stage two. Sampling of 12 communities were done in all, six from areas affected by flooding that experiences migration and six from areas without flooding and forced migration issues.
The third stage involves employing a systematic random sample technique to select 440 households in total, from the 12 communities. Sample size of 246 was selected for the treatment group and 194 for the control group based on their population sizes. The information on how this was done is also presented in Table 1.

Table 1: Sampling procedure

Captured LGAs (Migrant group)	Farming Population (70%)	Sample size	Captured LGAs (Non-migrant group)*	Farming Population (70%)	Sample Size
Ahoada East	167,440	58	Emohua	202,440	71
Ahoada West	250,880	88	Omuma	101,080	35
Ogba-Egbema-Ndoni	285,180	100	Etche	251,650	88
Total	**703,500**	**246**		**555,170**	**194**

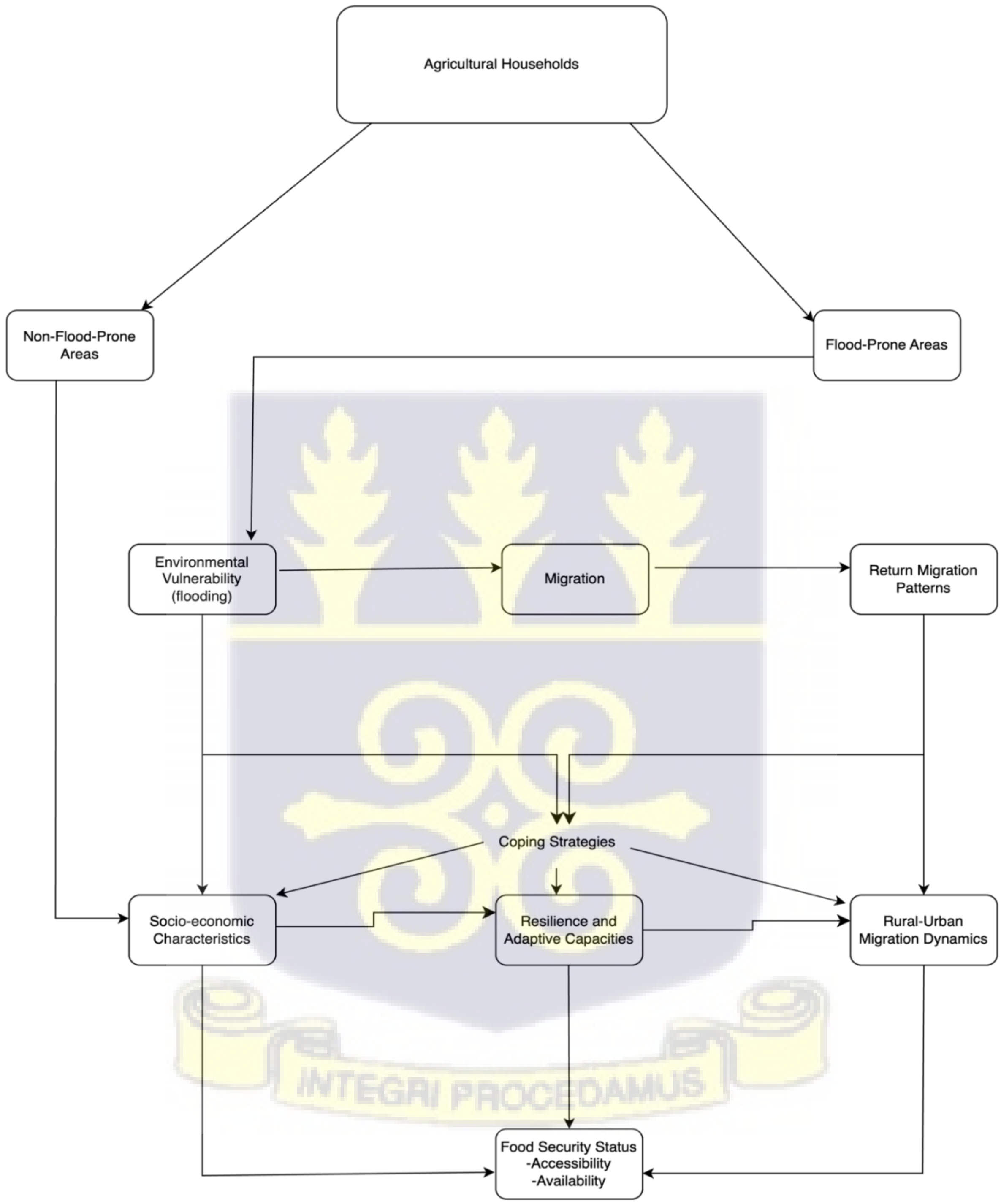
Source: Author's computation.
*Control group.

The sampling frame for this study comprised exclusively of crop farmers residing in flood-prone agricultural communities across selected Local Government Areas (LGAs) of Rivers State, Nigeria. Animal farmers were excluded, as the research focused solely on crop production systems and their relationship with flood-induced migration and farm technical efficiency. A multistage sampling technique was adopted. First, three LGAs with high exposure to seasonal flooding, Ahoada East, Ahoada West, and Ogba/Egbema/Ndoni were purposively selected. Within each LGA, communities were randomly selected, followed by random sampling of farming households. The sample size of 440 crop-farming households was proportionally distributed across the selected LGAs to ensure representation of the flood-affected agricultural population. The assumption of homogeneity within the crop farming population was considered valid due to similarities in environmental exposure, cropping systems, and socioeconomic conditions across the study area. Furthermore, the adequacy of the sample size allows for the application of inferential statistical techniques, supported by the Central Limit Theorem (CLT), which states that the sampling distribution of the mean will approximate normality as the sample size increases, regardless of the population's underlying distribution [38].

3.3 Conceptual framework

Central to the context of this study, is the need to investigate how agricultural households cope with environmental vulnerability due to escalating flooding. From immediate responses to the inundation of fields to long-term adaptations in the face of altered soil conditions, understanding the coping mechanisms is crucial. This involves a comprehensive examination of both conventional and innovative strategies employed by farm families. These all affect farm productive output and at the long-run also affects the status of food security of these farm families.

In essence, the conceptual framework in Figure 1, provides a structured lens through which the research will systematically explore the interplay of environmental vulnerability, return migration patterns, coping strategies, socio-economic characteristics, rural-urban migration dynamics, food accessibility (food security status), and resilience within the context of escalating flooding in Rivers State.



Source: Author (2024)

Figure 1: Conceptual Framework

Figure 1 illustrates the pathways through which agricultural households, differentiated by their exposure to flooding, experience and respond to food security challenges in the context of environmental stress.
At the top of the framework is the broader category of agricultural households within the study area, which includes all households under investigation. These are then categorized into two distinct groups based on their geographical location and exposure to environmental vulnerability.

On the right side, households residing in flood-prone areas are subject to environmental vulnerability, particularly seasonal flooding. These households typically experience displacement through migration, recurrently. Migration, in turn, gives rise to return migration patterns, as displaced households eventually return to their communities once the flood subsides. Upon return, these households adopt various coping strategies aimed at restoring livelihoods and rebuilding agricultural productivity. These strategies feed into their overall resilience and adaptive capacities, which determine how well they are able to absorb and recover from shock. Ultimately, this influences their food security status, particularly in terms of accessibility and availability of food.

On the left side, the framework depicts households in non-flood-prone areas who are not directly affected by environmental vulnerability. These non-migrant households do not face displacement but still experience socio-economic conditions that influence their food security. Their socio-economic characteristics such as income, education, asset ownership, and farm size, interact with their resilience and adaptive capacities, shaping their ability to withstand market or environmental shocks. Like their migrant counterparts, these households also arrive at the food security outcome, albeit through a different pathway.

By distinguishing between flood-affected and non-affected households, this framework supports a comparative analysis of how exposure to flooding and migration shapes coping strategies and food security outcomes. It also highlights the critical role of resilience as a central mechanism in determining food system stability under conditions of climate stress.

The interplay of environmental factors, migration patterns, and coping strategies form a complex structure. Understanding how these elements intersect is crucial for developing a holistic comprehension of the experiences of agricultural households facing the challenges of escalating flooding.

3.4 Analytical tools

First, the coping strategies adopted by farmers in mitigating the impact of flood were identified. Secondly, the effects of flooding-induced migration on the food security status of the farming households were determined. To explore how migration affects the food security status of farming households in Rivers State, with a focus on distinguishing effects between migrant and non-migrant households following flooding, the Endogenous Switching Regression (ESR) model was used. Farm revenues and household food insecurity access scale

(HFIAS) was used as indicators for food security. HFIAS was used as a proxy for food availability and farm revenues also a proxy mostly for food accessibility. This is as adopted from Issahaku [39] but amended to include HFIAS instead of household dietary diversity score (HDDS).

HFIAS: This approach uses respondents' responses to questions about how much food a household feels like it has and whether or not they are concerned about running out of food to quantify food security.

The responses are compiled into a scale, and a cut-off point is established and used to categorize families based on their degrees of food security. This process produces a continuous indication of the degree of food insecurity in households. Generally speaking, the purpose of this measure is to record how households behave when there is a lack of food, both in terms of quantity and quality, as well as anxiety over food shortages.

It is used to measure households' level food security and accounts for the food availability and utilization dimension of food security.

The degree of food insecurity in the household during the last four weeks (30 days) is continuously measured by the HFIAS score. Initially, each household's HFIAS score variable is determined by adding the codes for all frequency-of-occurrence questions. We code frequency-of-occurrence as 0 before adding up the codes for all instances in which the response to the associated occurrence question was "no" (that is, if Q1=0, then Q1a=0, if Q2=0, etc.). A home can receive a maximum score of 27 if all nine frequency-of-occurrence questions are answered "yes," with a response code of 3. A household can have a minimum score of 0 if all nine frequency-of-occurrence questions are skipped and marked as 0. The household's level of food insecurity increased with a higher score. A household's level of food insecurity decreased with a lower score.

As a categorical variable, households are categorized as food secure, mildly food insecure, moderately food insecure, or severely food insecure. For this objective, the indicator for use is HFIAS score and not the prevalence indicator which captures the categorizations.

HFIAS Score (0-27) = Sum frequency-of-occurrence question response code

$$Q1a + Q2a + Q3a + Q4a + Q5a + Q6a + Q7a + Q8a + Q9a \quad \ldots\ldots\ldots\ldots \quad (2)$$

(Sum of the frequency-of-occurrence during the past four weeks for the 9-food insecurity-related conditions).

Next, the indicator, average Household Food Insecurity Access Scale Score, is calculated using the household scores calculated above.

$$\text{Average HFIAS Score} = \frac{\textbf{Sum of HFIAS Scores in the sample}}{\textbf{Number of HFIAS Scores (households) in the sample}} \quad \ldots\ldots\ldots\ldots \quad (3)$$

(Calculate the average of the Household Food Insecurity Access Scale Scores).

Farm revenue: Primary data were collected from 440 respondents on their 2022 production activities. The households included in the sample were given a structured questionnaire. The questionnaire gathered a variety of data regarding their production activities which includes number of crops grown, size of farmland, quantity of output harvested per crop, price of a unit quantity of each crop output sold, etc. The farm revenue was then computed by multiplying the price of a unit of output sold by the quantity harvested. This was done for all the crops grown by the farmer and added to get each household's farm revenue. This was further divided by each household size to get the households revenue per head. This value was used as a proxy for food accessibility in determining the food security status of the respondents in the study area.

The next step in the analysis involved estimating an endogenous switching regression. Assuming there is full data on farmers and if they had been randomly assigned into categories of migrants and non-migrants, it will be easier to split their outcomes into groups of migrants and non-migrants. Afterwards, the difference in mean outcomes between the migrants and non-migrants' groups will be taken to determine the impact of migration. This idea denotes the average treatment effect (ATE) concept.

The interest here is to find the impact of migration on farmers who migrated during flooding and those who did not. (i.e., the average treatment effect on the treated (ATT) as well as the average treatment effect on the untreated (ATU)). There is however, possibly, heterogeneity across the data. Also, farmers self-selected into the migrants and non-migrants' groups based on their behaviours during flooding and since this is not randomly assigned, there may be observed as well as unobserved heterogeneity that influence their decision to migrate. Also, migrants may be demographically distinct from non-migrants, thereby influencing their migration decisions and, consequently, impacting their food security status. The problem of endogeneity that may arise could result in biased and inconsistent estimates and inaccurate policy recommendations [39,40]. Therefore, there is the need for Endogenous Switching Regression estimation.

ESR takes unobserved heterogeneity and selection bias into account by evaluating two separate outcome equations, one for migrants and another for non-migrants, contingent on their selection into treatment. ESR follows a two-stage framework, which by using a selection equation, divides farmers into migrants and non-migrants' categories and this is to accentuate unobserved differences between migrants and non-migrants that may bias the estimates. At least one variable from the selection equation will be excluded from the outcome equations to ensure proper identification in the estimation process.

The selection equation in the first stage of the switching regression is specified as:

$\boldsymbol{G_i^* = \alpha X_i} + \varepsilon_i$,

where $G_i = \begin{cases} 1, if\ G_i^* > 0,\ and \\ 0, \quad\quad if\quad otherwise \end{cases}$ ………………………………… (4)

Where;

$\boldsymbol{G_i^*}$ = vector of the binary unobservable or latent variable for the utility of migration to the farmer.

$\boldsymbol{G_i}$ = vector of the binary dummy (1 = migrate, 0 = 0therwise) for the migration equation where the farmer either migrated or did not.

$\boldsymbol{X_i}$ = vector of exogenous variables including the farm and household characteristics.

$\boldsymbol{\alpha}$ = vector of parameters to be estimated.

ε_i = the error terms.

The two regimes for the food security outcomes are specified as:

$Q_{1i} = \beta_1 Z_{1i} + \mu_{1i}$,   if G = 1 and …………………………………….. (5)

$Q_{0i} = \beta_0 Z_{1i} + \mu_{0i}$,   if G = 0, ………………………………………… (6)

Where;
Q_{1i} and Q_{0i} = the food security outcomes for migrants and non-migrants respectively.
$\boldsymbol{Z_i}$ = represents a vector of exogenous variables considered to influence Q_{1i} and Q_{0i}. At least one variable in X_i is excluded from Z_i.
Two sets of different ESR models were estimated similar to Issahaku [39], which accounts for the HFIAS and farm revenue.

3.4.1 Endogenous treatment effect

To model the effects of migration on HFIAS and farm revenue, we estimate the endogenous treatment effect model (endogenous switching regression). In Stata, this is modelled simultaneously in two stages and also accounts for selection bias. First, it is assumed that a farmer chooses any one of the migration statuses that maximize their utility. The first stage estimates a logit model with the outcome equation using sub-samples, while the second stage estimates the selection equation using the full sample.
The outcome equation for the individual migration statuses is specified as;
$E(Q_i = 1 \,|\, d_{ik}, z_i, \bar{z}_i, \varepsilon_i) = z_i\beta + \sum_{k=1}^{k} Y_k\, d_{ik} + \sum_{k=1}^{k} \lambda_k\, \xi_{ik} + \varepsilon_i$ .... (7)
Where;
Q_i = HFIAS or farm revenue.
z_i = is a set of exogenous covariates with associated parameter vector β.
d_{ik} = binary variables for observed treatment choice.
Y_k = is the treatment effects relative to non-migrants.
ξ_{ik} = is a set of latent factors.
$E(Q_i = 1 \,|\, d_{ik}, z_i, \bar{z}_i, \varepsilon_i)$ = is a function of each of the latent factors ξ_{ik}.
The resultant model was analysed with Stata tool using a Maximum Likelihood technique.

3.4.2 Propensity score matching

The final phase in the empirical analysis involves employing the propensity score matching method as a robustness check for the Maximum likelihood estimates of treatment effects for the ATT. PSM establishes an artificial control group to assess a program's counterfactual [41]. PSM enables the formation of a comparable treatment and control group based on observable exogenous factors influencing migration, facilitating the assessment of causal effects through the comparison of outcome variable disparities between the constructed treated and non-treated groups. Households in the treatment group (migrant households, Mi = 1) or the control group (non-migrant households, Mi = 0) have potential outcomes Z0i if untreated and Z1i if treated. The effect of migration on the outcome variable for migrant and non-migrant groups can be expressed as follows;
$E(Z_{1i} | M_i = 1) - E(Z_{0i} | M_i = 1)$, for the migrant group.......................... (8)
$E(Z_{1i} | M_i = 0) - E(Z_{0i} | M_i = 0)$, for the non-migrant group...................... (9)

In empirical estimation, we employ the most often utilised Nearest Neighbour (NN) matching for PSM. Specifically, we apply NN with two matching partners and restrict the matching within the common support.

4. Results

4.1 Descriptive statistics

Findings reveal that majority of the farmers are assigned lands in the community once married and thereafter go into farming. 96 percent of the migrants are married while 96 percent also of the non-migrants are married. Monogamy is prevalent in the study area with migrants having a 71 percent figure and non-migrants, 78 percent. The mean age with married partner for migrants is approximately 32 years, while that of non-migrants is approximately 31 years. The mean age of migrant farmers is approximately 63 years while that of non-migrant farmers is 60 years. The males dominate in all the two groups of farmers under study. Result shows that 98 percent are males in migrant group while 93 percent are males in non-migrant groups respectively. For females, 2 percent exist in migrant group while non-migrants have 7 percent. The average years of farming experience for the migrant group is approximately 29, that of non-migrants is 28 years. The mean household size for the migrant farmers is approximately 8 people per household while the mean household size for non-migrants is approximately 7 persons per household. Migrant farmers were also found to be educated to several levels, with only 6 percent having no formal education. For the non-migrants, only 2 percent lack formal education while the rest are educated to several levels.

The test of mean difference shows a significant difference exists between the migrants and non-migrants' type of marriage, household size, gender, age, age with married partner, ethnic group and level of education. The rest of the results for the socio-economic characteristics of farmers in the study area are presented in Table 2.

Table 2: Socio-economic characteristics of farmers in the study area

	Migrants (Treatment)		Non-migrants (Control)			
Variable	Mean	Std. dev.	Mean	Std. dev.	Diff. in mean	P-value
Family type					-0.003	0.914
Nuclear	0.915	0.280	0.918	0.276		
Extended	0.085	0.280	0.082	0.276		
Marriage type					0.072*	0.086
Polygamous	0.290	0.454	0.220	0.413		
Monogamous	0.711	0.454	0.784	0.413		
HHSize	7.711	2.929	6.840	2.676	-0.871***	0.001
Gender					0.043**	0.029
Male	0.976	0.155	0.933	0.251		
Female	0.024	0.155	0.067	0.251		
Age	62.882	9.720	60.041	11.210	-2.841***	0.005
Marital status					-0.032	0.638
Married	0.963	0.188	0.959	0.199		
Separated	-	-	0.021	0.142		
Divorced	-	-	0.005	0.072		
Widowed	0.033	0.178	0.015	0.124		
Never married	0.004	0.064	-	-		
Age with married partner	31.821	4.180	30.912	4.186	-0.909**	0.024
Years of farming experience	28.780	9.520	28.170	9.646	-0.616	0.504
Religion					-0.135	0.245
No religion	0.024	0.155	0.046	0.211		
Catholic	0.374	0.485	0.418	0.494		
Protestant	0.297	0.458	0.258	0.439		
Ch'matic	0.215	0.412	0.201	0.402		
Islam	0.008	0.090	0.005	0.072		
Traditionalist	0.081	0.274	0.072	0.259		
Ethnic groups					-71.740***	0.000
Ekpeye people	0.236	0.425	0.005	0.072		
Ikwerre	-	-	0.361	0.481		
Igbo	0.004	0.064	0.619	0.487		
Ijaw	-	-	0.005	0.072		
Ogba	-	-	0.005	0.072		
Other	0.760	0.428	0.005	0.072		
Education					0.527***	0.000
None	0.057	0.232	0.015	0.124		
Primary	0.549	0.499	0.454	0.499		
Secondary	0.309	0.463	0.273	0.447		
Polytechnic	0.024	0.155	0.026	0.159		
University	0.061	0.240	0.227	0.420		
Uni. (postgraduate)	-	-	0.005	0.072		

Source: Field survey, 2024

4.2 Coping strategies adopted by farming households in Rivers State, in mitigating the impacts of flooding

The results from data collected and analysed shows that 97.2% (239) of the farmers in the study area affected by flooding have crop damage as their primary concern with flooding while 2.8% (7) stated infrastructural damage as their main concern. Result from data analysed showed that migrants have a mean cassava output of 2795.13kg with a mean loss of 966.90kg for the same crop. Their non-migrant counterparts who have mean output of 2772.07kg have no recorded losses due to flood. Result shows that migrants on the average harvested more cassava than the non-migrants who are not in flooding areas. But a closer look at data showed the migrants harvest early before the flood comes and at those times, the cassava is considered immature. Such harvested cassava roots end up giving less quantity of the processed cassava (garri). This is because of the immature cassava harvested earlier than the maturity time due to flood. This type does not yield as much as the matured ones when harvested.

For maize, the mean output for migrants is 1482.03kg with a loss of 910.39kg. Also, for non-migrant the mean for maize output is 4217.15kg with no recorded losses due to flood. For plantain, migrants harvested 1350kg with a loss of 400kg. Also, the non-migrants harvested on average 200kg with no recorded losses.

The result on the outputs and losses are represented in Table 3.

Table 3: Mean output and losses for crops due to flood

Variable	Migrants		Non-migrants	
	Mean	**Std. dev.**	**Mean**	**Std. dev.**
Output (Kg)				
Cassava	2795.134	1608.712	2772.07	1358.62
Maize	1482.031	927.133	4217.151	2350.307
Plantain	1350.0	919.239	200.00	-
Losses (Kg)				
Cassava loss	966.897	595.942	0	0
Maize loss	910.393	558.468	0	0
Plantain loss	400	141.421	0	0

Source: Field survey, 2024

The coping strategies adopted by these farmers as gathered from the data collected are identified as early planting and harvesting. The results show that all the respondents (100%) from the migrant LGAs (Ahoada East, Ogba Egbema-Ndoni and Ahoada West) reported early planting and harvesting as a coping strategy to flooding episodes and this was found to be ineffective in the study area. Other strategies identified in literature (elevated construction techniques, traditional knowledge, cultivating flood-resistant crop varieties, modern technologies, adoption of innovative approaches to water management, global initiatives related to flooding, government assistance and NGO/Private sector assistance) were not adopted in the study area. The reasons they gave for this ranges from climate variability to lack of information on the said strategies. It is worthy of note too that neither the government nor the private sector comes to their aid as regards coping after flooding episodes. They reported being fed in the IDPs for the number of months they migrated out of the communities and nothing more was received as help. When the water recedes, they return home without any assistance from any source, to face rebuilding and coping after every episode. Usually coping in this instance is merely by falling back on what they had saved up or stored before migrating out of the communities.

This is in line with the work of Ajibade *et al.* [42] who analysed data from 240 smallholder rice farmers in Kwara state Nigeria, an area faced with flooding episodes. According to the survey, the majority of rice farmers (79.5%) planted early-maturing rice seedling varieties in order to secure an early harvest before the peak of rainfall, when floods are typically observed. The adoption of early maturing rice varieties which was harvested early in the planting season became the strategy used by these rice farmers in coping with flooding episodes.

From data collected, the challenges faced by the farmers in the study area in utilizing the itemized coping strategies is shown in Table 4.

Table 4: Challenges of migrants in implementing the coping strategies

Challenges	**Respondents (%)**
Climate variability	0.40
Lack of resources	10.20
Limited access to information	89.0
Technical complexity	0.40
Total	100

Source: Field Survey, 2024.

Eighty-nine percent of the migrants stated limited access to information as their impediment to utilizing the other listed strategies. About 10% said lack of resources hinder them from utilizing strategies like flood-resistant varieties. Majority mentioned elevated construction techniques cannot be adopted there because the water level usually covers every structure once flood comes. No structure however high they said, can withstand the water level. These they have experienced in these communities for over a century. They plant early, harvest early and in the cases of cassava producers, the processed outputs are usually minimal as compared to farmers who are in the non-flooded LGAs that allow time for cassava to mature before harvest. Early harvest of cassava gives less harvest and conversely less bags of garri (processed cassava). This affects the income of those who plant cassava. For maize and yams, they harvest as expected but sometimes the water comes even before the expected time and covers up the whole farm. In this case, there will be a total loss of crops. This has been the pattern and all they do is just adopt early planting and harvesting which clearly has proven as not an effective strategy in tackling the flooding issue. If it is effective, they won't have losses and also, they will have optimum output all things being equal. Data shows that all the farmers (migrants) harvest less than expected for cassava, maize, yam and plantain.

4.3 Effects of migration on the food security status of farming households in Rivers State following flooding

The food security dimension measured in the study area is food accessibility. The level of food security was measured with HFIAS while economic access to food was proxied by farm revenue. The food security status of a household captured with HFIAS can be measured on a scale of 0 to 27. A household can receive a maximum score of 27 if all nine frequency-of-occurrence questions are answered "yes," with a response code of 3. A household can have a minimum score of 0 if all nine frequency-of-occurrence questions are skipped and marked as 0. The household's level of food insecurity increased with a higher score while household's level of food insecurity decreased with a lower score. The results obtained after analysis showed the migrants' average HFIAS as 13.4675 while that of the non-migrants is 2.1598. This shows that the migrants are more food insecure when compared with the non-migrant group. The exact difference in their average HFIAS was estimated using endogenous treatment effect.

However, as categorical variable households are categorized as food secure, mildly food insecure, moderately food insecure, or severely food insecure. The categorizations of the food security status of farming households in the study area is shown in Table 5. The table shows that 50 percent of the migrants are categorized as moderately food insecure while the other 50 percent are severely food insecure. This shows that the migrants indeed are not food secure and a look at their non-migrant counterparts shows otherwise. The result shows that 70.60 percent of the non-migrants are food secure, 5.70 percent are mildly food insecure, 10.80 percent moderately food insecure with the remaining 12.30 percent severely food insecure. The disparity in food security categorizations is also as a result of the differences in the average HFIAS for both groups.

Table 5: Food security status of farming households in Rivers state, Nigeria

HFIAS Categorisations	**Household type**	
	Non-migrants (%)	Migrants (%)
Food Secure	70.60	0.00
Mildly food insecure	5.70	0.00
Moderately food insecure	10.80	50.00
Severely food insecure	12.30	50.00
Total	100	100

Source: Field survey, 2024.

In the aspect of food accessibility proxied by farm revenue, the average farm revenue of migrant households per head is 54509.34 naira while that of non-migrants is 183153.6 naira (USD 128.9 and USD 433 respectively). This shows that households who are not faced with flooding problems and who also do not migrate due to same, have more revenue. With more revenue, these non-migrants can access more food than their migrant counterparts who earn less revenue. This also explains why we have disparity in their food security categorizations. A farmer who has little money can only access food worth his money while a farmer who has more can access more food equivalent to his income. The exact difference in their farm revenue was estimated using endogenous treatment effect.

4.3.1 Treatment effects of migration on HFIAS and farm revenue

An important objective of this study is to determine the effect of flooding-induced migration on food security. The use of the ESR approach enables us to obtain the expected outcomes of food security, conditional on migration. The difference between the outcome of migrants who actually migrated and the expected outcomes if they (migrants) had not migrated, is called average treatment effect on the treated (ATT). The results of the estimated ATT are presented in Table 6.

Table 6: Treatment effects of migration on Household Food Insecurity Access Scale and Farm income

	ESR			PSM		
	ATT	ATU	ATE	ATT	ATU	ATE
Food Security (HFIAS)	9.17***	-11.59***	-2.14***	10.93***	-11.55***	11.28***
	(0.1868)	(0.1907)	(0.2306)	(1.2575)	(0.6167)	(0.6917)
Farm Revenue (Naira)	-290.45	114439.5***	128353.8***	-118065.33***	145499.54***	-131430.71***
	(20575.09)	(4878.95)	(23542.74)	(14265.97)	(22454.03)	(16721.62)

Source: Field survey, 2024.
Note: ***, **, * represent 1%, 5% and 10% significance levels, respectively. Figures in parenthesis are std. errors. ESR, Endogenous Switching Regression; PSM, propensity score matching,
423 naira = USD 1 (2022).

The results from the endogenous treatment effect analysis of food security reveal significant differences between migrant and non-migrant households. The average treatment effect on the treated (ATT) shows a mean difference of 9.17 with a statistical significance of 1 percent. This means that flooding problems and conversely migrating out of the affected communities increases food insecurity. The average treatment effect on the untreated (ATU) shows a mean difference of negative 11.59 which is also statistically significant. This means that if the migrants were not faced with flooding issues which led to migration, their food insecurity would have reduced by 11. 59. Worthy of note is the fact that HFIAS score ranges from 0 to 27 and having an expected scale reduction of 11.59 will mean moving towards food security. Indeed, there is a significant difference in the average HFIAS of the migrants and non-migrants. While the migrant household tend towards food insecurity, their non-migrant counterparts tend towards food security.

Issahaku, [39] also reported similar findings that households who adopted climate smart practices improved their food security, but in this case a negative treatment (migration) which is reducing their food security and bringing about food insecurity.

The average treatment effect (ATE) is statistically significant with a value of negative 2.14 and also means a reduction in food insecurity for the entire sample.

For the robustness check of estimates, the Nearest Neighbor Matching (NNM) method was used. The treatment effects estimation using the Nearest Neighbor Matching method, with a 3(1) match and bootstrapped standard errors was done. The result provides an insight into the impact of migration on average HFIAS of migrants and non-migrants. These results are also presented in table 6 and show significant, positive coefficients for ATT, ATE and a negative coefficient for ATU. These were not as robust as the ESR model estimates, so interpretation was made based on ESR results.

The results from the endogenous treatment effect analysis of farm revenue in Table 6 showed that the average treatment effect on the treated (ATT) has a mean difference of negative 290.45 naira (USD 0.69) which is not statistically significant. The average treatment effect on the untreated (ATU) has a mean difference of 114439.5 naira (USD 270.54) which is statistically significant at 1 percent level. This means that if the migrants are not faced with flooding issues and eventual migration, their expected farm revenue will increase by 114439.5 naira per head. This result is quite similar to the findings of Issahaku [39]. He found that adopting climate smart practises improved farm income, although in this case migration is a negative treatment which reduced farm revenue. In this case, farm revenue reduced by 290.45 naira per head if there is migration and increased by 114439.5 naira per head if there is no migration. Indeed, flooding and migration reduce farm revenue generatable by migrants and if there is no flooding and migration, revenue will increase.
The average treatment effect (ATE) is statistically significant with a value of 128353.8 naira (USD 303.44) and means on an average farmers earn 128353.8 naira per head.

For the robustness check of estimates, the Nearest Neighbor Matching (NNM) method was used. The treatment effects estimation using the Nearest Neighbor Matching method, with a 1(1) match and bootstrapped standard errors was carried out. The result gives an insight into the impact of migration on the farm revenue of migrants and non-migrants. These results are also presented in table 6 and show significant, negative coefficients for ATT, ATE and a positive coefficient for ATU. These estimates were not as robust as the ESR model estimates, so interpretation was made based on ESR results.

The results generated from the Endogenous Switching Regression (ESR) model proved to be more consistent and statistically robust compared to those from the Propensity Score Matching (PSM) technique, even though both were applied to the same dataset. This outcome aligns with expectations, given the methodological strengths of the ESR approach. While PSM adjusts only for differences in observable variables and is sensitive to issues like sample trimming and match quality, ESR simultaneously accounts for both observable and unobservable influences on treatment assignment and outcome. It does so by explicitly modelling the selection mechanism and allowing for correlation between the error terms in both the selection and outcome equations, thereby correcting for endogeneity and selection bias. This yields more precise and credible estimates, particularly in situations such as this study, where migration is triggered by environmental shocks like flooding, and where unmeasured factors such as the degree of flood exposure or spatial disadvantage may not be fully captured by observed variables. As a result, the ESR model offers more reliable insights into the causal impact of migration on household food security outcomes. Therefore, interpretations were done with ESR estimates.

5. Summary of findings, Conclusion and recommendations

This study assessed the dynamics of flooding-induced migration, coping strategies and food security status of agricultural households in the context of escalating flooding in Rivers State, Nigeria. The specific objectives were to identify and analyse the coping strategies adopted by farming households in mitigating the impacts of flooding, and to estimate migration effects on the food security status of farming households in the study area, with a focus on distinguishing effects between migrant and non-migrant households. Primary data were collected from 440 respondents in the study area. Data collected were analysed using simple statistical tools, Endogenous Switching Regression and Propensity Score Matching approaches with the help of Stata software.

The coping strategies adopted by these farmers as gathered from the data collected are identified as early planting and harvesting. The reasons they gave for not using other strategies identified in literature ranges from climate variability, lack of resources, lack of information on the said strategies, to technical complexity.

The average HFIAS and farm revenue were analysed and result showed that migrants' average HFIAS was 13.4675 while that of the non-migrants was 2.1598. This shows that the migrants are more food insecure when compared with the non-migrant group. The exact difference in their average HFIAS was estimated using endogenous treatment effect.
The result of this analysis showed that the average treatment effect on the treated (ATT) had a mean difference of 9.17 with a statistical significance of 1 percent. This means that flooding problems and conversely migrating out of the affected communities increases food insecurity. The average treatment effect on the untreated (ATU) showed a mean difference of negative 11.59 which is also statistically significant. This means that if the migrants were not faced with flooding issues which led to migration, their food insecurity would have reduced by 11. 59. Worthy of note is the fact that HFIAS score ranges from 0 to 27 and having an expected scale reduction of 11.59 will mean moving towards food security. Indeed, there is a significant difference in the average HFIAS of the migrants and non-migrants.

Finally, the result on average farm revenue showed a mean value of migrant household's farm revenue per head was 54509.34 naira while that of non-migrants was 183153.6 naira (USD 128.9 and USD 433 respectively). This shows that households who are not faced with flooding problems and who also do not migrate due to same, have more revenue. With more revenue, these non-migrants can access more food than their migrant counterparts who earn less revenue. A farmer who has little money can only access food worth his money while a farmer who has more can access more food equivalent to his income. The exact difference in their farm revenue was estimated using endogenous treatment effect.

The result from the endogenous treatment effect analysis of farm revenue showed that the average treatment effect on the treated (ATT) had a mean difference of negative 290.45 naira (USD 0.69) which is not statistically significant. The average treatment effect on the untreated (ATU) had a mean difference of 114439.5 naira (USD 270.54) which is statistically significant at 1 percent level. This means that if the migrants are not faced with flooding issues and eventual migration, their expected farm revenue naira will increase by 114439.5 naira per head. Migration indeed reduces farm revenue as the result depicts a reduction of 290.45 naira per head if there is migration. Therefore, flooding and migration reduce farm revenue generatable by migrants and if there is no flooding and migration, revenue will increase.

Based on the findings from this study, the following conclusions are drawn.

First, coping strategies has to be adopted by farmers in the study area. The identified strategies from literature should be implemented either in part or as a whole in mitigating the effect of persistent flood in the study area. It is clear from the results that early planting and harvesting is not effective in the study area as a coping mechanism to flood disasters.

Secondly, on the aspect of the level of food security, average HFIAS showed migrants are food insecure while non-migrants are more food secure. Migration makes it worse for the migrant farmers since it affects their output and conversely revenue generatable from their farms.

For economic access to food, farm revenue reduces for migrants who face flooding issues with imminent migration and returns. They also have losses in output due to flood disasters and this cuts down on their revenue. Their counterparts who do not face flooding challenges are better off. This also explains why they are more food secure. With more revenue per head, they access more food in comparison with the migrants.

Therefore, the study recommends the following.

The government and stakeholders alike should endeavor to initiate and equally execute projects meant to curb flood in these communities affected by flood. The government can build embarkments around the river banks to stop the overflow which occurs at certain times of the year. There are practices that have worked in this regard in other parts of the world where flood is an issue. The federal government of Nigeria can emulate this in curbing the menace of flood in Rivers state and other parts of Nigeria where farmers are affected by flooding episodes.

Also, the government can give these farmers grants and credits to assist with coping after flooding episodes. These farmers have lands that are fertile and if assisted during rebuilding times after flooding episodes, they can have more output. This is because most times after floods, the depend on savings for rebuilding and end up with little to nothing left for the next year planting season. Therefore, grants and credit from the government can help them cope in such times. With effective coping strategies, farmers output and conversely revenue will improve. This will in turn improve their food security.

Private sector and the government alike should engage in projects in these rural areas which will lead to income generation through non-farm activities. Industries can be built in these areas to assist the farmers in diversifying their sources of income. When the farmers earn more income, they will be empowered to access more food. When they access more food, their HFIAS will equally improve.

Ethical declaration

Ethical clearance, with number ECBAS 065/23-24, was obtained from the Ethics Committee for Basic and Applied Sciences (ECBAS), University of Ghana for the collection of primary data. All participants signed a consent to participate, form indicating their willingness to be interviewed.

Data availability statement

The data used for this study are available from the corresponding author upon request.

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CRediT authorship contribution statement

Jacinta Nmutaka Umechukwu: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Daniel Bruce Sarpong**: Supervision, Writing – review & editing. **Akwasi Mensa-Bonsu**: Supervision, Writing – review & editing. **Ama Ahene-Codjoe**: Supervision, Writing – review & editing. **Taeyoon Kim**: Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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