



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

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ABSTRACT

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 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 flooding-induced 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 switching regression models were then estimated to identify the average treatment effects of flooding-induced 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 on the other hand flooding-induced 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 54,509.34 naira while that of non-migrants was 183,153.6 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.

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Introduction

Flooding has become one of the most recurrent environmental hazards affecting agricultural livelihoods in Rivers State, Nigeria. Located within the Niger Delta region, the state experiences seasonal flooding arising from intense rainfall, river overflow, poor drainage systems, and the broader effects of climate change. Over the past decade, flood events have increased in both frequency and severity, resulting in repeated destruction of farmlands, crop losses, damage to rural infrastructure, and disruptions to household livelihoods [1,2]. As agriculture remains a primary source of income and food for rural households in the state, recurrent flooding poses a significant threat to household welfare and food security.

The impacts of flooding on agriculture extend beyond the immediate destruction of crops and farm assets. Floodwaters alter soil conditions through erosion, sediment deposition, nutrient depletion, and changes in soil structure, thereby affecting the long-term fertility and productivity of agricultural land [5,6]. These environmental consequences persist long after floodwaters recede, creating enduring challenges for agricultural production and rural livelihood sustainability. For farming households whose welfare depends heavily on crop production, the resulting decline in productivity can reduce income-generating capacity and increase economic vulnerability. Smallholder farmers, who constitute a large proportion of the agricultural population, are particularly susceptible to these adverse effects and often face heightened risks of poverty and livelihood insecurity following recurrent flood events [5,7].

Beyond the immediate destruction of crops and productive assets, flooding often compels affected households to temporarily relocate from their communities. During severe flood episodes, many farming families abandon their homes and farms and move to internally displaced persons (IDP) camps or safer locations until floodwaters recede. Such temporary migration disrupts farming activities, reduces agricultural production, interrupts income generation, and weakens households' capacity to access sufficient food [3,4]. Consequently, flooding-induced migration has emerged as an important pathway through which environmental shocks affect rural food security.

The severity of this challenge was particularly evident during the 2022 floods in Nigeria, widely regarded as the worst flooding event since 2012. According to official reports, >1.4 million people were displaced nationwide, over 603 lives were lost, and hundreds

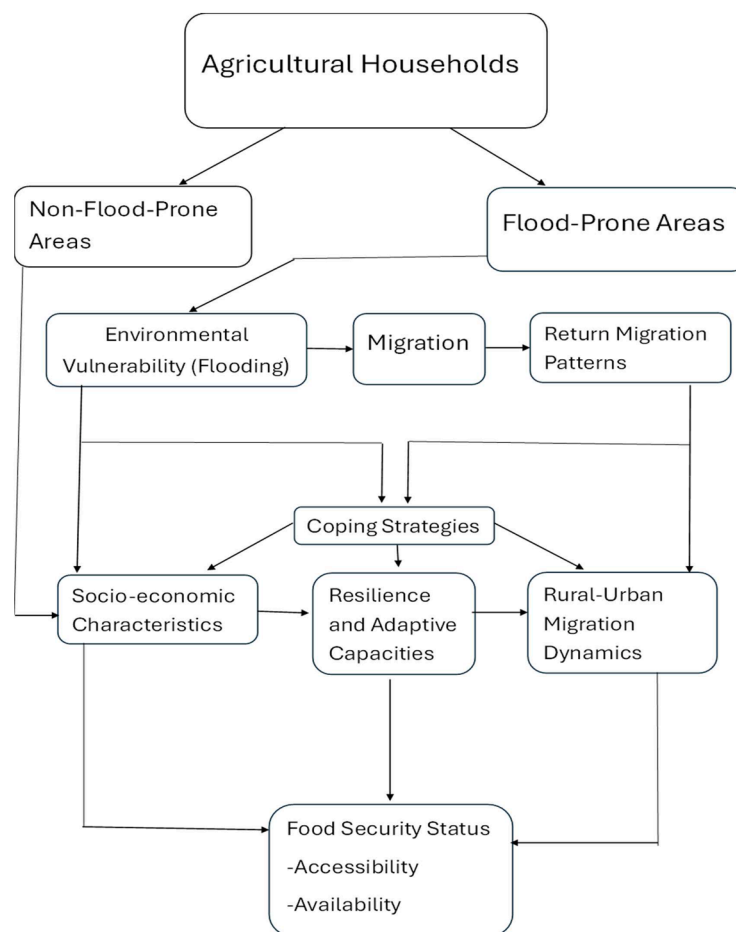


Fig. 1. Conceptual framework.
Source: Author (2024)

of thousands of hectares of agricultural land were affected [1]. Rivers State was among the states severely impacted by the disaster, with numerous farming communities experiencing prolonged inundation and temporary displacement. Although emergency relief was provided during the displacement period, many households returned to damaged farms and limited livelihood opportunities after floodwaters subsided.

Food security remains a critical concern in flood-prone rural communities. The Food and Agriculture Organization defines food security as a situation in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food [5]. For farming households, flooding can undermine food security directly through losses in agricultural production and indirectly through reductions in farm income, both of which constrain household access to food. Understanding these pathways is particularly important in regions where agriculture constitutes the principal livelihood activity.

Existing studies on flooding in Rivers State and other parts of Nigeria have largely concentrated on the causes of flooding, vulnerability assessment, environmental impacts, adaptation strategies, and disaster risk reduction measures [1,2,4]. While these studies provide valuable insights into the consequences of flood events, limited attention has been given to the role of temporary migration as a household response to flooding and the implications of such migration for food security outcomes. Furthermore, little empirical evidence exists on the coping strategies adopted by displaced farming households after returning to their communities and whether these strategies are sufficient to mitigate food insecurity.

This study addresses this gap by examining the relationship between flooding-induced migration, household coping strategies, and food security outcomes among farming households in Rivers State, Nigeria. Specifically, the study identifies the coping strategies employed by flood-affected households and estimates the effects of migration on household food security using the Household Food Insecurity Access Scale (HFIAS) and farm revenue indicators. By focusing on the migration-food security nexus within a flood-prone agricultural region, the study contributes evidence that can inform policies aimed at strengthening the resilience of rural households facing recurrent flooding.

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 Fig. 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.

Fig. 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 reflect households' resilience and adaptive capacity, influencing how effectively they absorb, respond to, and recover from flood-related shocks. In the present study, resilience and adaptive capacity are treated as conceptual outcomes of coping behaviour rather than as separately measured variables in the empirical analysis. 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.

Review of literature

Flooding, migration and rural livelihoods

Flooding is among the most destructive natural hazards affecting agricultural production and rural livelihoods globally. In developing countries, where agriculture serves as the primary source of livelihood for a large proportion of the population, recurrent flooding often results in crop destruction, loss of productive assets, damage to infrastructure, and disruptions to local markets [1–4]. Beyond these immediate impacts, flooding alters soil conditions through erosion, sediment deposition, nutrient depletion, and changes in soil structure, thereby reducing land productivity and threatening long-term agricultural sustainability [5,6]. For farming households, these production shocks frequently translate into livelihood insecurity. Reduced agricultural output lowers farm income, weakens household purchasing power, and increases vulnerability to poverty [5,7,8].

One common response to severe flooding is temporary migration. Environmental migration occurs when individuals or households relocate either temporarily or permanently in response to adverse environmental conditions that threaten their livelihoods and well-being [8–10]. In flood-prone rural areas, households often move to safer communities or internally displaced persons (IDP) camps during periods of severe inundation and return after floodwaters recede. While migration may reduce immediate exposure to flood risks, it can disrupt agricultural activities, limit income-generating opportunities, and affect household welfare outcomes, including food security [8–12].

In Nigeria, recurrent flooding has become an increasingly important driver of temporary displacement. The 2022 flood disaster resulted in widespread displacement across several states, including Rivers State, disrupting farming activities and threatening the livelihoods of rural households dependent on agriculture [1,2,4].

Food security and measurement of food security

Food security exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life [13–15]. Contemporary literature recognizes food security as a multidimensional concept encompassing availability, access, utilization, stability, agency, and sustainability [16,17,15]. While food security is multidimensional, this study focuses specifically on the access dimension, which reflects a household's ability to acquire food through available resources and purchasing power.

The Household Food Insecurity Access Scale (HFIAS) is one of the most widely used tools for assessing household food access. Developed and validated for measuring food access-related experiences, HFIAS captures anxiety about food supply, food quality, and insufficient food intake [18–20]. Higher HFIAS scores indicate greater levels of food insecurity, while lower scores indicate improved food access [18–20]. In addition to HFIAS, economic access to food can be examined through income-related indicators. Farm revenue is particularly relevant in agricultural communities because it reflects income generated from farming activities and influences households' purchasing power [13,14,21–23]. Higher farm revenue generally improves the ability of households to acquire food, meet nutritional needs, and build resilience against shocks [14,21–23].

In this study, farm revenue is employed as an indicator of the economic access dimension of food security. Although farm revenue does not capture all potential income sources, such as remittances, transfers, or non-farm earnings, it provides a useful measure of the contribution of agricultural production to household food access. To account for the broader nature of food security, farm revenue is analysed alongside HFIAS, which directly measures household experiences of food insecurity [18–20,22,23].

Empirical evidence on flooding, migration and food security outcomes

Previous studies have documented significant impacts of flooding on agricultural production, livelihoods, and household welfare. Research in Nigeria and other developing countries consistently shows that flooding reduces crop yields, destroys productive assets, lowers farm incomes, and increases household vulnerability to food insecurity [1–8]. Several studies have examined adaptation and coping responses to flooding and climate-related shocks. Common responses include crop diversification, adjustments in planting and harvesting dates, flood-resistant crop varieties, livelihood diversification, temporary migration, reliance on indigenous knowledge systems, and social support networks [24–27,9–12,28].

Other studies have identified broader adaptation measures such as climate-smart agriculture, scenario planning, precision agriculture technologies, remote sensing applications, water-sensitive infrastructure development, soil bioengineering practices, waterlogging-tolerant crops, and integrated water management approaches [29–37]. The effectiveness and adoption of these strategies vary across locations depending on environmental conditions, institutional support, access to information, and resource availability [24–27,9–12,29–37].

Recent empirical studies have increasingly employed econometric approaches such as Propensity Score Matching (PSM), Endogenous Switching Regression (ESR), and related treatment-effect models to estimate the welfare impacts of adaptation and migration decisions while addressing selection bias [38–42]. For example, Issahaku [40] and Amadu [40] employed treatment-effect approaches to assess the impacts of climate-smart agricultural practices on farm performance, food security, and poverty outcomes.

Despite growing interest in environmental migration, empirical evidence on the relationship between flooding-induced migration and household food security remains limited, particularly in the Niger Delta region of Nigeria. Existing studies have largely focused on flood vulnerability, adaptation measures, and disaster impacts, with relatively little attention given to how temporary migration influences food security outcomes among farming households [1–25].

Research gap and contribution of the study

Although previous studies have examined flooding impacts [1–8] adaptation strategies [24–27,9–12,29–37,28], and food security measurement [43–47,13,15,16–23], limited empirical evidence exists on the food security consequences of flooding-induced migration among farming households in Rivers State. Furthermore, few studies simultaneously examine coping strategies and estimate the causal effects of migration on food security outcomes using treatment-effect approaches that account for selection bias and unobserved heterogeneity [38–41,43]. This study addresses these gaps by investigating the coping strategies adopted by flood-affected farming households and estimating the effects of flooding-induced migration on household food security using HFIAS and farm revenue indicators. By applying Endogenous Switching Regression and Propensity Score Matching techniques, the study contributes empirical evidence to the migration–food security literature in one of Nigeria’s most flood-prone agricultural regions.

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.

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 5198,716 in the 2006 census, and was projected as 7492,366 in 2023. Its coordinates are Latitude 4.75°N and longitude 6.50°E, and it encompasses an area of 11,077 km² (4,277m²). The Ijaw, Ikwerre, 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.

Rivers State is comprised of three agricultural zones, Degema (mangrove swamp/coastal), Eleme (upland/tropical rainforest), and Ahoadia (freshwater swamp) zones. The selection of Ahoadia Agricultural Zone for this study was informed by its recurrent exposure to seasonal flooding and its importance as a major agricultural production area in Rivers State. The zone is characterized by extensive cultivation of staple crops such as cassava, yam, maize, plantain, and vegetables, which are highly vulnerable to flood-induced production losses. Seasonal flooding, particularly during periods of intense rainfall and overflow from surrounding river systems, frequently results in farmland inundation, crop destruction, temporary displacement of farming households, and disruption of agricultural livelihoods [1,2].

The severe 2022 flooding event further highlighted the vulnerability of communities within the zone, with households from affected communities experiencing displacement and temporary migration to safer locations and internally displaced persons (IDP) camps before returning to their communities after floodwaters receded [1]. Given the dependence of households on agriculture as their primary livelihood source, flooding-induced disruptions have important implications for household food security. Consequently, the zone provides an appropriate setting for examining the relationship between flooding-induced migration and food security outcomes among farming households. The coexistence of migrant and non-migrant farming households within the same agricultural zone, operating under broadly similar agroecological and socioeconomic conditions, provides a meaningful basis for treatment-control comparisons and strengthens the assessment of migration-related differences in food security outcomes.

The predominance of agriculture as the principal livelihood activity in the study area makes household food security particularly sensitive to disruptions caused by flood-related displacement and loss of agricultural production.

Research design

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.

This study employed a cross-sectional survey design with a retrospective recall component. Respondents were asked to provide retrospective information on flooding experiences and coping strategies adopted during major flood episodes between 2011 and 2022. Information on migration status, household food security, and farm revenue was collected with reference to the 2022 production season, which coincided with one of the most severe flooding events recorded in the study area. Secondary data obtained from the

National Emergency Management Agency (NEMA) for the period 2011–2022 were used to verify flood occurrences, support the identification of flood-affected communities, and provide contextual information on flooding patterns within the study area. These secondary data were therefore used for contextualization and study-area characterization rather than as direct inputs in the econometric analysis.

Sample size determination

This study included a sample size of 440 farmers. Using the mathematical method developed by Miller and Brewer [38], 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 (target population) n = Sample size

α = Margin of error (precision level)

A 95% confidence level and 5% margin of error ($\alpha = 0.05$) 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 1258,670. Applying the formula;

$$n = \frac{1258670}{1 + 1258670(0.05)^2} = \frac{1258670}{1 + 3146.675} = \frac{1258670}{3147.675} = 399.87$$

Consequently, n = 399.87 (approx. 400)

The minimum required sample size was 400. To account for potential non-response and incomplete data, an additional 10% was added, resulting in a final sample size of 440 farming households. This approach is consistent with standard survey methodology [38]. This information is shown in Table 1.

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 purposive and simple random sample technique, the first stage involved clustering the farming households into migrants and non-migrants respectively. 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.

The sampling frame for this study comprised exclusively of crop farmers residing in flood-prone and non-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 food security. A multistage sampling technique was adopted. First, three LGAs with high exposure to seasonal flooding, Ahoada East, Ahoada West, and Ogba/

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.

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 [39].

The combination of purposive and random sampling was necessary because flooding in Rivers State is geographically concentrated; non-migrant households do not exist in flood-prone areas, and migrant households do not exist in non-flood-prone areas. Purposive selection of the treatment group ensured that all households in the sample had experienced flooding and migration, while random selection of the control group ensured representativeness of the non-flooded population. A total of 440 households were selected, 246 from flood-prone areas (migrants) and 194 from non-flood-prone areas (non-migrants), proportionally distributed based on population sizes.

The research design estimates the combined effect of flooding and migration, as all households in flood-prone areas migrate during flooding episodes. A control group of flooding-affected non-migrants does not exist in this context. Thus, our findings reflect the experience of households that both experience flooding and migrate in response. A map of Nigeria highlighting the study area Rivers State, is presented in Fig. 2.

Analytical tools

First, the coping strategies adopted by farmers in mitigating the impact of flood were identified. Secondly, the effects of flooding-

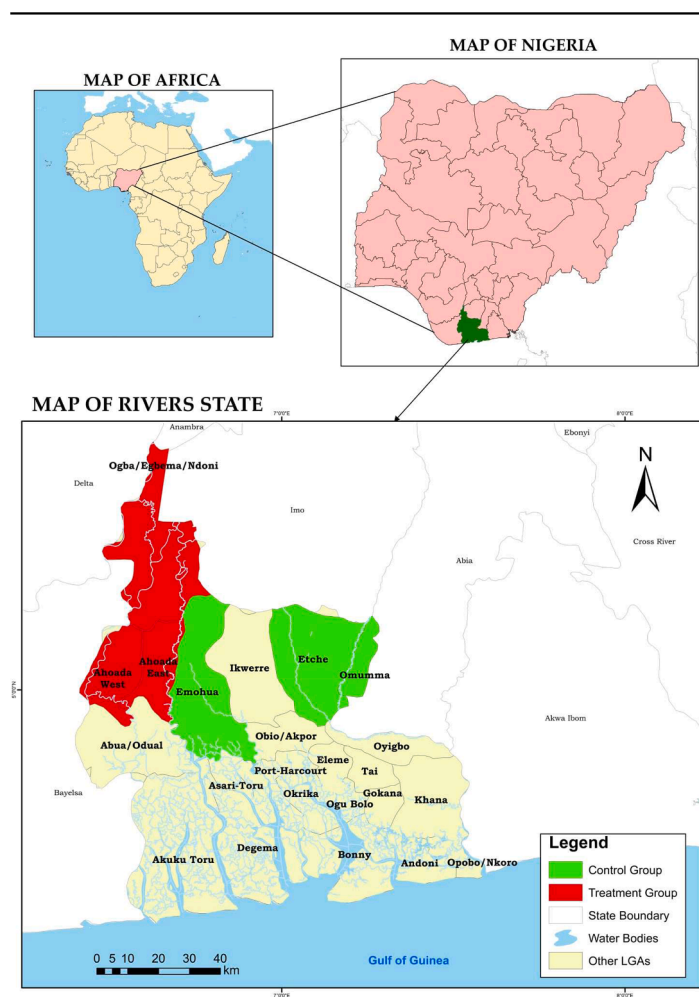


Fig. 2. The Nigerian map displaying the study area, Rivers State.

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

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 an indicator of the level of food insecurity and farm revenue as a proxy mostly for food accessibility. This is as adopted from Issahaku [40] who used HFIAS, farm revenue and household dietary diversity score (HDDS). This was amended to include HFIAS instead of 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

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

(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.

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

(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 [40,41]. 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 (migration status is the selection variable). 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:

$$G_i^* = \alpha X_i + \varepsilon_i,$$

where

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

Where;

G_i^* = vector of the binary unobservable or latent variable for the utility of migration to the farmer.

G_i = vector of the binary dummy (1 = migrate, 0 = Otherwise) for the migration equation where the farmer either migrated or did not.

X_i = vector of exogenous variables including the farm and household characteristics.

α = vector of parameters to be estimated.

ε_i = the error terms.

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

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

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

Where;

Q_{1i} and Q_{0i} = the food security outcomes for migrants and non-migrants respectively.

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 [40], which accounts for the HFIAS and farm revenue.

To model the effects of flooding-induced migration on HFIAS and farm revenue, we estimate an ESR model. In Stata, this is modelled simultaneously in two stages (as a two-stage procedure) 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;

$$E(Q_i = 1 | d_{ik}, z_i, \bar{z}_i, \varepsilon_i) = z_i \beta + \sum_{k=1}^k Y_k d_{ik} + \sum_{k=1}^k \lambda_k \xi_{ik} + \varepsilon_i \quad (7)$$

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.

Exclusion restriction (instrumental variable)

For the model to be identified, at least one variable must appear in the selection equation (Z_i) that is excluded from the outcome equations (X_i). This variable must affect migration status but have no direct effect on food security outcomes except through migration. Our exclusion restriction is ethnic group. In Rivers State, ethnicity is geographically concentrated and determines which Local Government Area (LGA) a household resides in. Flooding in the study area is geographically concentrated: households from Ekpeye and Ogba ethnic groups reside in flood-prone LGAs (Ahoada East, Ahoada West, Ogba-Egbema-Ndoni) and consequently face annual flooding and forced migration. Households from other ethnic groups (e.g., Ikwerre, Igbo, Etche) reside in non-flood-prone LGAs and experience neither flooding nor migration. Thus, ethnicity predicts migration status but has no direct theoretical or empirical link to food security outcomes except through its effect on flood exposure and migration. We therefore exclude ethnicity from the outcome equations, using it only to predict treatment assignment.

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 [42]. 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, $M_i = 1$) or the control group (non-migrant households, $M_i = 0$) have potential outcomes Z_{0i} if untreated and Z_{1i} if treated. The effect of migration on the outcome variable for migrant and non-migrant groups can be expressed as follows;

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

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

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.

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. 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 [42].

Results and discussion

Descriptive statistics

The socio-economic details of the farmers included in the research are shown in Table 2.

Table 2
Socio-economic characteristics 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						
Nuclear	0.915	0.280	0.918	0.276	-0.003	0.914
Extended	0.085	0.280	0.082	0.276		
Marriage type					0.072*	0.086
Polygamous	0.290	0.454	0.220	0.413	-0.871***	0.001
Monogamous	0.711	0.454	0.784	0.413		
HHSize	7.711	2.929	6.840	2.676		
Gender					0.043**	0.029
Male	0.976	0.155	0.933	0.251	-2.841***	0.005
Female	0.024	0.155	0.067	0.251		
Age	62.882	9.720	60.041	11.210		
Marital status					-0.032	0.638
Married	0.963	0.188	0.959	0.199	-0.909**	0.024
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		
Years of farming experience	28.780	9.520	28.170	9.646		
Religion					-0.135	0.245
No religion	0.024	0.155	0.046	0.211	-71.740***	0.000
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						
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	0.527***	0.000
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.

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.

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

Result from data analysed showed that migrants have a mean cassava output of 2795.13 kg with a mean loss of 966.90 kg for the same crop. Their non-migrant counterparts who have mean output of 2772.07 kg 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 1482.03 kg with a loss of 910.39 kg. Also, for non-migrant the mean for maize output is 4217.15 kg with no recorded losses due to flood. For plantain, migrants harvested 1350 kg with a loss of 400 kg. Also, the non-migrants harvested on average 200 kg with no recorded losses.

This finding aligns with Ajibade et al. [28], who documented similar early-harvest losses among rice farmers in Kwara State, Nigeria. However, our results extend that work by quantifying the differential impact across crops: maize (61% loss) is more severely affected than cassava (35% loss) or plantain (30% loss), suggesting that crop-specific adaptation strategies are needed.

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. [28] 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

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.

flooding episodes.

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

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 therefore, 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.

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 switching regression.

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.

In the aspect of food accessibility proxied by farm revenue, the average farm revenue of migrant households per head is 54,509.34 naira while that of non-migrants is 183,153.6 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 switching regression.

The stark contrast, 0% of migrants food secure versus 70.6% of non-migrants, is not merely descriptive. It reflects that flooding-induced migration systematically dismantles the household food supply chain. Displacement interrupts planting cycles, forces premature harvests, and diverts labor away from productive activities. These findings are consistent with studies from Bangladesh and Ghana where climate-induced displacement similarly eroded food security [5,26].

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.

The results from the endogenous switching regression analysis of food security reveal significant differences between migrant and

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.

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.

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*** (0.1868)	−11.59*** (0.1907)	−2.14*** (0.2306)	10.93*** (1.2575)	−11.55*** (0.6167)	11.28*** (0.6917)
Farm Revenue (Naira)	−290.45 (20,575.09)	114,439.5*** (4878.95)	128,353.8*** (23,542.74)	−118,065.33*** (14,265.97)	145,499.54*** (22,454.03)	−131,430.71*** (16,721.62)

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).

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 on the other hand, 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. Substantively, these counterfactuals reveal that migration is not a successful adaptation strategy but a distress response. Migrants do not choose to move for economic gain; they are forced to flee for safety. The consequence, a 9.17-point increase in food insecurity, places migration in the category of 'coping strategies that erode future resilience,' as distinguished from transformative adaptation in the climate change literature [2,4]. Unlike seasonal migrants in South Asia who use remittances to smooth consumption [32], households in our study area return with no new resources, trapped in a cycle of annual displacement and recovery.

Issahaku, [40] 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 switching regression 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 114,439.5 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 114,439.5 naira per head. This result is quite similar to the findings of Issahaku [40]. 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 114,439.5 naira per head if there is no migration. Indeed, flooding and migration reduce potential farm revenue generated by migrants and if there is no flooding and migration, revenue will increase. Also, IOM [44] in their Nigeria report, noted that food insecurity increased with displacement in North East Nigeria. This study's use of multiple indicators aligns with the multidimensional food security frameworks advanced by the FAO [14,15] and supported in empirical literature [45–47].

The average treatment effect (ATE) is statistically significant with a value of 128,353.8 naira (USD 303.44) and means on an average farmers earn 128,353.8 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.

We prefer ESR over PSM because migration in this context is not randomly assigned. Households in flood-prone areas all experience flooding and migrate. However, the decision of whether to return, and the post-return investment in farm recovery may be influenced by unobservable factors such as household risk tolerance, access to savings, or social networks in destination areas. These factors affect the migration outcome (food security). PSM cannot account for such unobservable factors but ESR addresses it by jointly estimating selection and outcome equations and allowing correlation between their error terms [40,41]. In our context, where treatment is uniform but post-return behaviour varies, ESR is methodologically preferable.

Also, regarding the difference in the ATE sign between ESR and PSM for farm revenue: The PSM ATE is negative and significant, while the ESR ATE is positive and significant. The difference between PSM and ESR ATEs reflects the bias introduced when unobservables are ignored. The ESR ATE is more credible because it accounts for selection bias. However, our primary conclusions are drawn from the ATT and ATU, not the ATE.

In this study of flooding-induced migration, to interpret these counterfactuals in concrete terms, consider a migrant farming household in Ahoada East, a family that floods forced to leave their farm each year, relocate to an IDP camp for three months, return home, and harvest whatever survived. Their observed HFIAS score is 13.47. The ATT of 9.17 tells us that if this same household, with the same soil, same skills, had somehow been able to stay on their land without flooding and without migrating, their HFIAS score would be 9.17 points lower. This is a substantial reduction, representing the portion of their food insecurity attributable to the experience of flooding and forced migration.

The ATU of -11.59 answers a different question. Take a non-migrant household in Etche, which never floods. Their observed HFIAS score is 2.16. The ATU tells us that if this same household were transplanted into a flood-prone area and forced to migrate annually, their food insecurity would increase by 11.59 points, rising to nearly 14, similar to actual migrants. This large counterfactual effect underscores that non-migrants are not inherently more resilient. They simply live where flooding does not occur. The difference in food security between the two groups is not driven by some inherent superiority of non-migrants, but by the environmental shock that migrants cannot escape.

The ATE of -2.14 pools both groups and asks: what is the average effect of flooding-induced migration on a randomly selected household from the entire population? The negative value indicates that, on average, exposure to flooding and forced displacement reduces food security across the study population as a whole.

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 findings revealed that early planting and harvesting constituted the major coping strategy adopted by farming households in response to recurrent flooding. The results further showed that flooding-induced migration significantly influenced household food security outcomes, as measured by HFIAS and farm revenue. The study concludes that recurrent flooding remains a major threat to agricultural livelihoods and food security in the study area. In specific terms, the study concludes that;

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 therefore, potential revenue generated 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 embankments 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, 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 on the other hand 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.

Limitations

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.

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.

The gender imbalance in our sample (98% male, 2% female for migrants and 93% male, 3% females for non-migrants), reflects the composition of household heads in crop-farming households in the study area. However, flooding-induced migration affects all household members regardless of gender, and food insecurity outcomes captured at the household level reflect the experiences of both men and women. Future research should specifically examine gender-differentiated impacts on food security.

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.

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.

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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.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.sciaf.2026.e03559](https://doi.org/10.1016/j.sciaf.2026.e03559).

Data availability

The data used for this study are available from the corresponding author upon request.

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