



EFFECTS OF FLOOD ON FOOD SECURITY OF ARABLE FARMERS IN NIGERIA

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ABSTRACT

The study assessed the effects and determinants of flood-induced food insecurity among 401 randomly selected arable farmers in Nigeria. Employing a multi-analytical approach, the study utilised the Food Insecurity Experience Scale (FIES), a Generalized Propensity Score (GPS) model to estimate a continuous dose-response function, and a Tobit regression for determinant analysis. Results revealed that the mean FIES score was 0.806, with majority (55%) of farmers experiencing severe food insecurity. The negative linear coefficient for flood (-0.00751, $p < 0.01$) and the positive quadratic term ($6.59e-05$, $p < 0.01$) revealed that food insecurity initially decreases slightly with minimal flooding but then increases at an accelerating rate as flood coverage. Crucially, Tobit regression analysis identifies key mediating factors: access to agricultural credit, extension services, and input subsidies, significantly mitigated food insecurity (-0.194, $p < 0.01$; -0.186, $p < 0.01$ and 0.252, $p < 0.05$ respectively). Conversely, larger household size, population ageing, and being a female household head were associated with increased food insecurity (0.003, $p < 0.01$; 0.101, $p < 0.01$ and -0.168, $p < 0.01$ respectively). The study concludes that while flood extent directly drives food insecurity, institutional resources (credit, extension, subsidies) significantly buffer this effect, whereas demographic pressures amplify it. Hence, flood impacts are contingent on farmers' access to support systems, not just on hazard exposure. We provide actionable policy recommendations, advocating for the proactive scaling of credit, extension, and subsidy programmes, and the implementation of demographically-sensitive, intensity-targeted disaster response protocols to build systemic resilience and safeguard national food systems against escalating climatic shocks.

Keywords: Food, Insecurity, Flood, Arable, Smallholder Farmers.

INTRODUCTION

Across the globe, climate change manifests as an intensifying rhythm of extreme weather events. Among these, flooding stands as one of the most pervasive and destructive, crippling infrastructure, displacing communities, and fundamentally destabilizing agricultural systems upon which human sustenance depends. The global agricultural sector bears approximately 23% of the total economic impact of floods, with losses concentrated in the cropland of developing nations (Rentschler *et al.*, 2022). This threat accompanied by acute severity into Sub-Saharan Africa (SSA), a region characterized by rain-fed agriculture, low adaptive capacity, and entrenched poverty (Aliyu *et al.*, 2023). Here, flooding compounds existing vulnerabilities, transforming fertile plains into landscapes of loss and jeopardizing the fragile food security of millions (Badamosi *et al.*, 2024).

Nigeria, SSA's most populous nation and agricultural powerhouse, embodies this risk and vulnerability. Its agricultural sector, dominated by an estimated 38 million smallholder arable farmers who contribute over 70% of the national food supply, is acutely exposed (FAO, 2025). Recurrent and intensified flooding, driven by erratic rainfall and inadequate water management, has become a chronic disruptor. The 2024 floods alone affected over 1.3 million people, vast (194637) number of farmlands were affected and 729310 households were displaced leaving farmers in alarming rate of food insecurity, this showed a climate-stressed future (National Emergency Management Agency [NEMA], 2025; Coordination of Humanitarian Affairs [OCHA], 2025). For the Nigerian arable farmer, a flood event is not merely an environmental inconvenience; it is a direct attack on livelihood capital (crops, soil, and stored harvest) that triggers an immediate crisis of food access and availability (Merz *et al.*, 2021; OCHA, 2025).



Food insecurity, defined as the “lack of consistent access to sufficient, safe, and nutritious food at all time” (Paslakis *et al.*, 2021), it remains a persistent challenge globally, with its most severe forms concentrated in SSA (Sara, 2024). Within Nigeria, despite its agricultural output, an estimated 30.6 million people faced crisis or worse levels of acute food insecurity in 2025 (FAO, 2025). Arable farmers, unfortunately, are not in isolation from this hunger; they are often its frontline victims when production shocks strike (Touch *et al.*, 2024). The relationship between flood and food insecurity is direct. flooding destroys standing crops and stored grain (Akukwe *et al.* 2020), erodes productive assets (Akukwe *et al.* 2020), disrupts local food markets (Badomosi *et al.*, 2024), and depletes household resources needed to purchase food (Reed *et al.*, 2022). This transforms the farmers into food-insecure populations, creating a devastating cycle where those tasked with feeding the nation struggle to feed their own families.

Despite the intuitive gravity of this problem, critical empirical gaps persist in the Nigerian context. Existing literature often treats flood impact as a binary event [affected/not affected] (Oskorouchi & Sousa-Poza, 2021) or before and after (Akukwe *et al.* 2020), some only describes the effects of the floods (Badomosi *et al.*, 2024) failing to capture the gradient of exposure, how different intensities of flooding relates with varying depths of food insecurity. Furthermore, while socioeconomic determinants of food security are well-studied in stable conditions, less is known about which specific factors (institutional access, demographic structure, asset bases) most powerfully mediate outcomes in the specific context of a post-flood shock. This limits the ability of policymakers to move from generic disaster response to precisely targeted resilience-building.

This study, therefore, seeks to bridge these gaps. We employ a multi-analytical approach, integrating descriptive statistics, a Generalized Propensity Score (GPS) model, and Tobit regression to achieve three core objectives: (i) to diagnose the severity and distribution of food insecurity among flood-affected arable farmers using the robust Food Insecurity Experience Scale (FIES); (ii) to estimate the dose-response relationship between the percentage of farm area flooded and the level of food insecurity; and (iii) to identify the key socioeconomic and institutional factors that determine hunger in the aftermath of the shock.

Our contribution to the literature is threefold. Methodologically, we demonstrate the value of the GPS framework in modeling continuous exposure to climatic shocks in agricultural economics, moving beyond simplistic binary treatment effects. Empirically, we provide nuanced, quantitative evidence on the specific pathways through which flooding translates into hunger for Nigeria's crucial smallholder sector. Politically, our findings speak directly to the Sustainable Development Goals (SDGs), specifically SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 1 (No Poverty). By pinpointing the most vulnerable groups and the most effective resilience buffers, this study provides an evidence-based roadmap for crafting policies that not only respond to disasters but actively build the capacity of agricultural households to withstand them, thereby securing food systems in an increasingly uncertain climate.

MATERIAL AND METHOD

Study Area

This study was conducted in Bauchi State, northeastern Nigeria, which lies between latitudes 9° 3' and 12° 3' N and longitudes 8° 50' and 11° E, a core region of the Sudan Savanna agro-ecological zone. The State is projected to have a population of approximately 9,281,000 by 2026 (Xplorer, 2026). The area is characterized by a unimodal rainfall pattern (May, September) that sustains rain-fed agriculture but also drives recurrent flooding through the Gongola and Jama'are River basins (Kafi, 2026). These rivers create fertile fadama (floodplain) lands, which are paradoxically the most productive for arable farming, dominated by maize, sorghum, millet, and rice and the most vulnerable to inundation.

Bauchi State is predominantly agrarian, with most of the population engaged in smallholder subsistence farming (Kafi, 2026). The study focuses on communities in highly flood-prone Local Government Areas (e.g., Katagum, Itas/Gadau, Gamawa, Shira) situated within these active floodplains. The State represents a classic high-productivity, high-vulnerability system where farmers are

economically incentivized to cultivate fertile floodplain soils yet are systematically exposed to catastrophic hydrological shocks.

The state has a documented history of severe floods (e.g., 2012, 2022, 2024), in 2024 alone, Over 94,000 people were affected, among which 36,000 people were displaced with 29 fatalities, making it an ideal case for investigating the microeconomics of climate impacts (ICIR, 2025; Ibrahim, 2024). The findings from this context are directly relevant to similar fadama based agricultural systems across the Sudano-Sahelian region of West Africa.

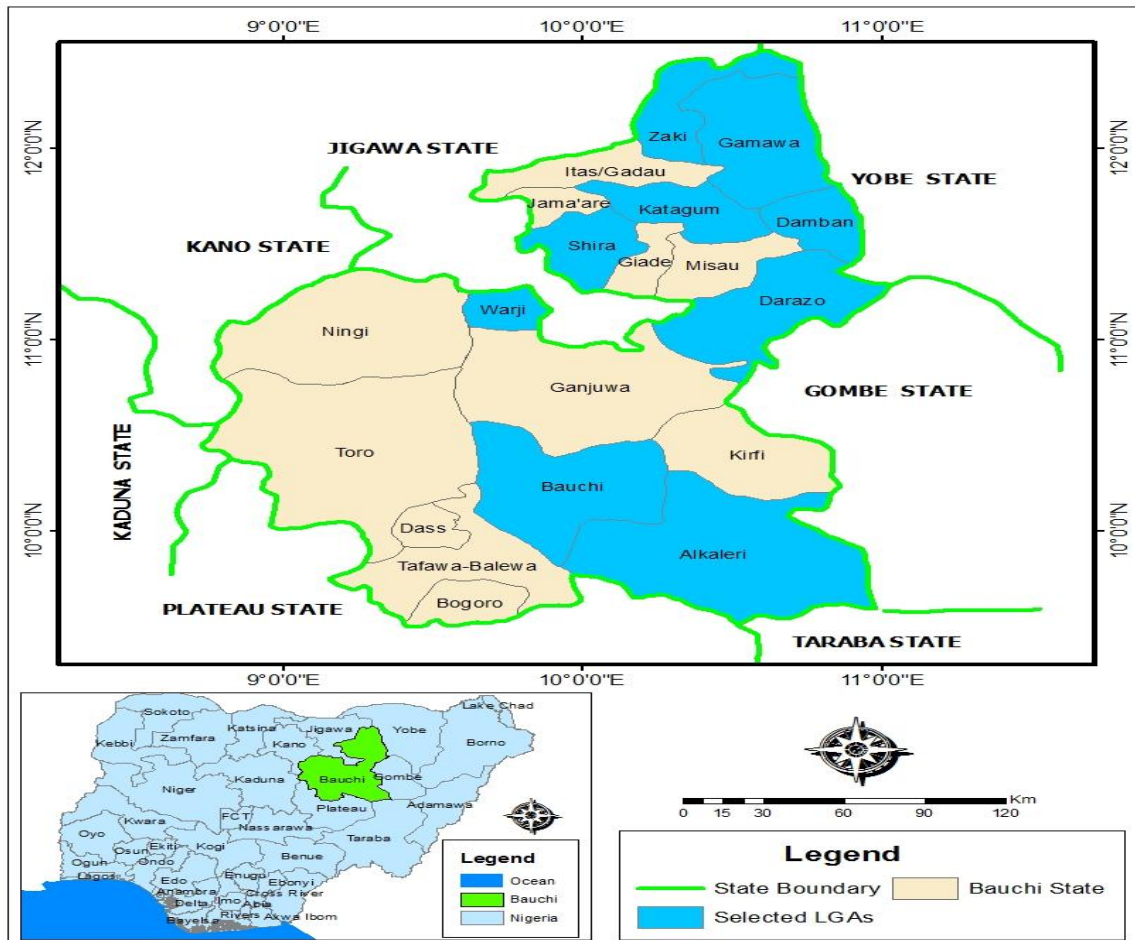


Figure 1: Map of the Study Area

Sampling Procedure and Sample Size

Multi-stage sampling procedure was employed for the study. In the first stage, all the flood affected areas identified in a reconnaissance survey were stratified based on agro-ecological zones (northern, central and western) they fall in. In a second stage, 16 Local Government Area (L.G.A) were identified out of which 50% of the L.G.As that falls within each zone were purposively and proportionately selected based on the concentration of the affected arable crop farmers, these comprises Gamawa, Shira, Katagum, Zaki and Dambam in northern zone, Warji and Darazo in central zone and Bauchi and Alkaleri in western zone. In the third stage, Yemane formular was used in selection of the respondents for the study from the sample frame of 224,365 flood affected arable crop farmers and spread across the L.G.A using the sample ratio formular, making 401 arable crop farmers for the study.

Method Data Collection

Data were collected using scheduled interview in September 2025 using well-trained enumerators by the team of researchers. Data collected were the socio-economic and institutional



characteristics, FIES questions. Also, nature, frequency, coverage of flood were also captured in the interview.

Method of Data Analysis

Data were analysed using both descriptive and inferential statistics, Descriptive statistic such as frequency, percentage, mean and Standard deviation were used to achieve objective (i) while inferential statistic (Generalised propensity score (GPS)) and Tobit regression were used to achieve objective (ii) and (iii) respectively.

The outcome variable

The FIES model had eight questions (worried about not having enough food, could not eat healthy and nutritious food, ate only a few kinds of foods, had to skip a meal, Ate less than you thought you should, household ran out of food, were hungry but did not eat and Went without eating for a whole day). At that point, 1s were assigned to affirmative responses and 0s to otherwise. Since the FIES consisted of eight questions, the raw score ranged from 0 to 8. The study used the Voices of the Hungry project’s FIES app (a free and simple analytical tool for analyzing FIES data) to produce the parameter estimates and other outputs related to statistical validation (Cafiero *et al.* 2022). Following the FIES data analysis methodology, cases with raw scores of 0 and 8 were considered extreme values and eliminated from the statistical validation process; however, they were included in the assessment of FI prevalence (Cafiero *et al.* 2016). However, 1000 or more complete (meaning they had no missing response) and non-extreme (raw score between 1 and 7) cases are required to have confidence in the statistical validation of FIES data (Cafiero *et al.* 2018).

We then equate all eight items to the FIES global standard scale. After that, two globally-comparable indicators of the prevalence of FI at different levels of severity: moderate or severe FI (raw score = 4 to 6) and severe FI (raw score = 7 to 8), were calculated. All analyses were adjusted for sampling weights.

Tobit Regression Model

A Tobit regression model was used to analyze the determinants of food insecurity because the FIES index is a limited dependent variable censored at 0 and 1. The model is specified as:

$$y_i^* = X_i\beta + u_i, \quad u_i \sim N(0, \sigma^2)$$

$$y_i = 0 \quad \text{if } y_i^* \leq 0$$

$$y_i = y_i^* \quad \text{if } 0 < y_i^* < 1$$

$$y_i = 1 \quad \text{if } y_i^* \geq 1$$

Where y_i^* is the latent food insecurity variable, y_i is the observed FIES index, X_i is a vector of explanatory variables (including flood coverage, socioeconomic characteristics, and institutional factors), β is a vector of parameters to be estimated, and u_i is the error term. The Robust standard errors were used in both models to account for potential heteroskedasticity, as suggested by Imbens & Kolesar (2016) and estimated using maximum likelihood estimation.

Generalized Propensity Score (GPS) Model

The GPS method was applied to estimate the causal effect of continuous flood exposure (Flood Coverage) on food insecurity. The model corrects for selection bias by conditioning on covariates that influence both the treatment level and the outcome. The GPS, denoted as R, is defined as the conditional density of the treatment given the observed covariates X:

$$R = f(T|X)$$

where T is the treatment variable (Flood Coverage) and X is a vector of pre-flood characteristics (e.g., age, education, farm size).

The outcome model was specified as a quadratic function of the treatment and the GPS:

$$Y = \beta_0 + \beta_1 T + \beta_2 T^2 + \beta_3 R + \beta_4 R^2 + \beta_5 (T * R) + \epsilon$$

where Y is the FIES index. The dose-response function was derived by averaging the conditional expectation of Y over the distribution of the GPS at each treatment level. The GPS analysis followed the three-step procedure: (1) estimation of the GPS using a normal distribution model, (2) estimation of the conditional expectation of the outcome, and (3) estimation of the dose-response function by



averaging the conditional expectation. The balancing property of the GPS was tested and confirmed. All the analyses were achieved using a STATA 19.

RESULT AND DISCUSSION

Description of the Flood Affected Arable Farmers

The result in Table 1 revealed that the mean of the output variable (FIES) for the arable farmers is 0.806, with a standard deviation of 0.26271. The scale ranges from 0 (no insecurity) to 1 (most severe insecurity).

It means that, an average score of 0.806 indicates that the typical flood-affected farmer in Bauchi State is experiencing food insecurity at a high level of severity. This is not merely anxiety about food; it translates to concrete experiences of reduced food quality, skipped meals, and going entire days without eating due to a lack of resources. This acute condition is the direct and compounded consequence of the flood. The inundation likely destroyed standing crops (current food stock and income source), damaged stored harvests, and devastated farm assets. This is in conformity with the findings of Akukwe *et al.* (2023) who found that farmers' food insecurity drastically increases after floods in South-East Nigeria. More so, as shown in Table 2, with 80% of the arable farmers receiving no aid and productive support being rare after the flooding, households are forced to deploy the most severe coping strategies, which the FIES is designed to measure. This agrees with Mohammed and Favretto (2025), who found poor institutional support for farmers who were affected by floods in dryland Nigeria.

This implies that the mean score, approaching the theoretical maximum of 1, signals a severe food security crisis within this arable farming population. This is not a marginal increase in hardship but a catastrophic erosion of dietary well-being. For agricultural economics and policy, this moves the discussion beyond abstract production losses. It quantifies the translation of a flood into a severe human welfare outcome. The low standard deviation suggests this misery is widespread and consistent across the arable farmers, not isolated to a few. This finding was unequivocally related the flood event to a failure in the household's ability to maintain basic food access, underscoring that without effective intervention to restore livelihoods, the flood's impact will extend far beyond the initial event, causing long-term nutritional and economic damage. This is in line with the findings of Akukwe *et al.* (2023). The result further showed that the average farmer was averagely 46 years old with substantial farming experience (24 years). The arable farmers were predominantly male (96%) and married (94%). They had a basic formal education (8.8 years, roughly Junior Secondary level) and operate on smallholdings averaging 2.6 hectares. Notably, average annual farm income (₦1,366,347) is nearly double non-farm income (₦773,965), and households are large, averaging 16 members. These affirmed the findings of Shehu *et al.* (2020) who found that farmers were in their active age, with substantial farming experience, mostly men and with low level of education in North-East Nigeria.

Furthermore, the typical respondent is a middle-aged, male head of a large household, relying primarily on farming for livelihood but with limited land resources and moderate education. This was probably due to the demographic structure of rural Nigerian agriculture, where farming is often a primary occupation passed through generations, with men typically controlling land assets. Large household sizes are consistent with extended family systems, providing labour but also increasing consumption needs. This profile revealed serious vulnerability. The heavy reliance on farm income, coupled with limited land holdings, means any flood shock to agricultural production directly and severely threatens household financial stability and food access. The large household size further intensifies food demand and security pressure post-disaster.

In addition, access to institutional support was low. Only 9% had contact with extension services, 14% accessed credit, and a mere 2% benefited from agricultural subsidies. In contrast, 46% had access to flood early warning signs.

These mean that most farmers are operating without formal agricultural guidance, financial services, or government input support. However, nearly half received some form of flood warning. The weak state of agricultural extension systems and stringent/absent credit mechanisms in rural Nigeria explains the low access. Early warning access, while still low, is relatively better, likely due to



dissemination through mass media or community channels by agencies such as NIMET. The near absence of extension, credit, and subsidies indicates a profound lack of resilience-building infrastructure. Farmers are essentially left to face climatic shocks with traditional knowledge and personal resources. The moderate access to early warnings implies a potential entry point for policy, but the result confirms that without complementary support (credit for recovery, extension for resilient practices), warnings alone are insufficient to mitigate food security impacts. This is in line with the findings of Madaki *et al.* (2025) who inferred the poor institutional support services for climate change adaptation in the study area.

Also, the prevalence of physical disability was low (2%), and most households are structured around one or two generations (mean 1.6). Physical challenges are not widespread among the sampled farmers, and complex multi-generational co-residence is not wide spread. While disability is not a major factor in this sample, the large household size itself remains the key demographic stressor. The household structure variable will be crucial in later multivariate analysis to unpack how different family compositions cope with and experience food insecurity following a flood. This is in conformity with the findings of Shehu *et al.* (2025) who found a low prevalence of disability within the farmers and majority were in second generation household structure in North-east Nigeria.

Table 1: Description of the Flood Affected Farmers Characteristics n= 401

Variable	Description	Mean	Std. Dev.	Min.	Max.
Output					
Food insecurity	Food insecurity experience scale index	0.806	0.26271	0	1
Age	Age of the flood affected farmers in years	45.95	13.135	18	85
Sex	Sex of the flood affected farmers Male=1, otherwise=0	0.96	0.202	0	1
Marital status	Marital of the flood affected farmers, Married=1, otherwise=0	0.94	0.247	0	1
Education	Years of formal education of the flood affected farmer	8.83	5.17	0	19
Farm size	Size of the cultivated land by the flood affected farmers in hectares	2.611	2.111	0.3	16
Ageing	Old age dependency ratio of the flood affected farmers. It is unitless	0.06	0.206	0	3
Household size	Household size of the respondents in years	15.94	12.391	1	90
Farming experience	Farming experience of the respondents in years	24.37	14.074	3	65
Farm income	Annual farm income of the flood affected farmers	1366347	1660189	25000	15000000
Non-farm income	Annual non-farm income of the flood affected farmers	773965.1	1119632	27000	8300000
Health factor					
Disability	Physical challenge status of the flood affected farmers Physically challenged=1, otherwise=0	0.02	0.156	0	1
Socio-cultural factor					
Household Structure	The type of generation in of the flood affected farmers' household, one generation= 1, two generation= 2, three generation= 3	1.6	0.697	1	3
Institutional factors					
Extension contact	Whether the flood affected farmer received extension contact =1, otherwise= 0	0.09	0.293	0	1
Access to credit	Whether the flood affected farmer accessed credit =1, otherwise= 0	0.14	0.344	0	1
Access to agricultural subsidy	Whether the flood affected farmer accessed agricultural subsidy =1, otherwise= 0	0.02	0.131	0	1
Access to Flood Early Signs	Whether the flood affected farmer accessed early warning sign information =1, otherwise= 0	0.46	0.499	0	1

Source: Field Survey (2025)

Note: NIMET= Nigeria Meteorological Agency, BSADP= Bauchi State Agricultural Development Programme, SEMA= State Emergency Management Agency, NEMA= National Emergency Management Agency

Distribution of Flood Affected Arable Farmers based on Receipt of Support and its Form after Flood

Table 2 revealed that only 19.5% of the affected arable farmers received some form of assistance following the flood, leaving the majority (80.5%) without any external support. That means, for every five farmers whose farms were flooded, four received no help whatsoever to recover.



This likely reflects the severe limitations of state and national emergency management agencies (SEMA/NEMA) in terms of funding, logistics, and coverage. Assistance may be concentrated in more visible urban or peri-urban areas, while dispersed rural farming populations are systematically overlooked. This implies that the inadequacy of a safety net forces the vast majority of farmers to rely solely on personal savings, informal networks, or distress sales of assets to survive and restart farming. This dramatically deepens the flood's impact, eroding productive capital and pushing households into negative coping strategies that compromise future food security. The result is a protracted recovery period and heightened vulnerability to subsequent shocks. This agrees with the findings of Odiana *et al.* (2023) who showed inadequate support to flood affected farmers in Edo State Nigeria.

Among the few who received aid, the form was predominantly short-term relief: food items (63.7%) and cash (21.2%). Basically, support aimed at restoring agricultural production, farm inputs, constituted a mere 6.2% of responses. Meaning for the small fraction that got help, it was mostly about keeping them fed today, not about helping them farm again tomorrow. Emergency responses often prioritize immediate humanitarian relief (food, shelter) over livelihood rehabilitation. This is compounded by a possible disconnect between emergency management agencies (focused on relief) and agricultural development agencies (focused on production), and by the simpler logistics of distributing food packs compared to sourcing and delivering quality seeds and fertilizers. This pattern of support revealed a flaw in the disaster response framework for an agrarian community. While alleviating acute hunger, providing only food aid fails to address the root cause of the impending food security crisis: the loss of productive capacity. Without inputs to replant, farmers miss the next planting season, transforming a short-term production shock into a long-term food security deficit. The assistance, therefore, treats the symptom but not the disease. This is in concordance with the findings of Umar *et al.* (2025) who found a flawed disaster response in Borno State Nigeria.

Table 2: Arable Farmers' Receipt of Support and Form after Flood

Variable		Frequency	%
Support after flood	Received assistance after flood	78	19.5
	Not received assistance after flood	323	80.5
	Total	401	100
Form of support	Food items	72	63.7
	Cash	24	21.2
	Building materials	3	2.7
	Blanket	7	6.2
	Farm inputs	7	6.2
	Total	113*	100

Source: Field Survey (2025)

Note: *= multiple response

Diagnostic Lens on The Precise Sequence of Food Insecurity Experienced by Flood Affected Arable Farmers

The items are ordered by increasing severity parameter (Table 3). Experiences like worrying about food (Worried: -0.737) and compromising on food quality (Healthy: -1.311) are the least severe and most common. Progressively more severe experiences such as reducing food intake (AteLess: -1.133), skipping meals (Skipped: -1.602), and running out of food (RunOut: -0.112) follow. The most severe items, experiencing hunger (Hungry: 2.591) and going a whole day without eating (WholeDay: 3.806), have high positive severity parameters.

This confirms that food insecurity of the flood affected arable farmers follows a predictable descent. It starts as anxiety and dietary compromise before escalating to actual reductions in quantity, and finally, for the worst-affected, to genuine hunger and starvation. This hierarchy is intrinsic to the validated FIES methodology, reflecting a universal progression of coping strategies under resource scarcity. The high severity scores for Hungry and WholeDay indicate these are rare, catastrophic events even within this distressed population. This implies that the statistically sound ordering validates our



measurement tool in this specific context. It confirms that the scale reliably distinguishes between different levels of deprivation. The high prevalence of early-stage items (e.g., Fewfood, Skipped) confirms widespread moderate to severe food insecurity, while the occurrence of the most severe items (Hungry, WholeDay) showed that a subset of households has entered a critical, famine-like phase (Cafiero *et al.*, 2018; Cafiero *et al.*, 2016).

Table 3: Diagnostic Food Insecurity Item Statistics

Item	Severity	S.E.	Infit	S.E.Infit	Outfit	N_Yes_Compl	N_if_any_valid
Worried	-0.737	0.291	1.321	0.185	2.512	138	0
Healthy	-1.311	0.326	0.975	0.214	0.358	145	0
Fewfood	-1.502	0.337	0.386	0.221	0.119	147	0
Skipped	-1.602	0.343	1.131	0.223	2.815	148	0
AteLess	-1.133	0.315	0.678	0.207	0.630	143	0
RunOut	-0.112	0.260	1.285	0.154	1.386	128	0
Hungry	2.591	0.235	0.831	0.158	0.838	46	0
WholeDay	3.806	0.289	1.002	0.188	0.790	15	0

Source: Field Survey (2025)

Classification of the Flood Affected Arable Farmers into Food Insecurity Severity Categories

Using globally comparable thresholds (Moderate+Severe FI ≥ -0.600 ; Severe FI ≥ 3.606), the result in Table 4 revealed the classification of the flood affected arable farmers. Majority (55.6%) of the flood affected arable farmers (those with a raw score of 8) have an 84.6% probability of being in *Severe* food insecurity. Most of the arable farmers with a raw score of 4 or higher exceed the threshold for *Moderate-or-Severe* food insecurity. Overall, the prevalence of *Moderate-or-Severe* food insecurity in this sample is exceptionally high (calculated from the rightmost columns), with *Severe* food insecurity concentrated in the large cluster at the highest raw score. This means that the flood has not just caused mild hunger. It has plunged the majority of affected arable farmers into a state of severe food deprivation, where skipping meals, going hungry, and not eating for a whole day are likely realities.

This catastrophic prevalence is the direct outcome of the production shock from the flood, compounded by the near-total lack of effective institutional safety nets (as shown in Table 2). The loss of crops, income, and assets forces households to rapidly exhaust all coping strategies, quickly moving them into the highest severity categories. This implies that the classification confirms a food security emergency within flood affected arable farmers. The extremely high probabilities associated with raw scores of 6, 7, and especially 8 mean that traditional survey measurement error is negligible for policy diagnosis; this group is unequivocally in crisis. For policymakers and responders, this table provides the actionable thresholds for targeting: interventions aimed at *Severe FI* must prioritize the majority (55.6%) at raw score 8, while broader food support must cover everyone from raw score 4 upwards. This quantification moves the narrative from qualitative description to precise epidemiology of hunger, enabling resource allocation based on calibrated need. It starkly illustrates that the flood's primary economic effect is a mass descent into acute food insecurity, threatening not just livelihood sustainability but immediate human welfare. This is in line with Parvez *et al.* (2022) who found that majority of the flood affected farmers were food insecure in Bangladesh.

Table 4: Severity of Food insecurity of the Flood Affected Arable Farmers

Raw score	Percentage of individuals	Comparable thresholds	Moderate+Severe FI	-0.600
			Severe FI	3.606
		Probability (mod+sev)		Probability (sev)
0	0.035	0.0000		0.0000
1	0.022	0.0255		0.0000
2	0.015	0.0821		0.0000
3	0.002	0.2798		0.0000
4	0.027	0.5983		0.0000
5	0.057	0.8570		0.0008
6	0.177	0.9697		0.0595
7	0.107	0.9981		0.4328
8	0.556	0.9999		0.8456

Source: Field Survey (2025)

Note: FI= Food insecurity

Factors Influencing Food Security of Flood Affected Arable farmers

Table 5 identifies the drivers of food insecurity following the flood. The access to institutional support significantly reduces food insecurity. Access to Credit (Coefficient: -0.194, $p < 0.001$) and Extension Contact (-0.186, $p = 0.003$) are both negatively and significantly related to the FIES index, meaning they improve food security. Similarly, Access to Agricultural Subsidy (0.252, $p = 0.017$) increases the food security index (i.e., lowers insecurity). The magnitude of damage is the primary driver: Flood Coverage is the strongest negative factor (-0.002, $p < 0.001$).

The arable farmers, who could get a loan, receive expert farming advice, or benefit from input subsidies suffered less hunger after the flood. Unsurprisingly, the more land that was flooded, the worse the hunger became. Credit likely enabled farmers to purchase food, replant, or hire labour for recovery, buffering the immediate shock. Extension services probably provided critical advice on post-flood management, salvageable crops, or alternative practices. Subsidies reduced production costs pre-flood, potentially increasing resilience. These factors represent actionable leverage points for intervention.

This implies that strengthening rural financial systems, revitalizing extension services, and expanding input subsidy programs are effective strategies for building resilience to climate shocks like floods. The coefficients quantify their protective effect. However, their currently low access rates (as shown in Table 1: 14% for credit, 9% for extension) represent a massive coverage failure, leaving most farmers exposed. Therefore, the policy imperative is not just to confirm these supports work, but to dramatically scale up their availability and targeting to vulnerable smallholders. This finding corroborates that of Abdi *et al.* (2024) and Wudil *et al.* (2022) who found that poor institutional quality exacerbates food insecurity in SSA.

Larger (0.003, $p \leq 0.01$) and a higher Ageing dependency ratio (0.101, $p \leq 0.05$) significantly increase food insecurity. Being Married (0.227, $p \leq 0.05$) is associated with greater food security. This means that more dependents in a household increase the risk of hunger after a shock, this is in line with Dumisa *et al.* (2025) who found who found larger household to be less food insecure in SSA countries and Ren *et al.* (2023) who found that ageing threatens food security in China, while the social and economic support of marriage appears to be protective which was contrary to the Dumisa *et al.* (2025). Social protection and recovery programs should be explicitly calibrated for household demographic composition, providing additional support to large households and those with elderly dependents, as they are predictably more vulnerable.

Notably, being female (Sex: -0.168, $p \leq 0.01$) and having more Farming Experience (0.003, $p = 0.053$) are associated with *greater* food insecurity, while larger Farm Size (-0.012, $p \leq 0.1$) shows a marginal tendency to reduce it. Marital Status (0.227, $p \leq 0.05$) is protective, this is in line with Umar *et al.* (2025). Hunger after a flood is worst for those with the most flooded land. The paradox of female and experienced arable farmers faring worse may reflect their role as primary household caregivers restricted mostly to the economic activities within their homes, and potentially a greater



reliance on traditional farming methods less adaptable to extreme floods. Larger Farm Size, while a risk factor for greater absolute loss, likely provides a critical buffer through scale, residual unaffected areas, or greater collateral for recovery.

This implies that investment in rural finance, advisory services, and input support as effective resilience-builders. Second, it identifies high-risk groups for targeted social protection: female-headed households, large families, and those with elderly dependents. The negative coefficient for female-headed households necessitates a re-evaluation of gender-focused aid, suggesting that the pressure of being the sole breadwinner in a crisis creates unique vulnerabilities. This was in conformity with the findings of Dumisa *et al.* (2025) who found females to be less food insecure in SSA countries. Finally, the positive role of farm size, though marginal, underscores that policies supporting land access and consolidation could enhance long-term climate resilience, this is in line with Abdi *et al.* (2024) and Dumisa *et al.* (2025) who found farm size to be improving food security in SSA countries.

Table 5: Factors Influencing Food insecurity of Flood Affected Arable Farmers

Variable	Coefficient	Robust S.E	T-value	P> t
Age	-0.002	0.002	-1.32	0.189
Sex	-0.168	0.060	-2.82	0.005
Marital status	0.227	0.089	2.55	0.011
Education	-0.001	0.002	-0.56	0.576
Farm size	-0.012	0.007	-1.74	0.083
Ageing	0.101	0.044	2.29	0.023
Household size	0.003	0.001	2.68	0.008
Farming experience	0.003	0.002	1.94	0.053
Disability	-0.001	0.078	-0.01	0.99
Household Structure				
Two generation	-0.045	0.029	-1.58	0.115
Three generation	-0.011	0.041	-0.27	0.791
Access to credit	-0.194	0.046	-4.23	0
Extension contact	-0.186	0.062	-3.02	0.003
Access to Agricultural subsidy	0.252	0.105	2.4	0.017
Flood early warning access	0.028	0.028	0.99	0.324
Flood coverage	-0.002	0.000	-4.2	0
Constant	0.860	0.099	8.65	0
var(e.FIES_Index)	0.055	0.007		
Log pseudolikelihood	-9.932			
F(16, 383)	9.77***			
Pseudo R ²	0.854			

Source: Field Survey (2025)

Impact of Flood on Food Insecurity of the Flood Affected Arable Farmers

Table 6 moves beyond simple relationship to estimate the *dose-response relationship* between flood intensity and food insecurity. It quantifies how each additional percentage of farmland flooded translates to hunger. The model revealed a significant and non-linear relationship. The negative linear coefficient for extent of flood (-0.00751, p<0.01) and the positive quadratic term (6.59e-05, p<0.01) indicate that food insecurity (measured as a continuous index) initially decreases slightly with minimal flooding but then increases at an accelerating rate as flood coverage intensified (Appendix I). This means that a small flood might not immediately crash a household's food security, perhaps due to partial harvests or stored food. However, after a certain threshold, the damage becomes catastrophic, each additional hectare flooded causes a disproportionately larger jump in hunger. The relationship is not a straight line but a steepening curve.

This was likely due to the initial resilience affects the buffering capacity of savings, alternative food stocks, or income sources and the flood comes along with nutrients. The accelerating negative impact occurs because beyond a critical point (the inflection point of the quadratic function), the flood destroys not just the current season's harvest but also seed stocks, soil fertility, and farm infrastructure,



eroding the very foundation of future production and pushing households into irreversible coping strategies.

This finding is important for policy and disaster assessment. It demonstrates that the impact of flooding on food security is non-linear and convex. Marginal damage assessments will underestimate total welfare loss. Targeting support based solely on a binary "affected/not affected" classification is inadequate; the *intensity* of exposure is a key determinant of need. Recovery programs must be scaled disproportionately to the severity of the flood coverage, with the most intensive interventions reserved for farms with high percentage losses, where the marginal increase in food insecurity is greatest. This provides an empirical basis for tiered post-disaster response. This agrees with the findings of Reed *et al.* (2022) who found mixed impact of flood on food security in Africa. Also, Yolchi *et al.* (2024) and Atanga *et al.* (2021) revealed that the flood reduced food security of household in Afghanistan and Northern Ghana respectively.

Table 6: Impact of Flood on Food Insecurity

Variable	Coefficient	S.E	T-value
Linear function	-0.00751	0.002587	-2.9
Quadratic function	6.59E-05	1.98E-05	3.33
GPS	0.019879	0.023902	0.83
GPS squared	-0.0001	0.000158	-0.65
Constant	0.053581	0.915272	0.06
F-value	6.88***		
R-squared	0.065		

Source: Field Survey (2025)

CONCLUSION AND RECOMMENDATIONS

The study employed a multi-method analytical framework, integrating descriptive statistics, the Food Insecurity Experience Scale (FIES), Generalized Propensity Score (GPS) modelling, and Tobit regression to assess the impact of flooding on the food security of arable farmers in Nigeria and to isolate its key determinants.

Flooding is not a marginal disruption but a catastrophic shock that plunges a majority of affected smallholders into severe food insecurity. The GPS model established a significant, non-linear dose-response relationship, where food insecurity increases at an accelerating rate with the percentage of farm area flooded. This convex relationship indicates that marginal damage assessments severely underestimate total welfare loss and revealed the need for post-disaster support scaled to the intensity of exposure.

The Tobit regression analysis, controlling for flood intensity, identified the critical factors mediating this outcome. Institutional access emerged as a powerful mitigating force: access to credit, extension services, and agricultural subsidies were all statistically significant in reducing food insecurity. This confirms their theoretical role as resilience-building buffers that enhance household adaptive capacity. Conversely, larger household size and a higher old-age dependency ratio significantly increased food insecurity, highlighting the role of demographic pressure as a risk amplifier. The counterintuitive result that male gender and greater farming experience were associated with heightened food insecurity suggests complex vulnerability pathways, potentially relating to gendered expectations of provision and path dependency in agricultural practice.

The study's contributions are threefold. *Methodologically*, it demonstrates the utility of the GPS approach for modeling continuous climate shock exposure in agricultural economics, moving beyond binary treatment effects. *Empirically*, it provides quantitative evidence on the specific pathways linking flood exposure to hunger for Nigeria's crucial smallholder sector. *Politically*, the findings offer direct guidance for achieving the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 1 (No Poverty).

The policy implications are immediate and actionable:



The Federal and State Ministries of Agriculture & Rural Development: Your mandate to ensure food security and support farmers is directly addressed by our findings. The evidence is unequivocal: scaling up access to credit, extension services, and input subsidies is your most effective tool for building pre-flood resilience. The current coverage rates of 14% for credit and 9% for extension represent a critical programmatic failure. We recommend you immediately:

- i. Launch a Targeted "Resilience Voucher" Program: Allocate a dedicated portion of the agricultural budget to provide smallholder farmers in high-flood-risk areas with vouchers redeemable for stress-tolerant seeds, fertilizers, and micro-insurance premiums, contingent on participation in extension-led climate-smart training.
- ii. Mandate Intensity-Based Disaster Assessment: Issue a directive that all post-flood damage assessments by SEMA, NEMA, and your own departments must record the *percentage of farmland inundated per household*. This data is non-negotiable for moving from blanket aid to the efficient, tiered support system our finding proves is necessary.

Moreover, the NEMA and SEMA should deploy a tiered disaster response framework: Our dose-response model shows that a farmer with 80% of land flooded is not just worse off than one with 20% flooded, they are *exponentially* worse off. Your standard relief packages must reflect this. The study recommends:

- i. Adoption of a Tiered Response Protocol: Develop clear response triggers where aid packages are scaled based on verified flood coverage thresholds. The most comprehensive packages, combining food aid, cash for work, and productive asset restocking, must be reserved for those above the high-severity threshold (3.606) identified in this study.
- ii. Formalize the Farmer-Institution Data Pipeline: Establish a mandatory data-sharing agreement with the Ministry of Agriculture. The list of farmers registered for subsidies or extension in flood-prone zones should be your primary targeting roster for early warnings and post-disaster support, ensuring help reaches those already engaged with the system.

Also, Commercial and Microfinance Banks should use the strong negative relationship between credit access and food insecurity to ensure that finance is a resilience asset, not just a debt instrument. However, it must be deployed *before* the crisis.

- i. Develop and Market "Climate-Resilience Loan Products": Create bundled loan products that finance climate-smart inputs (e.g., drought/flood-resistant seeds, water pumps) and are linked to a mandatory grace period triggered by an official flood declaration. These de-risks lending and provides a true safety net for the arable farmers.
- ii. Use Our Determinants Model for Client Risk Scoring: Partner with extension agencies to identify clients who match the high-vulnerability profile (e.g., female-headed, large household, experienced farmers). For these clients, proactively offer bundled resilience products to mitigate their statistically higher risk.

In addition, the Leaders of the Farming Associations (e.g., AFAN): Arm your members with evidence. This study gives you the data to advocate not just for aid, but for smarter investment.

- i. Demand Accountable Implementation: Use these findings in your consultations with government. Hold them accountable for the specific, measurable actions of increasing credit access to 40%, extension contact to 30%, and ensuring subsidies are delivered 3 months before the planting season in flood-prone areas.
- ii. Promote Demographic-Smart Planning: Educate your members on how household size and structure affect crisis vulnerability. Advocate for and help design community savings groups that account for these demographic pressures.



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