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Enhancing Rural Households' Resilience in the Face of Climate Change in Nigeria

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Abstract: Resilience to climate shocks is critical for sustaining rural livelihoods, improving agricultural productivity, and fostering long-term development. This study examines the effects of climate change and the resilience capacity of rural households in Nigeria using the General Household Survey (GHS) panel data from 2010/2011 and 2018/2019, covering 2,800 rural households. Descriptive statistics, an ordered probit model, and the Multiple Indicators Multiple Causes (MIMIC) model were applied. Results indicate that 50.3% of households are male-headed, with an average household size of six and a mean age of 49 years, while 41% of household heads have no formal education. Access to agricultural information remains limited, as only 17% received extension services. Households experienced a range of climate-related shocks: 25.21% reported harvest failure due to poor rainfall, 21.64% due to flooding, 10.57% from pest invasion, and 27.36% suffered livestock losses due to illness. Drought experience varies across the geopolitical zones in both waves. The MIMIC results show that a significant proportion of households fall within the low-resilience category, with male-headed households exhibiting relatively higher resilience levels. The ordered probit model further identifies education, dependency ratio, age, marital status, and social capital as major determinants of resilience. The study recommends strengthened fire and flood mitigation strategies, enhanced agricultural adaptation to rainfall variability and pest outbreaks, expanded access to education and extension services, and improved land governance, credit access, and social protection, particularly for women. Strengthening resilience is essential for safeguarding rural communities against the growing impacts of climate change.

Keywords: climate shocks; resilience; rural households; Nigeria

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1. Introduction

Climate change and variability constitute a serious global environmental issue (Nalwanga et al., 2022). The African continent's experiences of fluctuating temperatures, extreme weather events, and poor infrastructure, coupled with the level of poverty, make the continent more vulnerable to the impacts of climate change (Yusuf, 2019). Climate change occurs globally, and its impacts are also felt in developing economies. Nigeria is one of the most vulnerable countries to the impacts of climate change. The country's diverse geography and climate make it susceptible to various climate change impacts (Arowolo et al., 2018). Therefore, Nigeria has the potential to suffer various effects of climate change, some of which have already started manifesting, such as sudden changes in temperature and precipitation occurrences (Haider, 2019). Rain-fed agriculture practice in the country makes it more prone to climate shocks such as flooding and drought (Yusuf et al., 2024).

Climate change is already affecting land in many ways, including by increasing the frequency and intensity of droughts, floods, and storms (Chiriacò & Valentini, 2020). Land use can also impact climate change. For example, deforestation releases carbon dioxide into the atmosphere, while afforestation and reforestation can help to remove carbon dioxide from the atmosphere (Intergovernmental Panel on Climate Change, 2022). Desertification experience, especially in the northern part of Nigeria, has already caused many people and villages to migrate because of a lack of sustainable food production (Arowolo et al., 2018). Desertification from the cumulative effects of deforestation is an existential threat as it has been observed to be moving southwards (Yusuf et al., 2024). Land use can also affect the amount of sunlight reflected in space, which can impact the Earth's temperature. The interaction between climate change and land use is complex, and we still do not know how much. However, land use is a major factor that will influence the future of climate change (Thapa, 2022).

Although desertification and land degradation are acknowledged as complex environmental challenges in Nigeria, their implications for household resilience require explicit integration into the resilience framework. Land tenure security and land governance systems play a central role in shaping the adaptive, absorptive, and transformative capacities of rural households, particularly in regions facing desertification pressures. Secure land rights increase farmers' incentives to invest in soil conservation, agroforestry, irrigation, and climate-smart technologies investments that directly strengthen resilience by enhancing long-term productivity and reducing vulnerability to climate shocks. Conversely, weak tenure systems, highly customary land allocation processes, and gender-biased land access often limit households' ability to respond effectively to drought, flooding, erosion, and loss of soil fertility. In northern Nigeria, where desertification is advancing rapidly, land fragmentation, encroachment, and conflicts between farmers and pastoralists undermine social stability, disrupt livelihoods, and weaken resilience pathways. Governance failures such as poor land registration systems, inadequate enforcement of land policies, and limited community participation further exacerbate climate vulnerability by restricting long-term planning and sustainable land management. Therefore, situating land tenure and governance within the resilience framework is essential, as it clarifies how structural land constraints interact with shocks and adaptive strategies, ultimately influencing household welfare and sustainable rural development in Nigeria.

Shocks refer to sudden and unexpected events that can hurt the well-being of vulnerable populations and are classified into covariates and idiosyncratic shocks. These shocks can disrupt the normal functioning of communities and individuals and may lead to various adverse consequences. They can occur in rural and urban areas and affect people in developed, developing, and underdeveloped countries worldwide. Vulnerable populations are particularly susceptible to the negative consequences of these shocks because they often lack the resources or social safety nets to cope with such disruptions (Food and Agriculture Organization of the United Nations [FAO], 2016). Idiosyncratic shocks occur at the individual level, including loss of family members, protracted illness, and community unrest. Covariate shocks include catastrophic weather events, crop failures, and price declines in commodity export markets, all of which occurred at regional and national levels.

Resilience is seen as the capacity not only to absorb disturbances but also to reorganize while changes are taking place, to retain the same functions, structures, and feedback (Alinovi et al., 2008; Folke, 2006). Therefore, the reorganizational capacity of a household is seen as fundamental in reacting to a shock, especially a climate shock, and adapting to the new situation to get back to a given level of well-being. Moreover, climate resilience implies having good living conditions to withstand hazards or cope with, absorb, and return from shocks such as climate change effects (FAO et al., 2021). An analysis of how a socio-economic unit responds to shocks and risks, such as climate change effects, can serve as an avenue for understanding factors that influence coping and adaptive capacities. Such factors can be adjusted to maximize resilience and minimize vulnerabilities to climate shocks (Odozi et al., 2022). The concept of resilience is of increasing interest to policymakers. However, despite the growing importance of resilience, the concept has not yet been carefully defined or measured (Constas et al., 2014) and is still sometimes confused with the similar but yet different concept of vulnerability (Adger, 2006). Misconceptions of resilience may lead to a limited understanding of coping with or adapting to natural hazards effectively. To avoid such misconceptions, it is necessary to quantify resilience into specific and obtainable objectives (Quinlan et al., 2015).

This study provides more insights into how resilient rural households are to climate shocks and various factors that influence the resilience to climate shocks in rural Nigeria. Determining resilience to climate shocks could help land use and the livelihoods of farming households, improve their farm production, and increase their abilities to bounce back from the effects of climate change to contribute to economic growth and sustainable development. This is also critical for ensuring global food security, nutrition, proper land use, and sustainable natural resource management. This requires both enhancing the capacity of rural people to manage the risks they face and lowering their exposure and vulnerability levels. Therefore, the measures of the household capacity to overcome and recover (resilience) from natural shocks, especially climate change, are very important. The broad objective of this paper is to examine resilience to climate shocks among rural households in Nigeria. The specific objectives are to:

(i) Describe climate-related shocks affecting rural households in Nigeria.
(ii) Examine the level of resilience of rural households to climate shocks.
(iii) Identify factors influencing rural households' resilience to climate shocks in Nigeria.

2. Materials and Methods

2.1. Study Area

The study area is Nigeria. Nigeria lies between 4°–14° N and 3°–14° E, making it north of the equator and east of the Greenwich Meridian located on the West Coast of Africa and occupies approximately 923,768 square kilometers of land and shares borders with Chad and the Atlantic Ocean to the South, Niger Republic to the North, Cameroun to the East, and Benin to the West. The country is made up of 36 States and the Federal Capital Territory. The States and the Federal Capital Territory are divided into 774 Local Government Areas. The spatial distribution of the population is uneven, with the majority (63 percent) of the population living in rural areas and the remaining population living in urban areas (National Bureau of Statistics [NBS], 2019). The population of Nigeria was estimated at 214,587,291 as of February 2022, based on projections of the latest United Nations data reported by Worldometer. The country is divided into six geopolitical regions: North-Central, North-East, North-West, South-East, South-South, and South-West, and four agroecological zones, namely tropic-warm/semiarid, tropic-warm/sub-humid, tropic-warm/humid, and tropic-cool/sub-humid.

2.2 Type and Source of Data

Secondary data was used for this study. The required variables were extracted from the General Household Survey Panel Data (GHS-P) from the Living Standard Measurement Survey-Integrated Survey of Agriculture (LSMS-ISA). Data were repeatedly collected from the same households in 2010–2011, 2012–2013, 2015–2016, and 2018–2019. This survey was conducted by the National Bureau of Statistics, Federal Government of Nigeria (FGN) in collaboration with the Federal Ministry of Agriculture and Rural Development (FMA&RD), the National Food Reserve Agency (NFRA), the Bill and Melinda Gates Foundation (BMGF), and the World Bank (WB; NBS, 2019). The ability to follow the same households over time makes the GHS Panel a new and important tool for studying and understanding the dynamics of resilience. For this study, the 2010–2011 and 2018–2019 waves were used, where relevant information and variables relating more to households' resilience to climate change effects on households were extracted, sorted using STATA 16, and used for the analysis.

2.3. Methods of Data Analysis

Descriptive statistics were used to describe socio-economic characteristics of the rural households' heads and climate-related shocks; the multiple indicators multiple causes (MIMIC) model was used to examine the resilience index; and the ordered probit model was used to identify factors influencing rural households' resilience to climate shocks.

Several established resilience measurement scales, such as the BRACED index, the Self-Reliance Capacity (SRC) framework, and other composite tools, were set aside in this study due to conceptual and methodological limitations that make them unsuitable for the Nigerian rural context and incompatible with the econometric approach adopted. Although these frameworks have been applied in humanitarian and development settings, they often rely on context-specific indicators that lack theoretical coherence when transferred across countries or livelihood systems. More critically, they tend to conflate resilience, vulnerability, and adaptive capacity, thereby obscuring the analytical distinctions needed for robust empirical estimation.

A consistent challenge with these scales is their ambiguous indicator structure, which blends exposure, sensitivity, and adaptive capacity into single composite scores. This blurring of boundaries limits their usefulness in longitudinal analysis, especially when evaluating resilience trajectories using panel data such as the General Household Survey (GHS-Panel) for 2010/2011 and 2018/2019. Such conceptual overlap also complicates their integration with multidimensional and econometric methods, including the Multiple Indicators Multiple Causes (MIMIC) model, Principal Component Analysis (PCA), and the Coping Strategies Index (CSI), which require clear theoretical constructs and well-defined latent variables.

In contrast, this study adopts a theoretically grounded and empirically flexible resilience index derived through the MIMIC model, complemented by principal component analysis (PCA) to validate indicator weighting and structure. This approach allows for the decomposition of resilience into well-established pillars such as access to assets, adaptive capacity, income stability, exposure to shocks, reliance on social networks, access to basic services, and food security conditions. Importantly, the MIMIC framework simultaneously incorporates causal variables (e.g., education, land size, credit access, cooperative membership, climate shocks) and reflective indicators, ensuring internal consistency.

A central methodological concern guiding this decision is whether resilience metrics can capture socially differentiated dimensions of resilience among rural households. Resilience is inherently shaped by social and demographic factors such as gender, age, marital status, household size, land ownership, livelihood strategies, wealth status, and access to communication and social networks. Further inequalities in access to housing facilities, water, sanitation, waste disposal systems, and agricultural inputs influence how households prepare for, absorb, and recover from climate shocks. Frameworks like BRACED and SRC often overlook these nuanced structural determinants, which are crucial for understanding household heterogeneity.

By constructing a multidimensional index tailored to the Nigerian rural context and validated across two survey waves, this study provides a more precise assessment of resilience changes over time. The adopted methods ensure conceptual clarity, strengthen empirical validity, and provide robust statistical grounding for subsequent analyses using ordered probit, fuzzy logit, and marginal effects estimation. This integrated approach enables a deeper understanding of how climate shocks affect household welfare and how resilience capacities evolve within socially differentiated groups.

2.4. Objectives of the Research Study

Objective 1: Describe the climate-related shocks affecting rural households in Nigeria. Descriptive statistic was used to describe the climate shocks, such as floods, drought, and loss of land, identified in the study area.

Objective 2: Examine the level of resilience of rural households to climate shocks.

This objective was achieved using principal component analysis (PCA) and multiple indicators multiple causes (MIMIC) model at the different stages, which are:

(1) First stage: Principal Component Analysis (PCA) was used to determine the index of each of the pillars of resilience capacity of the rural household (d'Errico & Di Giuseppe, 2016). New variables are constructed as weighted averages of the original variables. The matrix of scores was referred to as the matrix *Y*. The basic equation of PCA is, in matrix notation, given by:

$$Y = W'X \tag{1}$$

$$y_{ij} = w_{1i}x_{1j} + w_{2i}x_{2j} + \dots + w_{pi}x_{pj} \tag{2}$$

Where *W* is a matrix of coefficients of variables *x* determined by PCA.

(2) Second stage: The levels of resilience to climate shock were determined using the Multiple Indicators Multiple Causes (MIMIC) model to estimate the resilience capacity index among the households following d'Errico and Di Giuseppe (2016). The MIMIC model is a causal model with one underlying latent variable, multiple indicators, and causes. In the linear MIMIC model, both the relationship between the latent variable and its causes and the relationship between the indicators and the latent variable are linear in the parameters. The MIMIC model is estimated using a Maximum Likelihood (ML) estimator. The latent variable Resilience is jointly estimated by its causes and indicators. The classical linear MIMIC model is specified as follows:

$$y_1 = \beta_0 + \beta_1\eta + \varepsilon_1 \tag{3}$$

$$y_2 = \beta_0 + \beta_2\eta + \varepsilon_2 \tag{4}$$

$$y_3 = \beta_0 + \beta_3\eta + \varepsilon_3 \tag{5}$$

$$y_n = \beta_0 + \beta_n\eta + \varepsilon_n \tag{6}$$

Equation (3–6) shows the relationship between the pillars (indicators) $y_1 \dots y_n$ depending on the number of pillars in use and the resilience capacity index (η), where β and ε are coefficients and error terms, respectively.

$$\eta = \alpha_0 + \alpha_1x_1 + \alpha_2x_2 + \dots + \alpha kxk + v \tag{7}$$

Equation (7) shows the relationship between the resilience capacity index (η) and the independent variables (causes $x_1 \dots x_n$) derived from the pillars through principal component analysis. It can also be specified as:

$$RL_h = f(P_1, P_2, \dots, P_n) \tag{8}$$

Where RL_h = Resilience capacity of the household h to climate change; $P_1, P_2, \dots, P_n$ = Pillars of Resilience.

$$RL_h = \beta_0 + \beta_1 P_1 + \beta_2P_2 + \beta_3P_3 + \beta_4P_4 + \beta_5P_5 + \beta_6P_6 + \beta_7P_7 + \varepsilon_i \tag{9}$$

Where P_1, P_2, P_3, P_4, P_5, P_6, and P_7 are the seven pillars of resilience (see Table 1).

Table 1. Seven Pillars and Variables.

Pillars	Indicators
Access to Basic Services (ABS)	Access to electricity (Yes =1, No = 0) Access to improved water facility (Yes = 1, No = 0) Access to toilet facility (Yes = 1, No = 0) Distance to water source (km) Access to health facilities (Yes = 1, No = 0)
Assets	Land ownership (Yes =1, No=0) Number of crops planted Number of livestock owned House condition index
Income and Food Access (IFA)	Income from main job (Yes =1, No=0) Income from other jobs (Yes =1, No=0) Total food expenditure (₦)
Social safety nets (SSN)	Assistance from government (Yes =1, No=0) Assistance from Charities or from NGOs (Yes =1, No=0) Assistance from private entities (Yes =1, No=0) Remittances received (Yes=1, No=0)
Adaptive capacity (AC)	Education of household head (number of years of formal education) Dependency ratio (number of children and aged members relative to the total household size) Household Head engaged in farming (Yes=1, No=0) Household Head engaged in wage employment (Yes =1, No=0) Household head with any form of job (Yes =1, No=0)
Access to Agricultural Input and Technology (AIT)	Access to Seed, (Yes =1, No=0) Access to Fertilizer, (Yes =1, No=0) Access to herbicide, (Yes =1, No=0) Access to Extension Services (Yes =1, No=0) Access to farm machines (Yes =1, No=0)
Sensitivity/Perceptions to climate change (How often the experience of climate shocks)	Drought experience, (Yes =1, No=0) Rainfall variability experience, (Yes =1, No=0) Livestock diseases experience, (Yes =1, No=0) Crop failure due to climate variability causes, (Yes =1, No=0) Price shocks, (Yes =1, No=0) Water shortages experience (Yes =1, No=0)

Source: computed, 2023 GHS 2010/2011 and 2018/2019.

These variables determine the latent resilience capacity. They are treated as exogenous predictors that contribute to building household resilience. They originate from the FAO's RIMA-II pillars but serve only as determinants, not indicators, in the MIMIC structure.

(a) In the formative model, the hypothesis is that resilience (η) is influenced by the pillars. Formative indicators are assumed to be correlated and to be measured. In the reflective part, the model's reflective indicator errors (ε) are correlated and assumed to contain measurement errors. The MIMIC model permits simultaneous estimation of the measurement model and the incorporation of causal variables in the structural model for the latent variable resilience, which is linearly determined (apart from random errors, ε) by formative indicators or pillars, and resilience determines the observed reflective indicators (apart from random errors, ε; d'Errico & Di Giuseppe, 2016).

(b) Reflective Indicators (Measurement Model)

These variables manifest or reflect the latent resilience capacity. They represent observable outcomes that are expected to improve as household resilience increases.

Reflective Indicators include: food consumption score (FCS), coping strategy index (reversed), income stability, ability to recover from previous shocks, and perceived well-being score. These indicators reflect the unobserved resilience capacity and form the measurement equation:

$$RCI_{it} = f(IFA_i , ABS_i, AST_i, SSN_i, AC_i , AIT_i , S_i) \tag{10}$$

$$\begin{bmatrix} Climate\ Shocks\ index \\ Climate\ Variables\ index \end{bmatrix} = \Lambda_1, \Lambda_2 \times (RCI) + (\varepsilon_1,\varepsilon_2) \tag{11}$$

Climate Shocks index was equated to 1, and the equation was linearized to solve for resilience index (η).

The basic causes of the structural model used in the modeling process of the MIMIC model are ABS, AST, SSN, IFA, S, AC, and AIT, in other words:

$$(RCI) = \left(\beta_1, \beta_2, \right) \times \begin{bmatrix} ABS & & AST \\ SSN & S & AC \\ IFA & & AIT \end{bmatrix} + (\varepsilon_1) \tag{12}$$

(3) Third stage: in this analysis, the level of resilience was classified into three categories (see Table 2) using Markov chain analysis into least resilience, less resilience and most resilient as used by Ayantoye et al. (2011) and Obayelu and Akpan (2021).

Table 2. Markov Transition Matrix for Resilience.

	Period t			
	Level of Resilience	Least resilient (P_1)	Less resilient (P_2)	Most resilient (P_3)
Period t−1	Least resilient	P_{11}	P_{12}	P_{13}
	Less resilient	P_{21}	P_{22}	P_{23}
	Most resilient	P_{31}	P_{32}	P_{33}

Source: Author's computation 2023 GHS 2010/2011 and 2018/2019.

In this study, resilience capacity is specified as a latent variable (RCI) that is jointly determined by formative causes and measured through reflective indicators, consistent with the Multiple Indicators Multiple Causes (MIMIC) framework. To avoid conceptual ambiguity, the seven resilience pillars are not treated simultaneously as both indicators and causes. Instead, their associated variables are explicitly divided into formative causes (structural model) and reflective indicators (measurement model).

Objective 3: Identify factors influencing rural households' resilience to climate shocks.

The ordered probit regression model was used to identify and analyze the factors of households 'resilience to climate change-induced shocks. Resilience in this measurement involved ordered outcomes. This is with the basic hypothesis that a given natural shock will have a differential impact on households' resilience. Following Tesso et al. (2012) and Adepoju et al. (2011).

$$Y^x = X^1{}_j \beta + U_{1j} \tag{13}$$

$$Y = 0 \ if \ Y^x \leq 0 \tag{14}$$

$$Y = 1 \ if \ 0 \leq Y^x \leq 1 \quad (15)$$

$$Y = 2 \ if \ 1 \leq Y^x \leq 2 \quad (16)$$

*Y** is the level of resilience and involves an ordered outcome, that is:
Y = 0 is given to the least resilient households
Y = 1 is given to less resilient households
Y = 2 is given to the most resilient households
The *Xij* are the explanatory variables.
The independent variables included in the model are:
X_1 = Age of household head (Years),
X_2 = Income in Naira,
X_3 = Livestock owned (yes = 1, otherwise = 0),
X_4 = Marital status (married = 1, otherwise = 0),
X_5 = Dependency ratio,
X_6 = Access to credit (yes = 1, otherwise = 0),
X_7 = Social capital (number of institutional involvement),
X_8 = Levels of education (no formal education = 0, primary = 1, secondary = 2, tertiary = 3),
X_9 = Household head job (agriculture = 1, otherwise = 0),
X_{10} = Household Food consumption in Naira,
X_{11} = Remittance in Naira,
X_{12} = Access to extension services (yes = 1, otherwise = 0),
X_{13} = Household size (number), X_{14} = Farm size (hectare)
β's are parameters estimated and *Uij* is the disturbance term.

3. Results

Socioeconomic Characteristics of Rural Households

Descriptive statistics in Table 3 showed that 50.3% are males, while 49.7% are females. This indicates that there are more male-headed households than female-headed households among rural households in Nigeria. This result is in line with Olaosebikan et al. (2023) and Ibitola et al. (2019), who also found that there were more male than female household heads in rural households. The distribution of the age indicates that 26% of the households' heads are below 25 years old, 64% are between 26 and 50 years old, 8% fall within the 51–75 age range, and less than 2% are in the 76–100 age category. The mean age is 49 years, implying that most household heads are still within the active age and productive life stages. The result of this study supports the findings of Olajide and Omonona (2019) and Fasakin et al. (2022), who found that most household heads in rural communities are in their productive age range of 40 to 60 years. It means that household heads are of age and mature enough to make decisions and take responsibility in the homes, even in the face of climate shocks. The marital status of the married reveals that 25% are monogamous, while 11% are polygamous. Less than 1% are divorced or separated, while 2% are widowed. 62% are never married. They are still single and have not given birth, or are single parents without the context of cultural or legal marriages among rural households. This means that the never-married are more than the married. Household size indicates that 49% of rural households have household sizes between 1 and 5, while 41% have 6 to 10 household sizes. 10% have 11–15, and less than 1% have a household size greater than 15 family members. The mean household size is found to be 6. Large household size could contribute to an increase in family labor, which could reduce the cost of farm production and increase productivity. This is relevant to the findings of Itunnu (2022), who discovered that an increase in family size would lead to an increase in labor available to cultivate the land, and this shows the relationship between farm size and household size**.** Level of Education shows that about 41% of the rural households have no formal education, while about 26% attain primary education level, about 20% have secondary education, and 14% have tertiary education. It shows that the majority of rural households have no formal education. It implies that many rural households might be unable to apply educational knowledge to improve their economic performance, which could have affected their productivity. This is relevant to the findings of Adetunji (2015), who discovered that rural households have low formal educational attainment, and a lot of people in rural areas have no formal education.

Table 3. Socio-economic characteristics of the rural households.

Socio-economic Characteristics	Frequencies	Percentage (%)	Resilience index
Sex			
Male	1408	50.29	0.0817
Female	1392	49.71	−0.0069
	2800	100	
Age			
<25	722	25.79	0.0329
26–50 Mean = 49	1794	64.07	0.0433
51–75	232	8.29	0.0637
75–100	52	1.86	0.7048
	2800	100	
Marital status			
Married (monogamous)	701	25.04	0.1401
Married (polygamous)	296	10.57	−0.0545
Divorced	6	0.21	−1.5555
Separated	3	0.11	−0.5915
Widowed	67	2.39	0.1652
Never married	1727	61.68	0.0135
	2800	100	
Household size			
1–5	1375	49.11	0.0443
6–10 mean = 6	1135	40.54	0.0522
11–15	271	9.68	−0.0351
16–20	19	0.68	−0.2851
	2800	100	
Level of Education			
No formal education	1140	40.71	0.0229
Primary level	716	25.57	0.0408
Secondary level	552	19.72	0.3677
Tertiary education	392	14.00	−0.2827
	2800	100	

Source: Author's computation 2023 GHS 2010/2011 and 2018/2019.

4. Discussions

4.1 Descriptive Statistics of Climate Shocks in Rural Nigeria

The percentages at which each climate shock occurred in the year 2010/2011 as shown in Table 4 are 1.21% of the destruction of harvest by fire, 5.32% of dwellings damaged/demolished, 25.21% of poor rain that caused harvest failure, 21.64% of flooding that caused harvest failure, 10.57% of pest invasion that caused harvest failure or storage loss, 6.5% of loss of property due to fire or flood, 2.18% of loss of land and 27.36% of death of livestock due to illness. Table 4 also shows the percentages of each climate shock occurred in 2018/2019 are 8.21% of the destruction of harvest by fire, 22.39% of dwelling damaged/demolished, 19.43% of poor rain that caused harvest failure, 31.43% of flooding that caused harvest failure, 6.68% of pest invasion that caused harvest failure or storage loss, 0.04% of loss of property due to fire or flood, 0.04% of loss of land and 11.79% of death of livestock due to illness. Table 5 indicates variations in drought experience in each of the six geopolitical zones in the two waves.

Table 4. Tabulation of climate shocks.

Climate Shocks	2010/2011		2018/2019	
	Freq.	Percent	Freq.	Percent.
Destruction of harvest by fire	34	1.21	230	8.21
Dwelling damaged/demolished	149	5.32	627	22.39
Poor rains that caused harvest failure	706	25.21	544	19.43
Flooding that caused harvest failure	606	21.64	880	31.43
Pest invasion that caused harvest failure or storage loss	296	10.57	187	6.68
Loss of property due to fire or flood	182	6.50	1	0.04
Loss of land	61	2.18	1	0.04
Death of livestock due to illness	766	27.36	330	11.79
	2800	100	2800	100.00

Source: Author's computation 2023 GHS 2010/2011 and 2018/2019.

Table 5. Drought experience across the six zones in 2010/2011 and 2018/2019.

Drought	North-central	Northeast	Northwest	Southeast	South-south	South west	Total
2010/2011	13	20	31	1	10	4	79
	(16.46)	(25.32)	(39.24)	(1.27)	(12.66)	(5.06)	(100.00)
2018/2019	61	71	69	64	60	25	350
	(17.43)	(20.29)	(19.71)	(18.29)	(17.14)	(7.14)	(100.00)

Source: Author's computation 2023 GHS (2010/2011 and 2018/2019); () parenthesis are percentages.

In 2010/2011, the Northwest had the highest (39.24%) drought experience, followed by the Northeast (25.32%), Northcentral (16.46%), South-south (12.66%), Southwest (5.06%), and Southeast (1.27%). In 2018/2019, the Northeast had the highest 20.29% drought, while the north central had 17.43%. The Northwest had 19.71%, the Southeast 18.29%, the south-south 17.14%, and the Southwest 7.14%. Drought experiences have greatly increased within ten years. Climate shocks significantly impacted the livelihood activities of rural households in the study areas. For example, the destruction of harvests by fire, flooding, or pests reduced food security and income for households, while the loss of property, such as the death of livestock, degraded the asset base of households, which could reduce the ability of the households to cope with the negative effects of climate change. Moreover, poor rain that caused harvest failures also increased household dependence on food aid and other forms of support. Dwelling damage, demolition, and loss of land also affected households' ability to access basic infrastructure such as healthcare, education, and transportation. Overall, these climate shocks exacerbated the vulnerability and reduced resilience capacity of rural households in the study areas, put additional stress on their livelihoods, and affected their ability to cope with future climate shocks.

4.2. Levels of Resilience and MIMIC Model Estimates of the Correlates of Resilience

This section explains the factors that determine the resilience capacity index among households. These factors are often referred to as pillars of resilience. The seven pillars of resilience are used in this study (see Table 6). These are access to basic services, adaptive capacity, assets, access to agricultural input technology, income and food access, safety nets, and stability over time. An index was generated for each pillar through observable variables of each of the seven pillars of resilience using principal component analysis. The eight climate shocks identified in the study areas created the climate shocks index. Lastly, climate change indicators of rainfall and temperature were also indexed using PCA. The MIMIC model, estimated using the Maximum Likelihood (ML) estimator, was used to determine the levels of resilience. The levels of resilience capacity index generated were classified into the least, less, and most resilient rural households based on the mean of the resilience index generated (see Table 7). The mean of RCI is 0.0376. Households whose resilience index is below one-third or equal to one-third of the mean are classified as least resilient (≤ 0.0125). Less resilient households are the households whose resilience index is greater than one-third but less than two-thirds of the mean ($> 0.0125 < 0.0251$), while households whose resilience index is equal to or greater than two-thirds ($\geq$ 0.0251) are classified as most resilient. The classification is adopted and used by Adepoju et al. (2011). The resilience index examined using the MIMIC model showed that 52.96 % were least resilient, 34.68 % less resilient, and 12.36 % most resilient to climate shocks in the study area in the pooled data. The Multiple Indicators

Multiple Causes model also determines resilience determinants. The chi-square statistics show 1% significance, and that the result of the MIMIC model is a good fit. Among the seven selected pillars of resilience that formed the resilience capacity index of rural households, the results of the findings indicate that income and food access, social safety nets, agricultural input and technology, and stability measures have significant effects on the resilience capacity of the rural households to climate change effects compare with access to basic services, adaptive capacity, and assets of the rural household heads.

Table 6. Structural Equation Mimic Model (Maximum Like hoods estimation).

Resilience Capacity Index	Coefficient	Std. error	P>z
Access to Basic Services	−0.021 (−0.720)	0.020	0.289
Adaptive Capacity	0.018 (0.089)	0.019	0.342
Assets	−0.008 (0.420)	0.030	0.792
Income and Food Access	−0.095 (1.400) ***	0.030	0.001
Social Safety Nets	0.134 (−1.600) ***	0.019	0.000
Access to Agricultural Input Technology	−0.103 (−0.850) ***	0.027	0.000
Stability over time	−0.080 (−0.290) ***	0.025	0.001
Measurement model			
Climate Shocks < −Resilience	1		
Climate Variables < −Resilience	0.122 (0.140) ***	0.019	0.000
No of Observations	2800		
Chi square	442.44		
Prob. > chi^2	0.0000		
RMSEA	0.039		
Probability RMSEA < 0.05	0.972		
CFI	0.952		
TLI	0.927		

Source: Author's computation GHS (2010/211 and 2018/2019). () parenthesis is standard deviations.
*** Level of significant at 1% ** 5% * 10%.

Table 7. The Levels of Resilience.

Levels of resilience	Freq	Percentage
Least resilient	1,483	52.96
Less resilient	971	34.68
Most resilient	346	12.36
Total	2,800	100

Source: Author's computation 2023 GHS (2010/2011 and 2018/2019).

Evidence of metric and scalar invariance demonstrates that differences in the resilience index reflect true substantive differences, not measurement artefacts.

4.2.1. Common-Method Bias Diagnostics

To address potential inflation of relationships due to common-method variance, two procedures were applied:

- Harman's single-factor test: No single factor accounted for the majority of variance, indicating that common method bias was not a major threat.
- Single-factor latent method construct: Including a method factor in the model did not significantly improve fit, further confirming robustness.

4.2.2. Structural Validity and Model Adequacy

Finally, the MIMIC model was assessed using comparative model-fit indices reported in Table 6 (CFI, TLI, RMSEA, Chi square). All values fell within acceptable thresholds, providing additional support for the adequacy of the latent structure. Embedding these validation steps ensures that the latent resilience index is psychometrically reliable, conceptually coherent, empirically distinct across pillars, comparable across gender and ecological regions, free from major common-method bias, and suitable for econometric analyses such as ordered probit, fuzzy logit, MIMIC structural estimation, and subgroup comparisons.

4.3. Factors Influencing Resilience to Climate Shocks Among Rural Households

This section discusses the ordered probit regression model of the factors influencing resilience to climate shocks among rural households (see Table 8). The dependent variable is resilience categories into least resilience when the resilience index is 0, less resilience when the resilience is 1, and most resilience when the resilience is 2. The explanatory variables included are sex of the household head, age, age squared, marital status, social capital, livestock owned by the household, household size, access to credit, remittance, dependency ratio, levels of education of the household head, access to extension, farm size, household head income, household food consumption, and household head job. The Probability of the chi-square (P > chi^2 = 0.0000) and pseudo-R-squared of 0.2741 indicate that the model is a good fit.

Table 8. Factors influencing Resilience to climate shocks among rural households.

Variables	Coef. / t-value	dy/dx; r=0	dy/dx; r=1	dy/dx; r=2
Sex: Female	−0.085 (−1.68) *	0.021(1.420)	−0.012 (−1.410)	−0.008 (−1.420)
Age	0.007 (3.95) ***	0.007 (4.950) ***	−0.004 (−4.900) ***	−0.003 (−4.810) ***
Age squared	0.00037 (6.76) ***	−0.000 (−6.890) ***	0.000 (6.750) ***	0.000 (6.520) ***
Marital status	0.035 (2.56) **	0.005 (1.200)	−0.003 (−1.190)	−0.002 (−1.190)
Social capital	−0.036 (−4.67) ***	0.014 (6.020) ***	−0.008 (−5.940) ***	−0.006 (−5.760)
Livestock owned	−0.017 (−20.04) ***	0.05 (25.580) ***	−0.003 (22.670) ***	−0.002 (14.520) ***
Household size	−0.049 (−6.26) ***	0.014 (6.340) ***	−0.008 (−6.240) ***	−0.006 (−6.030) ***
Access to credit	−0.251 (−3.66) ***	0.074 (3.800) ***	−0.004 (−3.770) ***	−0.030 (−3.750) ***
Remittance	5.978 (0.950)	−1.837 (−0.070)	1.093 (0.070)	0.744 (0.070)
Dependency ratio	0.043 (3.23) ***	−0.013 (−3.430) ***	0.008 (3.420) ***	0.005 (3.370) ***
Levels of education				
Primary	0.336 (5.29) ****	−0.097 (−5.280) ***	0.062 (5.170) ***	0.035 (5.170) ***
Secondary	0.454 (5.88) ***	−0.130 (−5.780) ***	0.080 (6.060) ***	0.050 (4.980) ***
Tertiary	0.505 (6.16) ***	−0.149 (−6.380) ***	0.089 (6.810) ***	0.060 (5.300) ***
Access to Extension	0.419 (6.44) ***	−0.115 (−6.190) ***	0.068 (6.080) ***	0.046 (5.920) ***
Farm size	0.018 (0.13)	0.013 (0.340)	−0.008(−0.340)	−0.005(−0.340)
Income	0.000 (-0.03)	0.000 (0.030)	−0.000(−0.030)	−0.000(−0.030)
HH Food consumption	−2.678 (−22.56) ***	0.784 (23.770) ***	−0.466 (15.240) ***	−0.317 (23.140) ***
Household head job	−0.007 (−5.79) ***	0.000 (6.190) ***	−0.001 (−6.100) ***	−0.001 (−5.890) ***
Pseudo r-squared 0.274		The number of obs. 2800		

Author's computation 2023 GHS 2010/2011 and 2018/2019. Note: dy/dx for factor levels is the discrete change from the base level.
*** p < .01, ** p < .05, * p < .1.

4.3.1. Least Resilient Level, (r = 0)

From Table 8, the sex of the household is negative using males as the baseline, with resilience at a 10% significance level. This implies that female gender resilience capacity decreases by 0.24 units compared with male counterparts. This confirms the result of the resilience index in Table 1 that the male resilience index is higher than that of the female, which also means male-headed households could be more resilient than female-headed households. The male gender is more resilient than the female. The finding of Olaosebikan et al. (2023) also stated that males are more resilient than their female counterparts. Age and the square of age are significant at 1% where the age square has a negative coefficient. This means that a 0.007 unit increase in age of a rural household increases the least resilience capacity of that household head, while 0.0001 unit of age squared decreases the resilience level of the household head. It means resilience increases with age. Also, marital status, social capital, livestock owned by the household, household size, and access to credit are significant at 1% and have a positive relationship with resilience at least resilient level. This means that household heads who are married, have good social capital, own livestock with a considerable household size, and have access to credit, are more resilient and able to cope with climate shocks to some extent.

Levels of education, either primary, secondary, or tertiary, have a negative interaction with the level of resilience, and this could either decrease or increase resilience capacity based on the application of knowledge acquired to climate shocks. Most household heads in rural areas have no formal education, and those who have acquired knowledge through education are not applying the knowledge to climate shock challenges, so their resilience capacity decreases with their levels of education. Access to extension should increase resilience, but it is negative with resilience. This means that resilience is reduced by the inability of households to have access to extension services, especially land use for farm operations. Resilience increases with household food consumption and the household head's job. 0.784 unit increases in household food consumption could lead to a unit increase in the level of resilience capacity of the household. At the same time, 0.002 unit increases in household head job or household head sources of income could increase a unit level of a household's resilience.

4.3.2. Less Resilient Level, (r = 1)

The significant variables at 1% that have a negative influence on resilience to climate shocks are age, marital status, social capital, livestock owned, household size, and access to credit. This implies that rural households could be regarded as less resilient if there is a reduction in age and the household size. That means household heads are less resilient to climate stress when they are younger, and they have low household sizes to cater to. The age coefficient becomes negative while its squared term turns positive, producing a U-shaped relationship. This pattern may signal the influence of health shocks, declining labor productivity, and increased vulnerability among aging rural populations. In such cases, the quadratic term captures a real non-linear deterioration rather than statistical noise. Age effects show non-linear declines in resilience among older households, motivating health interventions and cash transfers for the elderly. Substantively, this finding has policy relevance. A documented late-life decline would justify targeted interventions such as rural health insurance, mobile clinics, old-age cash-transfer schemes, chronic-disease screening, and strengthened community support systems for elderly farmers. Identifying whether ageing depresses resilience because of physical limitations, income loss, or reduced social capital would help refine these interventions and ensure they reach the affected demographic groups effectively.

However, marital status, social capital, livestock ownership, and access to credit, which have positive interactions with the least resilient, now have negative relationships with less resilient capacity levels. This indicates the dynamics of resilience as it is not static. Moreover, it could be explained that households that are married (monogamous), widowed, and never married are less resilient with a higher resilience index than married (polygamous) and separated households, as indicated in Table 1. The reasons could be that households that are married (polygamous) and separated have more burdens to take care of or add more pressure on resources available to cope with shocks than households of other marital statuses, and therefore, their ability to withstand climate shocks decreases. At lower resilient levels, social capital, access to credit, and the number of livestock owned tend to decrease. This result explains why households could transit from one resilience level to another at different times.

The significant factors at 1% that have a positive relationship with less resilient households include age squared, dependency ratio, levels of education (primary, secondary, and tertiary), and access to extension. Age squared means older age. It means that older household heads might be less resilient due to experiences acquired while facing life difficulties over the years, and the accumulation of assets over the years to cope and overcome shocks. Moreover, the positive relationship indicates that resilience is positively influenced by a 0.008 unit increase in dependency ratio, 0.062unit increase in primary education, 0.08unit increase in secondary education, 0.089unit increase in tertiary education, and 0.68unit increase in access to extension services. Hence, a unit increase in dependency ratio, levels of education, and access to extension services increases resilience at the less resilient level.

4.3.3. Most resilient level, (r = 2)

Resilience is dynamic and changes over time (d'Errico & Di Giuseppe, 2016). This is why rural households transit from one level or category of resilience to another over time. The significant variables that determine resilience at each level vary from one level to another. The significant variables that have a negative influence on the most resilient category of the rural households at 1% are age, social capital, livestock owned, household size, access to credit, household food consumption, and household head job while age squared, dependency ratio, levels of education and access to extension have a positive relationship with resilience and are also significant at 1%. The negative coefficient on age alongside a positive and significant coefficient on age squared suggests a non-linear (U-shaped) relationship between age and household resilience. This pattern typically implies that resilience declines at younger middle-ages but begins to rise again at older ages or vice versa, depending on the turning point. This may indicate that health shocks, declining labor capacity, or increased dependency burdens are eroding resilience among older households. Such evidence would strengthen the case for targeted policy interventions, including age-sensitive social protection measures, community-based health programs, and conditional or unconditional cash transfer schemes aimed at enhancing the resilience and welfare of older rural households.

Rural households could transition from least resilient to most resilient if there is a unit decrease in age, social capital, livestock owned, household size, access to credit, household food consumption, and household head job, while their resilience capacity improves with increased levels of education, access to extension, and dependency ratio. This implies that rural household heads who fall into the most resilient category are old and not young, with improved levels of educational attainment over the years. The study's result is relevant to previous studies, such as Raghunathan et al. (2022), who stated that resilience meant that people in the educational environment continued to function, albeit differently. UNESCO (2021) emphasized that strengthening education systems ensures people can overcome adversity easily and are resilient to the risks they face. In times of adversity, education retains high public value, reaches populations on a large scale, and serves as a critical hub for information sharing. A strong education system can potentially improve individual community and institutional resilience. Therefore, education is a very important factor that influences the resilience capacity of the rural household. Levels of education could indicate the level of acquired knowledge over the years, which could also influence other indicators of resilience capacity levels, such as social capital, access to credit, access to extension, number of household members to have, and livestock owned in a time-variant.

The Variance Inflation Factor (VIF) values presented in Table 9 indicate that multicollinearity is not a concern in the model. All variables exhibit VIF values well below the conventional threshold of 10, and even below the more conservative threshold of 5. The highest VIF in the table is 2.26 for age, followed closely by marital status (2.23), both of which remain substantially low and acceptable. All other variables, including sex, age squared, household size, access to credit, cooperative membership, and farm size, have VIF values close to 1, suggesting minimal correlation with other explanatory variables. The mean VIF of 1.27 further confirms the absence of multicollinearity. Therefore, the explanatory variables included in the regression model are sufficiently independent, and the parameter estimates can be considered reliable.

Table 9. Result of variance inflation factor.

variables	**vif**	**1/vif**
Sex	1.06	0.946
age	2.26	0.441
Age squared	1.06	0.957
Marital status	2.23	0.448
Monogamous	1.06	0.947
Polygamous	1.25	0.976
Divorced	1.05	0.948
Separated	1.08	0.923
Widowed	1.10	0.911
Never married	1.19	0.837
Household size	1.23	0.813
Access to credit	1.05	0.948
Membership of cooperative	1.05	0.957
Farm size	1.06	0.947
Mean VIF	1.27	

Source: Author's computation 2023 GHS 2010/2011 and 2018/2019.

5. Conclusion

Determining resilience to climate shocks is crucial for enhancing the livelihoods of rural households, improving agricultural productivity, and strengthening their capacity to recover from the adverse effects of climate change, thereby contributing to economic growth and sustainable development. Climate shocks demonstrate the urgent need for effective adaptation strategies to mitigate and manage the risks associated with climate change-induced shocks. Implementing measures to reduce the risk of fires and floods is essential, such as fire safety measures and constructing flood-resistant buildings. Additionally, actions to enhance agricultural resilience to poor rainfall and pest invasions should be prioritized to ensure food security, reduce harvest losses, and reduce loss of land. Appropriate veterinary care and disease prevention measures can help reduce livestock mortality rates. Formal education should be enhanced among rural households to strengthen their resilience capacity to overcome the negative impacts of climate change. Educating married households, primarily middle-aged households, should be intensified. Efforts on agricultural extension services should also be intensified to enforce land use policy to improve access to land, especially among women, and to promote land governance among rural households. Gender inequality should be addressed to build resilience to climate change. Giving women more access to resources, property rights, especially land use, and decision-making power, even to utilize land by themselves, can help to ensure that they are not disproportionately affected by the adverse effects of climate change.

Substantial social capital can help rural households cope with the negative impacts of climate change by providing them with support and resources. The study's findings also recommend that policies and interventions that aim to increase income and food access, strengthen social safety nets, improve agricultural input and technology, and promote stability measures would be most effective in helping rural households become more resilient to climate change. Age effects show non-linear declines in resilience among older households, motivating health interventions and cash transfers for the elderly. Policies and interventions should also be tailored to the specific needs of the communities and the specific climate change effects they face. It is also crucial to address climate challenges through policies and actions that prioritize resilience and sustainable development.

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Abbreviations

The following abbreviations are used in this manuscript:

BMGF	Bill and Melinda Gates Foundation
BRACED	Building Resilience Adapting to Climate Extremes and Disasters
FMA&RD	Federal Ministry of Agriculture and Rural Development
GHS-P	General Household Survey Panel Data
LSMS-ISA	Living Standard Measurement Survey-Integrated Survey of Agriculture
MIMIC	Multiple Indicator Multiple Causes
NBS	Nigerian Bureau of Statistics
NFRA	National Food Reserve Agency
PCA	Principal Component Analysis
SRC	Self-Reliance Capacity
WB	World Bank

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