

Assessment of Flood Vulnerability among Smallholder Farmers in Niger State, Nigeria.

Nofiu Babatunde Nofiu^{1,2*} and Siti Aisyah Baharudin^{1*}

¹School of Social Sciences, Universiti Sains Malaysia, 11800 USM Penang, Malaysia.

²Department of Agricultural Economics and Extension Services, Kwara State University, 1530 P.M.B, Malete, Nigeria

* Corresponding authors' email: sab16@usm.my ; babatunde.nofiu@kwasu.edu.ng

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Abstract

Flooding significantly impacts livelihoods, poverty, and human populations. This study assessed flood vulnerability among smallholder farmers in Niger State, Nigeria. Specifically quantifying flood vulnerability at the farmer level and identifying vulnerability levels across three zones. The study employed Principal Component Analysis, Multiple Correspondence Analysis, and the Farmers' Vulnerability Index to analyzed data collected from 350 smallholder farmers across three zones in Niger State, with post-estimation tests conducted to confirm result reliability. Key findings revealed significant variations in vulnerability levels across zones, with Zone A exhibiting the highest vulnerability (Farmers' Vulnerability Index (FaVI): 0.914), followed by Zone C (FaVI: 0.646), while Zone B showed notably lower vulnerability (FaVI: 0.174). The vulnerability patterns were primarily influenced by exposure and sensitivity levels, with Zone A showing the highest exposure (0.829) and sensitivity (0.341) to flooding, while Zone B demonstrated superior adaptive capacity (0.490). Largely, 63.71% of farmers fell into the high vulnerability class, while 36.29% showed lower vulnerability levels. These findings highlight the heterogeneous nature of flood risks and adaptive capacities within the state. The study recommends improving drainage systems, constructing flood barriers, and providing subsidized fertilizers and NGO relief in vulnerable zones, while maintaining effective practices in resilient areas to enhance agricultural resilience.

Keywords: Principal Component Analysis, Multiple Correspondence Analysis, Farmers vulnerability index, Adaptive capacity, Sensitivity, Exposure.



Introduction

Flooding is a significant natural disaster that poses serious threats to livelihoods, poverty levels, and human populations, particularly in Low-and-Middle-Income Countries (22). It is characterized by the inundation of typically dry land with excessive water (29). This natural disaster impedes progress toward several United Nations Development Programme (UNDP) Sustainable Development Goals, including those focused on poverty eradication, hunger elimination, climate action, decent work provision, inequality reduction, and terrestrial ecosystem preservation (26 and 11). The World Economic Forum (WEF) in 2022 reports that during a flood incident occurring once every ten decades, approximately 23% of the global population, or 1.81 billion individuals, are at risk of flooding depths exceeding 0.15 meters, which endangers lives and livelihoods (28). Notably, 1.61 billion of these individuals reside in developing and middle-income nations which represents 62% of the world's poor (27). The immediate impacts of flooding include

substantial property damage and a significant risk to human life, especially for those living in flood-prone areas (2).

Low-and-Middle-Income countries are particularly vulnerable to the adverse effects of flooding due to their limited coping capacities (24 and 15). For instance, the floods in Bangladesh in 2023 resulted in over 51 fatalities, affected 1.2 million people, and incurred severe estimated losses (6). In Nigeria, the National Emergency Management Agency reported that the 2022 floods, caused by excessive rainfall, were among the worst in a decade, submerging extensive urban and rural areas. These floods resulted in at least 662 deaths, displaced 2,430,445 individuals, and impacted over 4,452,802 Nigerians (17). In Niger State alone, the floods affected approximately 1,030,215 farmers and submerged 610,210 hectares of farmland (20). Based on historical records as shown in Figure 1, it is evident that flooding has wreaked havoc in Niger State.

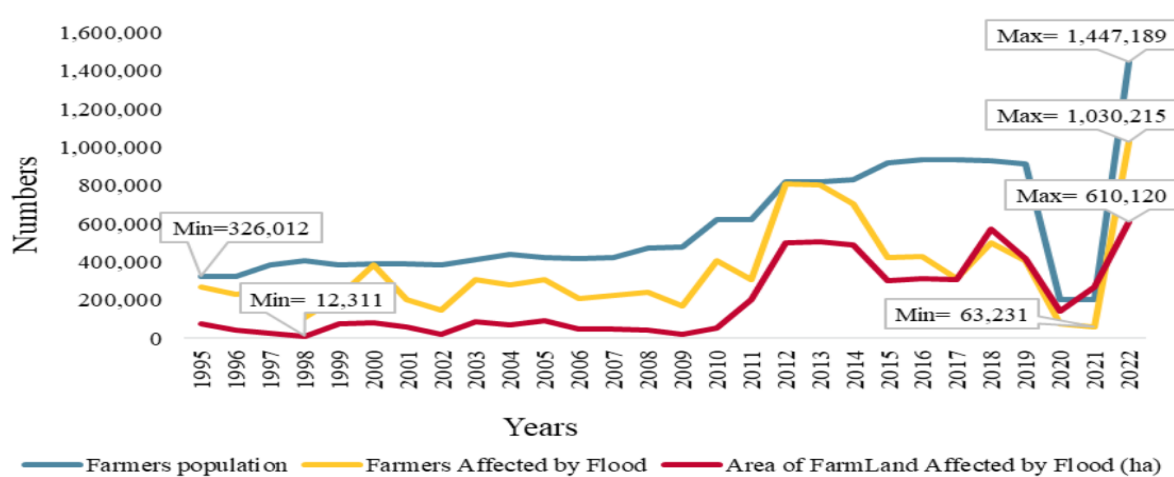


Figure 1. Flood events in Niger State from 1995 to 2022

Source: NEMA (18)

Recent studies have focused on the vulnerability of agricultural communities to climate change across various regions. Kheiri *et al.* (13) conducted a comprehensive assessment in northwestern Iran, utilizing a multi-dimensional approach that combined quantitative and qualitative methods. Their findings indicated varying levels of vulnerability among rural districts, with factors such as net income, labour force availability, medical insurance, and access to agricultural inputs significantly influencing resilience. Similarly, Ahmad *et al.* (2) explored the effects of climate change on livelihood vulnerability in flood-prone areas of Punjab, Pakistan, using the Livelihood Vulnerability Index (LVI), which revealed vulnerability scores ranging from 0.358 to 0.442. Tran *et al.* (25) applied the LVI approach to assess vulnerability among rice farmers in Vietnam, identifying floods, droughts, and socio-demographic factors as significant influences on household vulnerability. In Niger State, Eze *et al.* (10) evaluated social vulnerability to floods, finding that severe rainfall, intensified by dam water release, was a primary cause of flooding, with socioeconomic factors significantly affecting households' vulnerability and coping capacities.

Despite extensive research on vulnerability to climate change, much of the literature has concentrated on environmental and biophysical factors at the household level. There is a notable gap in studies addressing flood vulnerability specifically at the smallholder farmer level. This oversight is significant, as rural households face unique challenges and vulnerabilities distinct from urban

counterparts. Various methodologies have been used to assess flood vulnerability. For example, Eze *et al.* (10) quantified household vulnerability through social vulnerability indices, while Kheiri *et al.* (13) employed multi-criteria analyses to evaluate district-level vulnerability. Eze *et al.* (9) examined broader climate change impacts, including erosion and drought. These approaches emphasize the need for tailored assessments that consider local flood vulnerability at the farmer level. These approaches emphasize the necessity for tailored assessments that consider vulnerability to flooding local at the farmer level. Moreover, Nofiu and Barahudin (22) identified a gap in the literature regarding the quantification of vulnerability at the individual or farmer level in their systematic review of smallholder farmers' vulnerability to flooding, poverty, and coping strategies.

Past studies have largely focused on environmental and biophysical factors at the household level, overlooking the specific flood vulnerabilities of smallholder farmers, particularly in terms of quantifying vulnerability at the individual farmer level. Consequently, this study assesses vulnerability to flooding among smallholder farmers in Niger State, specifically focusing on the quantifying vulnerability to flooding among farmers using.

Materials and methods

Study Area

Niger State, established in 1976, is Nigeria's largest state, covering 9.3% of the nation's land area (86,000 km²). Located in the North Central Geopolitical Zone, it borders seven states and the

Republic of Benin. As shown in Figure 2, the state is divided into three geopolitical zones (A, B, and C), comprising 25 Local Government Areas. Niger State is crucial to Nigeria's agriculture, producing staple and cash crops that significantly contribute to its GDP and employment. The state features three major hydrological dams (Kainji, Jebba, and Shiroro) and several

principal rivers, including the Niger and Kaduna. As of 2006, Niger State's population was 4,260,429, with an annual growth rate of 3.4%. The state is home to diverse ethnic groups, including Nupes, Hausa, and Gbagyi (20 and 21). These factors, particularly the presence of rivers and hydrological dams, make the state vulnerable to flooding (1).

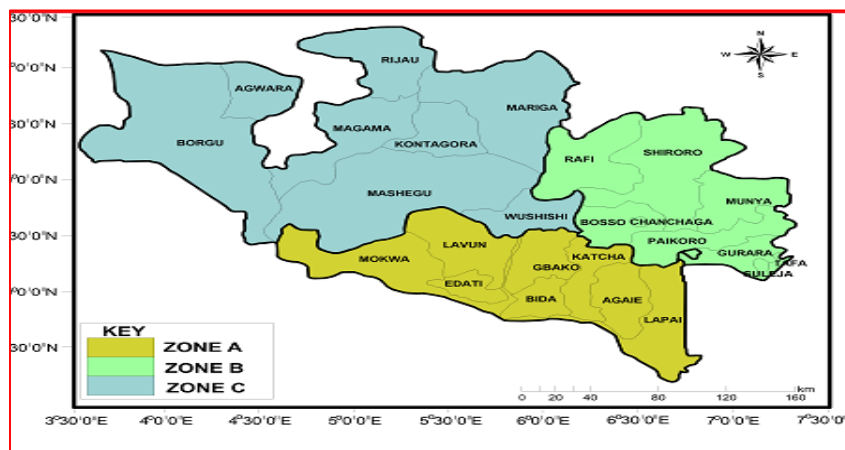


Figure 2. Map of Niger State showing the Zones

Source:

Authors'

diagram

Data Collection and Sampling Methods

The study population comprised 1,541,724 registered farmers in Niger State as shown in Table 1. Using the Taro Yamane formula (31), a sample size of 356 farmers was calculated with a 0.053 margin of error.

$$Ss = \left(\frac{N}{[1 + Ne^2]} \right) \quad 1$$

Where: Ss = sample size; e = margin of error; N = population size.

$$Ss = 355.92 \approx 356$$

Questionnaires were administered across each agro-ecological zone, with 350 successfully retrieved. The study employed proportionate sampling to select farmers, ensuring representation from different areas within the state.

Primary data was collected through a field survey using structured questionnaires. The questionnaire was designed to gather information on socioeconomic characteristics and indicators of vulnerability, including adaptive capacity, sensitivity, and exposure. This comprehensive approach aimed to determine the vulnerability pattern of each agroecological zone to climate change in Niger State, Nigeria, based on farmer-level data. Ethical considerations and reliability tests were conducted to ensure the integrity and validity of the collected data.

Table 1. Estimated population and sample size in each zone of Niger State

Zone	Population	Percentage (%)	Sample Size
A	451,725	29.3	104
B	653,823	42.4	151
C	436,176	28.3	101
Total	1,541,724	100	356

Source: Niger State Bureau of Statistic (19).

Data Analysis Method

The study employed STATA 18 to analyse farmer vulnerability through various statistical techniques, including descriptive statistics, Principal Component Analysis (PCA), Correspondence Analysis (CA), and the Farmers' Vulnerability Index (FaVI). These methods were applied to thirteen socioeconomic and environmental

variables, as detailed in Table 2. While the adaptive capacity, sensitivity, and exposure indicators were adapted from the Ludena and Yoon (14). The study introduced an additional indicator for adaptive capacity—fertilizer subsidy and modified the sensitivity and exposure indicators to better reflect farmers' perspectives.

Table 2. Components of Vulnerability, Indicator and Description

Components of Vulnerability	Indicators of each component	Description of the Indicators
Exposure	Frequency of flood in last 1 year	Number of flood events experienced in the last 1 year
	Severity of flooding in last 1 year	Number of item damage by flood in the last 1 year
	Flood type	Type of flood experienced in the last 6 months (1= flash flood, 2= river flood; 3= dam break flood)
Sensitivity	Flood height on farmland	Highest flood height experienced on farmland in the last 1 year (in meters)
	Flood duration	Longest flood duration experienced in the last 1 year (in days)
Adaptive capacity	Fertilizer subsidy	Access to subsidized fertilizer (Yes=1; No=0)
	Remittance	Amount of remittance received (Naira)
	Relief from NGOs	Access to relief from NGOs (Yes=1; No=0)
	Loan access	Access to government loan or credit scheme (Yes=1; No=0)
	Family support	Number of family and friends the farmer can ask for support
	Livelihood diversification	Diversify of livelihood (Yes=1; No=0)
	Agroforestry practices	Practice of agroforestry (Yes=1; No=0)
	Awareness of flood	Numbers of times farmers is aware of flood before its occurrence.



Source: Adapted from Ludena and Yoon (14)

PCA was particularly important for assigning weights to the vulnerability variables, capturing their explanatory power within the population. This deterministic approach is commonly used in geographic studies to derive component scores that serve as weights for the variables included in the vulnerability index. Multiple Correspondence Analysis (MCA) complemented PCA by transforming non-metric vulnerability indicators into a metric scale, facilitating dimensional reduction. The results from both PCA and MCA were then employed to compute the Vulnerability Index (VI), based on the equation proposed by Deressa *et al.* (8). The formula for calculating vulnerability is defined as:

$$\begin{aligned} \text{Vulnerability} &= (\text{exposure} + \text{sensitivity}) \\ &\quad - (\text{adaptive capacity}) \quad 2 \end{aligned}$$

Source: Deressa *et al.* (8)

Equation 2 as employed by Xu *et al.* (30); Morzaria-Luna *et al.* (16); Cinner *et al.* (7) reflect a more realistic view of vulnerability, acknowledging that even systems with robust adaptive capacity may remain significantly vulnerable due to high exposure and sensitivity. It emphasizes the interrelationship between exposure, sensitivity, and adaptive capacity in

determining vulnerability. This equation was expanded to formulate the FaVI, incorporating weights derived from the first principal component scores and variables representing adaptive capacity, sensitivity, and exposure as seen in equation 3.

$$\begin{aligned} \text{FaVI} &= [(w_1 \text{Exp}_1 + w_2 \text{Exp}_2 + w_3 \text{Exp}_3) \\ &\quad + (w_1 \text{Sen}_1 + w_2 \text{Sen}_2)] \\ &\quad - (w_1 \text{Adpt}_1 + w_2 \text{Adpt}_2 \\ &\quad + \dots . w_8 \text{Adpt}_8) \quad 3 \end{aligned}$$

A higher positive index of 33% or more indicates greater vulnerability, while lower values suggest lesser vulnerability. The robustness of the model was evaluated through standard econometric tests, including the Shapiro-Wilk W test for normality and the Jackknife Stability Test, ensuring the validity of the findings.

Results

Quantification of flood vulnerability among smallholder farmers

Table 3 revealed the principal component scores for vulnerability indicators in Zone A. The analysis revealed that exposure indicators, such as the frequency and severity of flooding, are significantly high, with scores of 0.830 and 0.720, respectively.

Table 3. Principal Component scores for Zone A

Vulnerability indicators	Components		
Exposure	PCA 1	PCA 2	PCA 3
Frequency of flood in last 1 year	0.830	0.972	0.525
Severity of flooding in last 1 year	0.720	0.663	0.711
Flood type	0.694	0.526	0.684
Sensitivity			



Flood heigh on farmland	0.407	0.871	0.532
Flood duration	0.651	0.707	0.647
Adaptive Capacity			
Fertilizer subsidy	0.305	-0.279	-0.364
Remittance	0.591	-0.321	0.209
Relief from NGOs	0.424	0.433	-0.129
Loan access	-0.358	-0.155	0.552
Family support	-0.386	0.454	0.241
Livelihood diversification	0.422	0.435	-0.155
Agroforestry practices planting	0.346	-0.074	0.202
Awareness of flood	-0.372	0.514	0.231
Eigen Values	6.251	3.783	2.120
% of explained variance	51.432	31.126	17.443

Source: Authors' computation using STATA 18

In Table 4, the component scores for Zone B indicated a different vulnerability profile compared to Zone A. The adaptive capacity indicators, particularly livelihood diversification and access to fertilizer subsidies, showed higher scores, suggesting that farmers in this zone may have better resources to mitigate flood impacts. However, exposure indicators like the frequency of floods remain concerning, with a score of 0.612. The results indicate that farmers in Zone A face heightened vulnerability due to frequent and severe flooding, with factors like flood height and duration significantly contributing to this risk. Limited adaptive capacity, such as insufficient fertilizer subsidies and family support, highlights the challenges they face in coping with flood impacts, consistent with Rakotobe *et al.* (23).

Table 4. Principal Component scores for Zone B

Vulnerability indicators	Components		
Exposure	PCA 1	PCA 2	PCA 3
Frequency of flood in last 1 year	0.612	0.279	0.121
Severity of flooding in last 1 year	0.243	0.317	-0.314
Flood type	-0.133	-0.135	0.267
Sensitivity			
Flood height on farmland	0.410	0.327	0.213
Flood duration	0.149	0.204	0.192
Adaptive Capacity			
Fertilizer subsidy	0.709	-0.042	0.822
Remittance	0.546	0.306	-0.008
Relief from NGOs	-0.132	-0.641	-0.027
Loan access	0.694	-0.142	-0.010
Family support	0.432	-0.152	0.012
Livelihood diversification	0.940	-0.176	0.016
Agroforestry practices	0.727	0.636	-0.025
Awareness of flood	0.671	0.121	-0.003
Eigen Values	7.630	2.142	4.262
% of explained variance	54.368	15.263	30.369

Source: Authors' computation using STATA 18



Table 5 presents the vulnerability indicators for Zone C. The scores indicate that exposure remains a critical concern, with the frequency of floods and severity of flooding both scoring above 0.5. However, the adaptive capacity indicators, particularly access to relief from NGOs

and awareness of flood risks, show relatively higher scores compared to Zones A and B. This suggests that farmers in Zone C may have better access to support systems that can help them cope with flooding.

Table 5. Principal Component scores for Zone C

Vulnerability indicators	Components		
Exposure	PCA 1	PCA 2	PCA 3
Frequency of flood in last 1 year	0.579	-0.562	0.591
Severity of flooding in last 1 year	0.703	0.186	-0.612
Flood type	0.544	0.806	0.234
Sensitivity			
Flood height on farmland	0.624	0.351	0.190
Flood duration	-0.128	-0.075	0.112
Adaptive Capacity			
Fertilizer subsidy	0.655	-0.307	0.475
Remittance	0.411	-0.186	-0.385
Relief from NGOs	0.531	0.592	0.191
Loan access	0.279	-0.207	-0.102
Family support	-0.468	-0.036	-0.051
Livelihood diversification	-0.340	0.193	-0.137
Agroforestry practices	0.215	0.241	0.122
Awareness of flood	0.450	-0.169	-0.053
Eigen Values	5.235	2.513	1.861
% of explained variance	54.480	26.153	19.367

Source: Authors' computation using STATA 18

Table 6 revealed the Multiple Correspondence Analysis (MCA), which further explained the relationships between vulnerability indicators across the three zones. The results indicated that farmers in Zone A exhibit the highest frequency of flooding, while those in Zone B have the

highest access to adaptive resources like remittances and NGO support. This analysis stressed the heterogeneous nature of vulnerability across zones, emphasizing that strategies to enhance resilience must be made to the specific conditions and resources available in each zone.

Table 6. Multiple Correspondence Analysis results

Vulnerability indicators	Zones		
Exposure	A	B	C
Frequency of flood in last 1 year	0.372	0.783	0.441
Severity of flooding in last 1 year	0.311	0.347	0.255
Flood type	0.426	0.320	0.392
Sensitivity			
Flood height on farmland	0.435	0.212	0.544



Flood duration	0.251	0.374	0.391		
Adaptive Capacity					
Fertilizer subsidy	0.192	0.011	0.222		
Remittance	0.381	0.231	0.173		
Relief from NGOs	0.246	0.173	0.361		
Loan access	0.316	0.135	0.214		
Family support	0.202	0.130	0.201		
Livelihood diversification	0.127	0.051	0.273		
Agroforestry practices	0.224	0.172	0.008		
Awareness of flood	0.212	0.081	0.021		
Source:	Authors'	computation	using	STATA	18

The findings in Table 7 categorized farmers into vulnerability classes based on their Flood Vulnerability Assessment Index (FaVI) scores. A significant portion of farmers (63.71%) falls into the high vulnerability class, indicating that a majority of smallholder farmers in Niger

State are at risk. While, the low vulnerability class, comprising 36.29% of farmers. According to Aqib *et al.* (3), farming communities with better adaptive capacities can be leveraged to inform broader resilience-building strategies.

Table 7. Grouping of farmers into vulnerability classes

FaVI score	FaVI class	Number of Farmers	% of Farmers	
>=33%	High	223	63.71	
<33%	Low	127	36.29	
Source:	Authors'	computation	using STATA	18

Level of vulnerability to flood among smallholder farmers based on Zones

As revealed in Table 8, smallholder farmers vulnerability to flood varied significantly across three zones. Zone A shows the highest level of vulnerability with a total Farmers' Vulnerability Index (FaVI) of 0.914, classified as "High". Zone C also falls into the "High" vulnerability category with an FaVI of 0.646. While Zone B exhibited a much lower vulnerability level, with an FaVI of 0.174, categorized as "Low". The components contributing to these indices revealed that Zone A has the highest exposure (0.829) and sensitivity (0.341) to flooding, while Zone B has the highest

adaptive capacity (0.490). These findings are in line with regional and international studies that emphasize the importance of localized flood risk management. For example, Asfaw *et al.* (5) found that West African farmers in flood-prone areas face similar vulnerability due to limited adaptive capacity, while Aryal *et al.* (4) reported comparable challenges for Bangladeshi farmers who lack government support. In Southeast Asia, farmers in Vietnam demonstrate stronger adaptive capacities due to better flood management systems (25) and in Pakistan, farming communities with better adaptive capacities leveraged to inform broader resilience-building strategies (3), paralleling Zone C. Sub-Saharan African



farmers, like those in Zone B, remain highly exposed to floods, with Kakota *et*

al. (12) stressing the role of infrastructure in vulnerability.

Table 8. Level of vulnerability to flood among smallholder farmers based on Zones

Components of FaVI	Zone A	Zone B	Zone C
Exposure	0.829	0.521	0.649
Sensitivity	0.341	0.143	0.289
Adaptive Capacity	0.256	0.490	0.292
Total Farmers' Vulnerability Index	0.914	0.174	0.646
Class	High	Low	High
Source: Authors' computation using STATA			18

Analysis for Zone A:

Total Exposure (Zone A) = $(0.372 \times 0.830) + (0.311 \times 0.720) + (0.426 \times 0.694)$

Total Exposure (Zone A) = 0.829

Total Sensitivity (Zone A) = $(0.435 \times 0.407) + (0.251 \times 0.651)$

Total Sensitivity (Zone A) = 0.341

Total Adaptive Capacity (Zone A) = $(0.192 \times 0.305) + (0.381 \times 0.591) + (0.246 \times 0.424) + (0.316 \times -0.358) + (0.202 \times -0.386) + (0.127 \times 0.422) + (0.244 \times 0.346) + (0.212 \times -0.372)$

Total Adaptive Capacity (Zone A) = 0.256

Total FaVI Zone A = $0.829 + 0.341 - 0.256$

Total FaVI Zone A = 0.914

Analysis for Zone B:

Total Exposure (Zone B) = $(0.783 \times 0.612) + (0.347 \times 0.243) + (0.320 \times -0.133)$

Total Exposure (Zone B) = 0.521

Total Sensitivity (Zone B) = $(0.212 \times 0.410) + (0.374 \times 0.149)$

Total Sensitivity (Zone B) = 0.143

Total Adaptive Capacity (Zone B) = $(0.011 \times 0.709) + (0.231 \times 0.546) + (0.173 \times -0.132) + (0.135 \times 0.694) + (0.130$

$\times 0.432) + (0.051 \times 0.940) + (0.172$

$\times 0.727) + (0.081 \times 0.671)$

Total Adaptive Capacity (Zone B) = 0.490

Total FaVI Zone B = $0.521 + 0.143 - 0.490$

Total FaVI Zone B = 0.174

Analysis for Zone C:

Total Exposure (Zone C) = $(0.441$

$\times 0.579) + (0.255 \times 0.703) + (0.392 \times 0.544)$

Total Exposure = 0.649

Total Sensitivity (Zone C) = $(0.544$

$\times 0.624) + (0.391 \times -0.128)$

Total Sensitivity = 0.289

Total Adaptive Capacity (Zone

C) = $(0.222 \times 0.655) + (0.173 \times 0.411) + (0.361$

$\times 0.531) + (0.214 \times 0.279) + (0.201 \times$

$0.468) + (0.273 \times -0.340) + (0.008$

$\times 0.215) + (0.021 \times 0.450)$

Total Adaptive Capacity (Zone C) = 0.292

Total Vulnerability (Zone

C) = $0.649 + 0.289 - 0.292$

Total Vulnerability (Zone C) = 0.646

Post Estimation Test

Table 9 presents the results of a Shapiro-Wilk W test, which was used to assess the normality of the distribution of the

Farmer's Vulnerability Index (FaVI) data. The test was conducted on a sample of 350 observations. The W statistic of 0.955 is relatively close to 1, indicating that the data approximates a normal distribution. The associated p-value of 0.074 is greater than the conventional significance level of 0.05, suggesting that we fail to reject the

null hypothesis of normality. This means that the FaVI data does not significantly deviate from a normal distribution, which is important for the validity of certain statistical analyses and inferences made from this data.

Table 9. Shapiro-Wilk W Normality Test

Variable	Obs.	W	V	Z	Prob>z
FaVI	350	0.955	10.896	2.648	0.074
Source:	Authors'	computation	using	STATA	18

Table 10 revealed the results of a Jackknife stability test on the estimates of farmer's vulnerability to flooding. The Jackknife method is a resampling technique used to assess the stability and reliability of statistical estimates. The test result indicates a coefficient of 0.3969 with a very small standard error of 0.0080. The large t-statistic (49.15) and the extremely

low p-value (0.0000) suggest that this estimate is highly stable and statistically significant. This provides strong evidence that the vulnerability index is a robust measure, as it remains consistent even when subsets of the data are systematically excluded during the Jackknife procedure.

Table 10. Jackknife Test Result

	Coefficient	Std. Error	T-statistics	P-value	
JK_1	0.3969	0.0080	49.61	0.0000	
Source:	Authors'	computation	using	STATA	18

Conclusion

This study assessed flood vulnerability among smallholder farmers in Niger State by using the Farmers' Vulnerability Index (FaVI). The study employed a robust methodology, combining Principal Component Analysis, Multiple Correspondence Analysis, and the Farmers' Vulnerability Index, ensuring the reliability of results as confirmed by post-estimation tests. The result revealed Zone A exhibits the highest vulnerability with a Farmers' Vulnerability Index (FaVI) of

0.914, followed closely by Zone C (FaVI: 0.646), while Zone B demonstrated notably lower vulnerability (FaVI: 0.174). These findings emphasized the heterogeneous nature of flood risks and adaptive capacities within the state. The high vulnerability in Zones A and C is primarily attributed to elevated exposure and sensitivity to flooding, coupled with lower adaptive capacities. Conversely, Zone B's lower vulnerability stems from higher adaptive capacity, despite moderate exposure levels. These revelations stressed the need for targeted, zone-specific



interventions to enhance resilience among smallholder farmers. The study recommends prioritizing flood mitigation strategies such as improving drainage systems and constructing flood barriers, and bolstering adaptive capacities, such as providing of subsidized fertilizers and relief from NGOs, particularly in Zones A and C, while maintaining and further strengthening the effective practices observed in Zone B. These findings provide a key foundation for policymakers and stakeholders to develop localized approaches to flood management and agricultural resilience in Niger State.

Conflict of interest

The authors declare no conflict of interest.

References

1. **Abiodun, O.A.; A.O. Emmanuel and A.A. Suleiman. 2016.** Spatial vulnerability assessment of flood in Niger State. *International Journal of Science for Global Sustainability* 2(2):12-12. <https://fugus-ijsgs.com.ng/index.php/ijsgs/article/download/260/223/224>
2. **Ahmad, D.; S. Khurshid and M. Afzal. 2023.** Climate change vulnerability and multidimensional poverty in flood-prone rural areas of Punjab, Pakistan: An application of multidimensional poverty index and livelihood vulnerability index. *Environmental Development and Sustainability*. <https://doi.org/10.1007/s10668-023-04207-8>
3. **Aqib, S.; M. Seraj; H. Ozdeser; S. Khalid; M.H. Raza and T. Ahmad. 2024.** Assessing adaptive capacity of climate-vulnerable farming communities in flood-prone areas: Insights from a household survey in South Punjab, Pakistan. *Climate Services* 33:100444. <https://doi.org/10.1016/j.cliser.2023.100444>
4. **Aryal, J.P.; T.B. Sapkota; D.B. Rahut; T.J. Krupnik; S. Shahrin; M.L. Jat and C.M. Stirling. 2020.** Major climate risks and adaptation strategies of smallholder farmers in coastal Bangladesh. *Environmental Management* 66:105–120. <https://doi.org/10.1007/s00267-020-01291-8>
5. **Asfaw, S.; F. Di Battista and L. Lipper. 2016.** Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger. *Journal of African Economies* 25(5):637-669. <https://doi.org/10.1093/jae/ejw005>
6. **Bangladesh Red Crescent. 2023.** Partnership Meeting Report 2023. Retrieved from <https://bdrcs.org/partnership-meeting-2023/> (Accessed 16 August 2024)
7. **Cinner, J.E.; T.R. McClanahan; N.A. Graham; T.M. Daw; J. Maina; S.M. Stead and Ö. Bodin. 2012.** Vulnerability of coastal communities to key impacts of climate change on coral reef fisheries. *Global Environmental Change* 22:12–20. [http://refhub.elsevier.com/S0308-597X\(13\)00238-8/sbref12](http://refhub.elsevier.com/S0308-597X(13)00238-8/sbref12)
8. **Deressa, T.; R.M. Hassan and C. Ringler. 2008.** Measuring Ethiopian farmers' vulnerability to climate change across regional states. *Intl Food Policy Research Institute*.
9. **Eze, J.N.; U. Aliyu; A. Alhaji-Baba and M. Alfa. 2018a.** Analysis of farmers' vulnerability to climate change in Niger State,



- Nigeria. International Letters of Social and Humanistic Sciences 82:1-9.
<https://doi.org/10.18052/www.scipress.com/ilshs.82.1>
10. **Eze, J.N.; C. Vogel and P.A. Ibrahim. 2018b.** Assessment of social vulnerability of households to floods in Niger State, Nigeria. International Letters of Social and Humanistic Sciences 84:22-34.
<https://doi.org/10.18052/www.scipress.com/ILSHS.84.22>
11. **Ibrahim, M. and S. Tasnim. 2023.** Strengthening Sustainable Development Goals – SDG 9 concerning flooding in Malaysia. Accounting and Finance Research.
<https://doi.org/10.5430/afr.v12n4p117>
12. **Kakota, T.; D. Nyariki; D. Mkwambisi and W. Kogi-Makau. 2015.** Determinants of household vulnerability to food insecurity: A case study of semi-arid districts in Malawi. Journal of International Development 27(1):73-84.
<https://doi.org/10.1002/jid.2958>
13. **Kheiri, M.; J. Kambouzia; S. Soufizadeh; A.M. Damghani; R. Sayahnia and H. Azadi. 2024.** Assessing vulnerability to climate change among farmers in northwestern Iran: A multi-dimensional approach. Ecological Informatics 102669.
14. **Ludena, C.E. and S.W. Yoon. 2015.** Local vulnerability indicators and adaptation to climate change: A survey. Inter-American Development Bank, Technical Note No. 857 (IDB-TN857), Washington DC.
<http://dx.doi.org/10.18235/0009259>
15. **Mondal, P.; C. Chatterjee and B. Bhattacharya. 2020.** Flood risk assessment under future climate change scenarios and development of damage curves for West Bengal, India. Science of the Total Environment 705:135870.
<https://doi.org/10.1016/j.scitotenv.2019.135870>
16. **Morzaria-Luna, H.N.; P. Turk-Boyer and M. Moreno-Baez. 2013.** Social indicators of vulnerability for fishing communities in the Northern Gulf of California, Mexico: Implications for climate change. Marine Policy 45:182–193.
<https://doi.org/10.1016/j.marpol.2013.10.013>
17. **National Emergency Management Agency. 2022a.** NEMA situational report on 2022 flooding in Nigeria. Retrieved from <https://nema.gov.ng/sitrep/> (Accessed 7 July 2024)
18. **National Emergency Management Agency. 2022b.** Estimated cost of flood damage between 1995-2022.
<https://nema.gov.ng/estimated-cost-of-flood-damage-between-1995-2022/> (Accessed 22 July 2024)
19. **Niger State Bureau of Statistic. 2023.** Agricultural statistics: Nigeria statistical development project (NSDP), 2023 Edition.
20. **Niger State Government. 2023a.** About Niger State. Retrieved from <https://nigerstate.gov.ng/about-niger/> (Accessed 12 August 2024)
21. **Niger State Government. 2023b.** Niger State economic profile. Minna, Nigeria: Niger State Ministry of Economic Planning. Retrieved from <https://nigerstate.gov.ng/> (Accessed 12 August 2024)
22. **Nofiu, N.B. and S.A. Baharudin. 2024.** The vulnerability of smallholder farmers to flooding, poverty, and coping strategies: A



- systematic review. *Mesopotamia Journal of Agriculture* 52(2).
<https://doi.org/10.33899/mja.2024.149253.011424>
23. **Rakotobe, Z.L.; C.A. Harvey; N.S. Rao; R. Dave; J.C. Rakotondravelo; J. Randrianarisoa and J.L. MacKinnon. 2016.** Strategies of smallholder farmers for coping with the impacts of cyclones: A case study from Madagascar. *International Journal of Disaster Risk Reduction* 17:114-122.
<https://www.sciencedirect.com/science/article/pii/S2212420915301916>
 24. **Rentschler, J.; M. Salhab and B.A. Jafino. 2022.** Flood exposure and poverty in 188 countries. *Nature Communications* 13:3527.
<https://doi.org/10.1038/s41467-022-30727-4>
 25. **Tran, P.T.; B.T. Vu; S.T. Ngo; V.D. Tran and T.D. Ho. 2022.** Climate change and livelihood vulnerability of the rice farmers in the North Central Region of Vietnam: A case study in Nghe An province, Vietnam. *Environmental Challenges* 7:100460.
<https://doi.org/10.1016/J.ENVC.2022.100460>
 26. **United Nations Development Programme. 2024.** The SDGs in action. Retrieved from <https://www.undp.org/sustainable-development-goals> (Accessed 20 July 2024)
 27. **World Bank. 2023.** The World Bank in middle income countries. Retrieved from <https://www.worldbank.org/en/country/mic> (Accessed 12 August 2024)
 28. **World Economic Forum. 2022.** This is how many people would be displaced by extreme flooding. Retrieved from <https://www.weforum.org/agenda/2022/10/extreme-flooding-climate-change-displacement/> (Accessed 12 August 2024)
 29. **World Health Organization. 2023.** Floods. Retrieved from https://www.who.int/health-topics/floods#tab=tab_1 (Accessed 20 July 2024)
 30. **Xu, X.; L. Wang; M. Sun; C. Fu; Y. Bai; C. Li and L. Zhang. 2020.** Climate change vulnerability assessment for smallholder farmers in China: An extended framework. *Journal of Environmental Management* 276:111315.
<https://doi.org/10.1016/j.jenvman.2020.111315>
 31. **Yamane, T. 1967.** Statistics: An introductory analysis (2nd ed.). Harper and Row.

