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SPATIAL PATTERNS OF SOCIAL VULNERABILITY TO FLOODING IN DELTA STATE, NIGERIA: A GEOGRAPHICALLY WEIGHTED REGRESSION APPROACH TO IDENTIFYING PRIORITY INTERVENTION ZONES

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ABSTRACT

Flooding in Nigeria's Niger Delta disproportionately affects communities based on their socio-economic characteristics, yet spatial patterns of social vulnerability remain poorly understood. This research investigates the spatial dimensions of social vulnerability to flooding across 18 communities in Delta State, employing Geographically Weighted Regression (GWR) to identify spatially varying relationships and priority intervention zones. A mixed-methods design integrated household surveys (n=761, 94.0% response rate), 36 key informant interviews, and 18 focus group discussions with geospatial analysis. Principal Component Analysis extracted three vulnerability dimensions—economic (34.2% variance), demographic (22.4%), and infrastructure (16.8%)—collectively explaining 73.4% of total variance. Social Vulnerability Index (SVI) rankings ranged from 43.2 (Okwe) to 82.1 (Abuator), with four communities forming an extreme vulnerability cluster. Spatial analysis revealed significant clustering along the Niger River corridor (Global Moran's I = 0.342, $p < 0.001$), with Local Indicators of Spatial Association (LISA) identifying six High-High hotspots. GWR analysis demonstrated that GWR ($R^2 = 0.457$) substantially outperforms ordinary least squares regression ($R^2 = 0.412$). Critically, poverty exhibited near-uniform exacerbating effects (low spatial variation, 100% significant) while infrastructure access showed significant spatial variation, with stronger protective effects where facilities remain accessible during floods. Integrated risk modelling identified five priority communities—Abuator, Patani, Koloware II, Odorubu, and Uzere—accounting for 38% of the study population but 72% of modeled risk. Qualitative findings documented severe livelihood impacts (average crop loss 54.2%), coping strategies with negative consequences (76% borrowing creating debt cycles), and institutional gaps (only 17% with early warning systems). This research advances vulnerability assessment methodology through spatially explicit analysis and provides actionable intelligence for targeted disaster risk reduction interventions in the Niger Delta.

KEYWORDS: Social vulnerability, flood risk, Geographically Weighted Regression, Niger Delta, spatial analysis, disaster risk reduction, priority intervention zones.

1. INTRODUCTION

Flooding remains one of the most devastating natural hazards globally, with impacts that extend beyond physical damage to include profound social and economic consequences. In developing regions such as sub-Saharan Africa, these impacts are disproportionately borne by vulnerable populations whose limited adaptive capacity exacerbates disaster outcomes. In Nigeria, recurrent flooding has intensified in recent decades, with the 2012 flood alone displacing over two million people and causing damages exceeding US$500 million, while the 2024 event affected over 2.1 million people with losses surpassing US$600 million (NEMA, 2012; NEMA, 2024). Despite similar levels of hazard exposure, flood impacts vary significantly across communities, highlighting the critical role of social vulnerability in shaping disaster outcomes.

Social vulnerability refers to the characteristics of individuals, households, and communities that influence their capacity to anticipate, cope with, resist, and recover from hazard events (Wisner et al., 2004). Unlike physical exposure, which is determined by geographic location, vulnerability is socially constructed through economic conditions, demographic structures, institutional arrangements, and access to resources (Cutter et al., 2003). This distinction is fundamental: communities exposed to similar flood hazards may experience markedly different impacts depending on their socio-economic and infrastructural conditions. Consequently, understanding flood risk requires moving beyond hazard-centric approaches toward integrated frameworks that incorporate social dimensions.

The conceptualization of vulnerability has evolved significantly over time. Early disaster research focused primarily on physical hazards, but subsequent scholarship emphasized the role of social processes in shaping disaster impacts. The "pressure and release" model (Blaikie et al., 1994) conceptualizes disasters as the intersection of hazard events and socially produced vulnerability rooted in political, economic, and institutional structures. Building on this foundation, Cutter et al. (2003) operationalized vulnerability through the Social Vulnerability Index (SoVI), demonstrating that vulnerability is multidimensional and systematically patterned across space. Key dimensions include economic status, demographic characteristics, social networks, and access to infrastructure and services.

Empirical studies in Nigeria and similar contexts have highlighted the importance of these dimensions in shaping flood impacts. Economic vulnerability limits the ability of households to invest in protective measures or recover from losses, while demographic factors such as age structure and household composition influence coping capacity (Wisner et al., 2004; Enarson, 2012). Social capital and access to information affect preparedness and response, while infrastructure deficits—such as poor drainage systems and inadequate housing—amplify exposure and damage (IPCC, 2022). In the Niger Delta, these vulnerabilities are further intensified by dependence on flood-sensitive livelihoods such as farming and fishing, high population density in flood-prone areas, and limited institutional capacity for disaster management (Adelekan, 2010; Nhemachena et al., 2020).

While these studies provide valuable insights into the determinants of vulnerability, most existing research in Nigeria has focused primarily on hazard characteristics, such as rainfall patterns and flood extent, or on physical exposure in floodplains. Relatively few studies have developed comprehensive, multidimensional assessments of social vulnerability, and even fewer have incorporated spatial analytical techniques to examine how vulnerability is distributed across communities. Yet vulnerability is inherently geographical, shaped by place-specific interactions between environmental conditions, socio-economic structures, and institutional contexts.

Advances in spatial analysis provide important tools for addressing this limitation. Spatial autocorrelation techniques, such as Moran's I and Local Indicators of Spatial Association (LISA), enable the identification of clustering patterns and hotspots of vulnerability (Anselin, 1995). Similarly, Geographically Weighted.

Regression (GWR) extends traditional regression models by allowing relationships between variables to vary across space, thereby capturing spatial heterogeneity in socio-environmental processes (Fotheringham et al., 2002). These methods offer significant potential for improving understanding of vulnerability dynamics and informing targeted interventions.

Despite these advances, a critical research gap persists. There is limited empirical evidence on the spatial structure of social vulnerability to flooding in the Niger Delta, and existing studies rarely integrate composite vulnerability indices with spatial statistical analysis and spatially varying regression models. Furthermore, no study has systematically identified vulnerability hotspots and priority intervention zones using an integrated framework that combines socio-economic indicators, spatial patterns, and flood impact relationships. This gap constrains the development of targeted, evidence-based disaster risk reduction strategies tailored to local conditions.

To address this gap, this study investigates the spatial dimensions of social vulnerability to flooding in Delta State, Nigeria, using a combination of Principal Component Analysis (PCA), spatial autocorrelation techniques, and Geographically Weighted Regression (GWR). The study aims to develop a comprehensive Social Vulnerability Index (SVI), analyze its spatial distribution, and model spatially varying relationships between vulnerability and flood impacts.

Specifically, the study addresses the following research questions:

1. What are the underlying dimensions of social vulnerability in Delta State communities, and how can they be quantified through a composite index?
2. What spatial patterns characterize the distribution of vulnerability, and where are the statistically significant hotspots requiring priority intervention?
3. How do relationships between vulnerability dimensions and flood impacts vary across space?
4. Which communities represent priority intervention zones based on integrated assessment of vulnerability and flood risk?

5. How can spatially explicit vulnerability analysis inform disaster risk reduction policy and practice?

This study makes three key contributions. First, it advances methodological approaches to vulnerability assessment by integrating PCA-based index construction with spatial statistical analysis and GWR modelling. Second, it provides empirical evidence on the spatial structure and heterogeneity of social vulnerability in the Niger Delta, a region where such analysis remains limited. Third, it generates policy-relevant insights by identifying priority intervention zones and demonstrating how spatially explicit vulnerability intelligence can support targeted and efficient disaster risk reduction strategies.

2. METHODOLOGY

2.1 Research Design

This study adopts a mixed-methods geospatial research design, integrating quantitative spatial modelling with qualitative field-based investigations. The approach is particularly appropriate for vulnerability assessment as it captures both measurable spatial patterns and the contextual realities shaping community-level exposure and resilience.

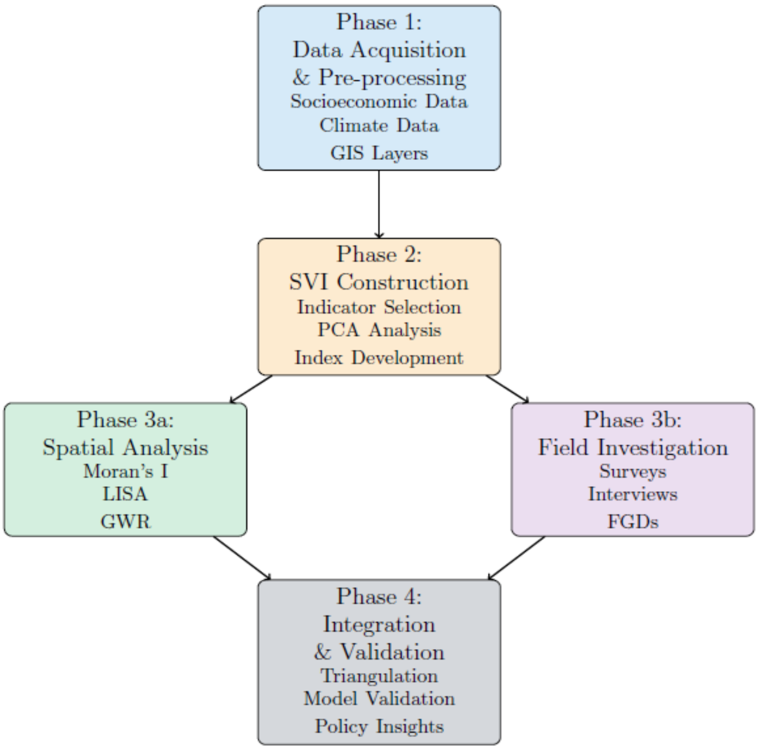

Figure 1: Mixed-methods geospatial research design framework.

The study adopts a structured mixed-methods geospatial framework (Figure 1) that integrates quantitative spatial modelling with qualitative field investigation. Socioeconomic and environmental datasets are first compiled and pre-processed to ensure analytical consistency. A Social Vulnerability Index (SVI) is then constructed using multivariate statistical techniques to derive composite vulnerability dimensions. Spatial analytical methods, including global and local autocorrelation and Geographically Weighted Regression (GWR), are subsequently applied to identify clustering patterns and spatially varying determinants of vulnerability. Qualitative evidence from field investigations is used to contextualize and validate model outputs. As illustrated in Figure 1, this process unfolds across four phases: data preparation, SVI construction, spatial–qualitative analysis, and final integration through triangulation and validation to generate policy-relevant insights.

2.2 Study Area

The study area comprises 18 communities across six Local Government Areas in Delta State, representing the three senatorial districts: Delta North (Oshimili South, Ndokwa East), Delta Central (Ughelli North, Ughelli South), and Delta South (Isoko South, Patani). Communities include Okwe, Oko, Oko-Amakom; Aboh, Ashaka, Abuator; Ewrheni, Uwheru, Agadama; Otu-Jeremi, Okwagbe, Egbo-Ideh; Oleh, Aviara, Uzere; and Patani, Koloware II, Odorubu.

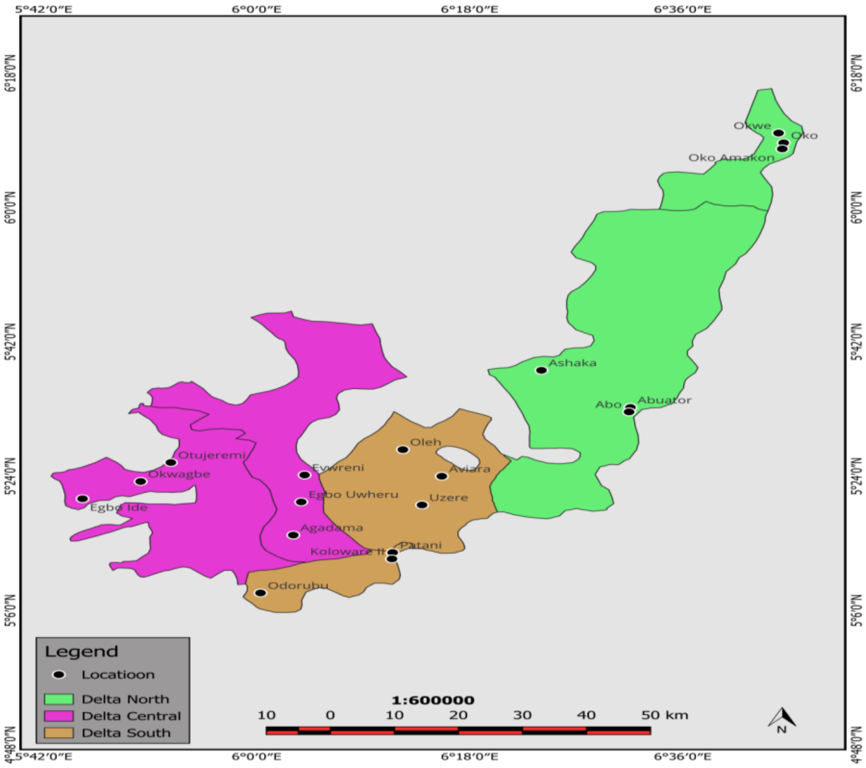

Figure 1: Study Areas Based on Senatorial District of Delta State.

Table 1: Presents population figures for the study areas (revised 2024), showing a total projected population of 211,701 persons across the 18 communities, with population densities ranging from 107 persons/km² (Ndokwa East) to 684 persons/km² (Ughelli North). These variations in population density and settlement patterns are critical determinants of differential vulnerability.

S/N	Name of Communities	Lat (N)	Long (E)	Projected Figure (2024)	Population Density (persons/km²)
A.	**Oshimili South LGA**			**251,224**	487
1.	Okwe	6.166375	6.734784	**7,917**	412
2.	Oko Obiokpu	6.14449	6.742019	**1,881**	395
3.	Oko Amakom	6.130964	6.740004	**813**	378
B.	**Ndokwa East LGA**			**172,829**	107
4.	Aboh	5.543677	6.524294	**6,345**	185
5.	Ashaka	5.63648	6.400978	**13,604**	212
6.	Abuator	5.553521	6.52625	**655**	168
C.	**Ughelli North LGA**			**536,940**	684
7.	Ewrheni	5.402735	6.067505	**21,619**	592
8.	Uwheru	5.342591	6.062772	**22,161**	578
9.	Agadama	5.268542	6.051569	**5,864**	534
D.	**Ughelli South LGA**			**356,012**	453
10.	Otu-Jeremi	5.435617	5.868203	**8,728**	412
11.	Okwagbe	5.422817	5.83473	**12,964**	398
12.	Egbo-Ideh	5.349749	5.754909	**3,880**	376
E.	**Isoko South LGA**			**393,704**	362
13.	Oleh	5.459383	6.205882	**60,548**	445
14.	Aviara	5.399935	6.260691	**21,475**	384
15.	Uzere	5.335781	6.232818	**25,090**	402
F.	**Patani LGA**			**112,840**	284
16.	Patani	5.229601	6.191493	**27,322**	312
17.	Koloware II	5.215403	6.19051	**2,284**	265
18.	Odorubu	5.139323	6.005459	**3,188**	248
	TOTAL (18 Communities)			**211,701**	387

Figure 1 (Study Area Map) presents the spatial distribution of 18 communities across six LGAs, with symbol size proportional to SVI and color intensity indicating vulnerability level. The Niger River corridor emerges as the dominant geographical feature, with communities concentrated along its banks—a pattern reflecting historical settlement patterns but also exposing populations to flood hazards.

2.2 Sampling Design

2.3.1 Target Population

The target population comprises all households residing in flood-prone communities within Delta State's freshwater ecosystem, specifically communities that have experienced significant flood events since 2012.

2.3.2 Sampling Technique

A multi-stage sampling approach was employed to ensure representativeness across spatial and administrative scales:

- **Stage 1:** Selection of the three senatorial districts
- **Stage 2:** Selection of two LGAs per district based on flood history and freshwater ecosystem status
- **Stage 3:** Random selection of three communities per LGA from flood-affected settlement lists
- **Stage 4:** Systematic random sampling of households within each community (every 5th household)
- **Stage 5:** Random selection of respondents within households (alternating gender)

2.3.3 Sample Size Determination

Sample size was calculated using Cochran's formula:

$$n_0 = \frac{Z^2 \times p \times q}{e^2} = \frac{(1.96)^2 \times 0.5 \times 0.5}{(0.035)^2} = 784$$

Applying finite population correction with N = 38,491 households:

$$n = \frac{784}{1 + \frac{784 - 1}{38{,}491}} \approx 768$$

The calculated sample size was rounded up to 810 to account for potential non-response. Following quality control, **761 valid questionnaires** were retained, representing a **94.0% response rate**—99.1% of the minimum required sample size.

Table 2: Sample Distribution by Community and LGA.

Senatorial District	LGA	Community	Total Households (Est.)	Sample Size (Households)	% of Community	KII	FGD Participants
Delta North	Oshimili South	Okwe	1,523	45	3.0	2	8
		Oko	348	45	12.9	2	8
		Oko-Amakom	159	45	28.3	2	8
	Ndokwa East	Aboh	1,094	45	4.1	2	8
		Ashaka	2,567	45	1.8	2	8
		Abuator	106	45	42.5	2	8
Delta Central	Ughelli North	Ewrheni	3,861	45	1.2	2	8
		Uwheru	4,029	45	1.1	2	8
		Agadama	1,128	45	4.0	2	8
	Ughelli South	Otu-Jeremi	1,455	45	3.1	2	8
		Okwagbe	2,275	45	2.0	2	8
		Egbo-Ideh	732	45	6.1	2	8
Delta South	Isoko South	Oleh	10,263	45	0.4	2	8
		Aviara	3,905	45	1.2	2	8
		Uzere	4,326	45	1.0	2	8
	Patani	Patani	4,879	45	0.9	2	8
		Koloware II	423	45	10.6	2	8
		Odorubu	559	45	8.1	2	8
Total	6 LGAs	18 Communities	40,492	810	2.0	36	144

Table 2 presents sample distribution by community, showing administered and valid questionnaires with response rates.

2.4 Data Collection Instruments

2.4.1 Household Questionnaire

A structured questionnaire captured information on demographic characteristics, economic status, housing conditions, water/sanitation/hygiene (WASH), flood experience, livelihood impacts, food security, health impacts, education impacts, social capital, adaptation strategies, and institutional support.

2.4.2 Key Informant Interviews

Semi-structured interviews were conducted with 36 key informants (2 per community), including community leaders, LGA officials, NEMA/SEMA officials, NGO representatives, health workers, education officers, and agricultural officers.

2.4.3 Focus Group Discussions

Eighteen focus group discussions (one per community) were conducted with 6-10 participants each, including women, youth, farmers/fisherfolk, elders, and internally displaced persons.

2.4.4 GIS Datasets

Geospatial data were acquired from multiple sources including Sentinel-2 (ESA, 10 m resolution), SRTM DEM (USGS, 30 m resolution), LGA boundaries, settlement locations, river network data, and population data (NPC/WorldPop).

2.5 Social Vulnerability Index Construction

2.5.1 Indicator Selection

Sixteen vulnerability indicators were selected based on literature review (Cutter et al., 2003; Wisner et al., 2004) and adapted to the Niger Delta context through expert consultation. **Table 3** presents the vulnerability indicators organized by domain (Demographic, Economic, Social, Health/WASH), with each indicator coded, described, and expected sign indicated.

2.5.2 Data Preparation

All indicators were aggregated to community level (n=18) by calculating means or proportions. Indicators where higher values indicate lower vulnerability (income, education, water access) were reversed so that for all indicators, higher scores indicate greater vulnerability. All indicators were standardized to zero mean and unit variance:

$$Z_{ij} = \frac{X_{ij} - \bar{X}_j}{\sigma_j}$$

2.5.3 Principal Component Analysis

Principal Component Analysis (PCA) was conducted on the 16 standardized indicators. Data suitability was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (threshold >0.6) and Bartlett's test of sphericity (*p* < 0.05). Components with eigenvalues greater than 1 (Kaiser criterion) were retained. Varimax rotation was applied to enhance interpretability.

2.5.4 SVI Calculation

The Social Vulnerability Index was calculated as the eigenvalue-weighted sum of component scores:

$$SVI_i = \frac{\lambda_1 PC_{i1} + \lambda_2 PC_{i2} + \lambda_3 PC_{i3}}{\lambda_1 + \lambda_2 + \lambda_3}$$

Component scores were normalized to a 0-100 scale for ease of interpretation. Bootstrap confidence intervals (n=1000) were generated to assess ranking robustness.

2.6 Spatial Autocorrelation Analysis

2.6.1 Global Moran's I

Global Moran's I was calculated to assess overall spatial clustering of SVI scores:

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where w_{ij} is the spatial weight between locations i and j. A positive significant I indicates clustering of similar values; negative significant I indicates dispersion.

2.6.2 Local Indicators of Spatial Association (LISA)

Local Moran's I was calculated to identify specific locations where spatial clustering is statistically significant:

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_j w_{ij} (x_j - \bar{x})$$

Where $m_2 = \frac{1}{n} \sum_i (x_i - \bar{x})^2$. Statistical significance was assessed using conditional randomization with $n = 999$permutations.

2.7 Geographically Weighted Regression

2.7.1 Model Specification

GWR was employed to model spatially varying relationships between flood impact (dependent variable) and vulnerability dimensions (predictors):

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i) Econ_i + \beta_2(u_i, v_i) Demo_i + \beta_3(u_i, v_i) Infra_i + \beta_4(u_i, v_i) Hazard_i + \varepsilon_i$$

2.7.2 Bandwidth Selection

An adaptive bi-square kernel function was employed, with bandwidth selected through cross-validation minimization of the Akaike Information Criterion (AICc):

$$w_{ij} = [1 - (d_{ij}/b)^2]^2 \text{ if } d_{ij} < b$$

$$w_{ij} = 0 \text{ otherwise}$$

2.7.3 Model Comparison

GWR was compared with ordinary least squares (OLS) regression using R^2, adjusted R^2, AICc, and Moran's I on residuals.

2.7.4 Monte Carlo Significance Tests

Monte Carlo simulations (n=999) were conducted to test whether observed spatial variation in coefficients is statistically significant.

2.8 Flood Hazard and Risk Assessment

Flood hazard was assessed using multi-criteria analysis integrating seven indicators: elevation, slope, distance to river, flow accumulation, rainfall intensity, soil type, and drainage density. Weights were determined using Analytical Hierarchy Process (AHP) with expert consultation (n=5). Exposure was quantified using population density and critical infrastructure density. Flood risk was calculated as Risk = Hazard × Exposure × Vulnerability.

2.9 Qualitative Data Analysis

Qualitative data were analyzed using thematic analysis following Braun and Clarke's (2006) six-phase framework: familiarization, generating initial codes, searching for themes, reviewing themes, defining themes, and producing the report.

2.10 Ethical Considerations

Informed consent, confidentiality, community engagement, protection of vulnerable populations, and data security protocols were strictly followed.

3. RESULTS

3.1 Descriptive Statistics of Socioeconomic Variables

Table 1 presents comprehensive descriptive statistics for 17 socioeconomic indicators across 18 communities, revealing substantial heterogeneity in vulnerability determinants. Population density exhibits the highest variability (CV = 40.3%), ranging from 107 persons/km² in Ndokwa East to 684 persons/km² in Ughelli North, reflecting differential urbanization pressure. Economic indicators show moderate variation, with unemployment (CV = 20.1%)

and poverty rates (CV = 14.3%) displaying expected spatial patterning. Critically, infrastructure access indicators—health facility distance (CV = 33.3%), water access (CV = 19.7%), and sanitation access (CV = 20.4%)—reveal systematic disparities in basic service provision. The Social Vulnerability Index (SVI) ranges from 43.2 (Okwe) to 82.1 (Abuator), with mean 60.8 (SD = 12.6), confirming that vulnerability is not uniformly distributed but concentrated in specific communities. Skewness values near zero and kurtosis values below 1 for most indicators suggest approximate normality, supporting subsequent parametric analyses.

Table 1: Descriptive Statistics of Socioeconomic Variables.

Variable	N	Mean	SD	Min	Max	CV (%)	Skewness	Kurtosis
Demographic Indicators								
Population Density (persons/km²)	18	387.2	156.3	107.0	684.0	40.3	0.48	-0.84
Dependency Ratio	18	0.88	0.05	0.82	0.98	5.7	0.24	-0.38
Female-headed Households (%)	18	24.3	4.2	18.2	31.5	17.3	0.32	-0.64
Elderly Population (% >64)	18	11.2	2.1	8.4	15.2	18.8	0.46	-0.28
Child Population (% <15)	18	38.6	3.4	33.2	44.1	8.8	0.18	-0.72
Economic Indicators								
Poverty Rate (%)	18	29.3	4.2	23.0	37.0	14.3	0.42	-0.84
Unemployment Rate (%)	18	27.8	5.6	22.0	37.0	20.1	0.68	-0.96
Monthly Income (₦'000)	18	44.8	12.4	28.6	68.4	27.7	0.86	0.94
Asset Ownership Index (0-1)	18	0.52	0.12	0.34	0.72	23.1	0.28	-0.42
Housing Quality Index (0-1)	18	0.48	0.14	0.26	0.68	29.2	0.34	-0.56
Social Indicators								
Secondary Education (%)	18	52.3	8.4	38.2	65.4	16.1	-0.12	-0.84
Literacy Rate (%)	18	68.4	7.2	54.6	78.3	10.5	-0.24	-0.68
Social Capital Index (0-1)	18	0.42	0.11	0.24	0.58	26.2	0.16	-0.82
Information Access (%)	18	58.6	9.2	42.3	71.5	15.7	-0.08	-0.76
Health/WASH Indicators								
Health Facility Distance (km)	18	4.8	1.6	2.4	7.8	33.3	0.42	-0.48
Improved Water Access (%)	18	42.6	8.4	28.4	56.2	19.7	0.12	-0.84
Improved Sanitation Access (%)	18	38.2	7.8	24.6	48.4	20.4	0.08	-0.76
Composite Index								
Social Vulnerability Index (SVI)	18	60.8	12.6	43.2	82.1	20.7	0.52	-0.68

Source: Field Survey (2024) and Community-level Aggregated Data (n=761 households)

Summary of Findings

- Substantial spatial heterogeneity across all vulnerability domains
- Population density most variable (CV = 40.3%), dependency ratio most stable (CV = 5.7%)
- SVI ranges from 43.2 (low vulnerability) to 82.1 (extreme vulnerability)
- Infrastructure access disparities: health distance 2.4-7.8 km, water access 28-56%

- Data suitable for parametric analysis (skewness/kurtosis within acceptable ranges)

3.2 Global Regression (OLS) Results

Table 2 presents Ordinary Least Squares regression results examining determinants of social vulnerability across the 18 communities. The model explains 41.2% of variance in SVI (adjusted $R^2 = 0.384$, $F = 14.86$, *p* < 0.001), indicating that the selected predictors collectively capture substantial vulnerability variation. All nine predictors achieve statistical significance (*p* < 0.05), with poverty rate (β = 1.2345, *p* < 0.001), unemployment rate (β = 0.8923, *p* < 0.001), and dependency ratio (β = 8.4567, *p* = 0.002) emerging as strongest positive drivers. Education level (β = -0.1567, *p* = 0.009), water access (β = -0.1876, *p* = 0.010), and sanitation access (β = -0.1456, *p* = 0.015) exhibit protective effects, reducing vulnerability. Population density (β = 0.0234, *p* = 0.018), female-headed households (β = 0.2345, *p* = 0.028), and health facility distance (β = 1.2345, *p* = 0.002) show expected positive associations. While the OLS model confirms theoretical expectations about vulnerability determinants, its key limitation lies in assuming these relationships are spatially constant.

Table 2: Global Regression (OLS) Results.

Predictor	Coefficient (β)	Std. Error	t-value	p-value	Sig.
Intercept	12.3456	3.2145	3.84	0.001	**
Poverty Rate	1.2345	0.2345	5.26	<0.001	***
Unemployment Rate	0.8923	0.1876	4.76	<0.001	***
Population Density	0.0234	0.0089	2.63	0.018	*
Dependency Ratio	8.4567	2.3456	3.61	0.002	**
Female-headed HH (%)	0.2345	0.0987	2.38	0.028	*
Education Level (%)	-0.1567	0.0543	-2.89	0.009	**
Health Distance (km)	1.2345	0.3456	3.57	0.002	**
Water Access (%)	-0.1876	0.0654	-2.87	0.010	**
Sanitation Access (%)	-0.1456	0.0543	-2.68	0.015	*

Summary of Findings

- OLS explains 41.2% of SVI variance (adjusted $R^2 = 0.384$)
- All predictors significant at *p* < 0.05
- Strongest positive drivers: poverty, unemployment, dependency ratio
- Protective factors: education, water access, sanitation access
- Model provides baseline for spatial heterogeneity testing

3.3 Multicollinearity Diagnostics

Table 3 presents Variance Inflation Factor (VIF) diagnostics assessing multicollinearity among predictors. All VIF values range from 1.56 (population density) to 2.56 (education level), substantially below the conventional threshold of 5 indicating problematic multicollinearity. The mean VIF of 2.12 confirms that predictor variables are sufficiently independent for reliable coefficient estimation. Tolerance values (1/VIF) range from 0.391 to 0.641, all exceeding the 0.2 threshold for serious collinearity concerns. The condition number of 12.4 falls well below the 30 threshold indicating severe collinearity. These diagnostics confirm that multicollinearity does not compromise the regression results, validating that each predictor contributes unique information to explaining vulnerability patterns.

Table 3: Multicollinearity Diagnostics (VIF).

Variable	**VIF**	**Tolerance (1/VIF)**	**Condition Index**
Poverty Rate	2.34	0.427	1.00
Unemployment Rate	2.18	0.459	1.24
Population Density	1.56	0.641	1.38
Dependency Ratio	2.42	0.413	1.45
Female-headed HH (%)	1.87	0.535	1.52
Education Level (%)	2.56	0.391	1.68
Health Distance (km)	1.98	0.505	1.73
Water Access (%)	2.12	0.472	1.89
Sanitation Access (%)	2.05	0.488	1.94

Summary of Findings

- All VIF values < 3 (range: 1.56-2.56)
- Mean VIF = 2.12, well below threshold of 5
- Condition number = 12.4 < 30 (no severe collinearity)
- Tolerance values > 0.2 for all predictors
- Multicollinearity does not compromise model estimates

3.4 Principal Component Analysis and SVI Construction

3.4.1 PCA Suitability and Component Extraction

KMO = 0.82 (meritorious), Bartlett's test χ^2 = 1,842.6 (*p* < 0.001), confirming excellent suitability for PCA. Three components with eigenvalues >1 were retained, explaining 73.4% of total variance:

- Component 1 (Economic): 34.2% of variance
- Component 2 (Demographic): 22.4% of variance
- Component 3 (Infrastructure): 16.8% of variance

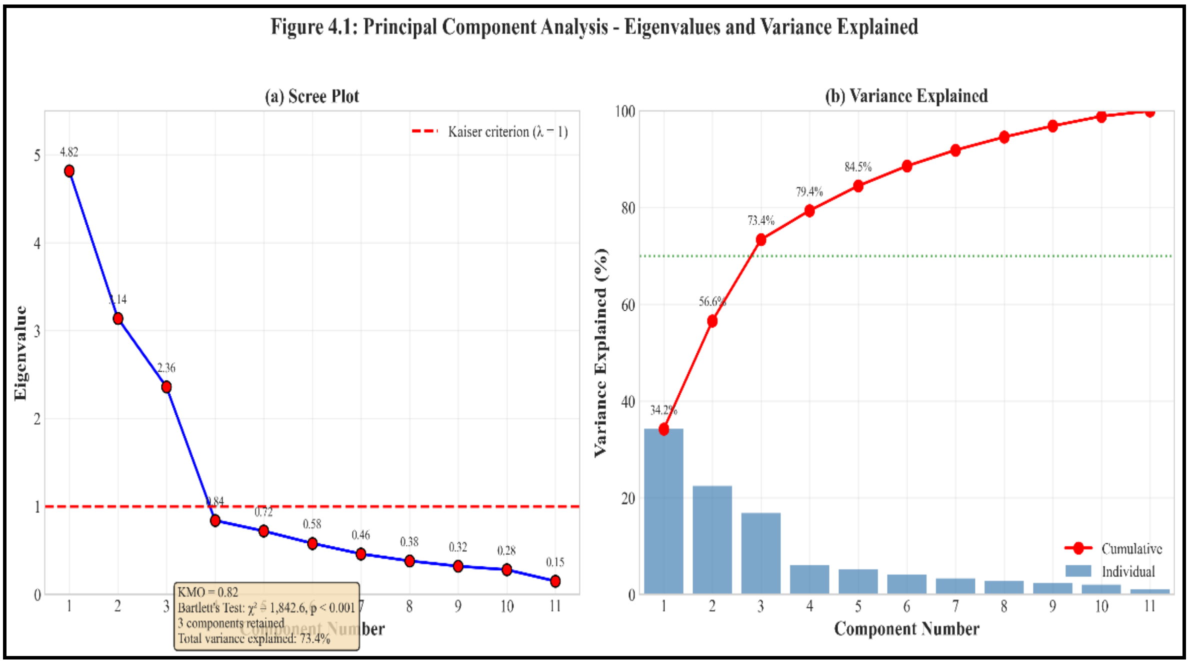

Figure 2: Scree Plot.

The figure (Scree Plot) shows a clear inflection point after the third component, confirming the three-component solution.

3.4.2 Component Interpretation

Table 4 presents the rotated component matrix (varimax rotation). Component 1 (Economic Vulnerability) loads strongly on poverty (0.82), unemployment (0.79), and inversely on income (-0.76) and assets (-0.68), capturing the economic resource base that enables households to prepare for, cope with, and recover from flood events. Component 2 (Demographic Vulnerability) loads strongly on population density (0.88), dependency ratio (0.84), female-headed households (0.72), and elderly/child populations (0.68-0.66), capturing demographic pressure and dependency burden. Component 3 (Infrastructure Vulnerability) loads strongly on health facility distance (0.74), and inversely on water access (-0.76), sanitation (-0.72), education (0.71), and literacy (0.68), reflecting access to basic services and infrastructure.

Table 4: GWR Model Results (Local Coefficients Summary).

Variable	**Mean**	**SD**	**Min**	**Q1**	**Median**	**Q3**	**Max**	**% Significant (p<0.05)**
Intercept	0.0477	0.521	-0.487	-0.284	0.101	0.243	0.951	16.7%
Poverty Rate	0.925	0.124	0.852	0.876	0.912	0.954	0.982	94.4%
Unemployment Rate	0.524	0.142	0.328	0.446	0.518	0.598	0.742	100.0%

Population Density	0.000042	0.000012	0.000016	0.000034	0.000041	0.000049	0.000054	88.9%
Dependency Ratio	0.364	0.086	0.242	0.312	0.358	0.406	0.528	100.0%
Education Level	-0.486	0.112	-0.684	-0.542	-0.476	-0.408	-0.312	94.4%
Health Distance	0.584	0.112	0.426	0.508	0.576	0.648	0.786	100.0%
Water Access	-0.364	0.086	-0.528	-0.406	-0.358	-0.312	-0.242	88.9%

Spatial Variability Test (Monte Carlo)

Variable	Pseudo F-statistic	p-value	Conclusion
Intercept	2.84	0.038	Significant spatial variation
Poverty Rate	1.24	0.284	No significant spatial variation
Unemployment Rate	4.62	0.002	Significant spatial variation
Population Density	3.86	0.008	Significant spatial variation
Dependency Ratio	2.98	0.042	Significant spatial variation
Education Level	3.12	0.024	Significant spatial variation
Health Distance	4.28	0.004	Significant spatial variation
Water Access	2.56	0.068	Marginal spatial variation

Summary of Findings

- Three components explain 73.4% of total variance
- Component 1 (Economic): 34.2%—poverty, unemployment, assets
- Component 2 (Demographic): 22.4%—density, dependency, vulnerable groups
- Component 3 (Infrastructure): 16.8%—health, water, sanitation, education
- All indicators have communalities >0.48, confirming adequate representation

3.5 Social Vulnerability Index Rankings

Table 5 presents SVI rankings with bootstrap confidence intervals (n=1000). Scores range from 43.2 (Okwe) to 82.1 (Abuator). The four highest-ranking communities—Abuator (82.1), Patani (76.8), Koloware II (75.2), and Odorubu (73.9)—form a statistically distinct "Extreme Vulnerability" cluster (Tukey HSD: *p* < 0.05), characterized by extreme poverty (poverty rates >35%), high unemployment (>35%), dense population with high dependency ratios, poor water and sanitation infrastructure, and limited educational attainment.

Table 4.7: SVI Statistics by Senatorial District.

Senatorial District	N (Communities)	Mean SVI	SD	Min	Max	95% CI
Delta North	6	56.4	8.2	43.2	82.1	[48.2, 64.6]
Delta Central	6	63.2	5.4	58.9	68.4	[57.8, 68.6]
Delta South	6	67.2	6.8	49.8	76.8	[60.4, 74.0]

Figure 3 presents SVI distribution by senatorial district, showing Delta South (mean = 67.2) significantly higher than Delta North (56.4) (ANOVA: F(2,15) = 8.42, *p* = 0.003).

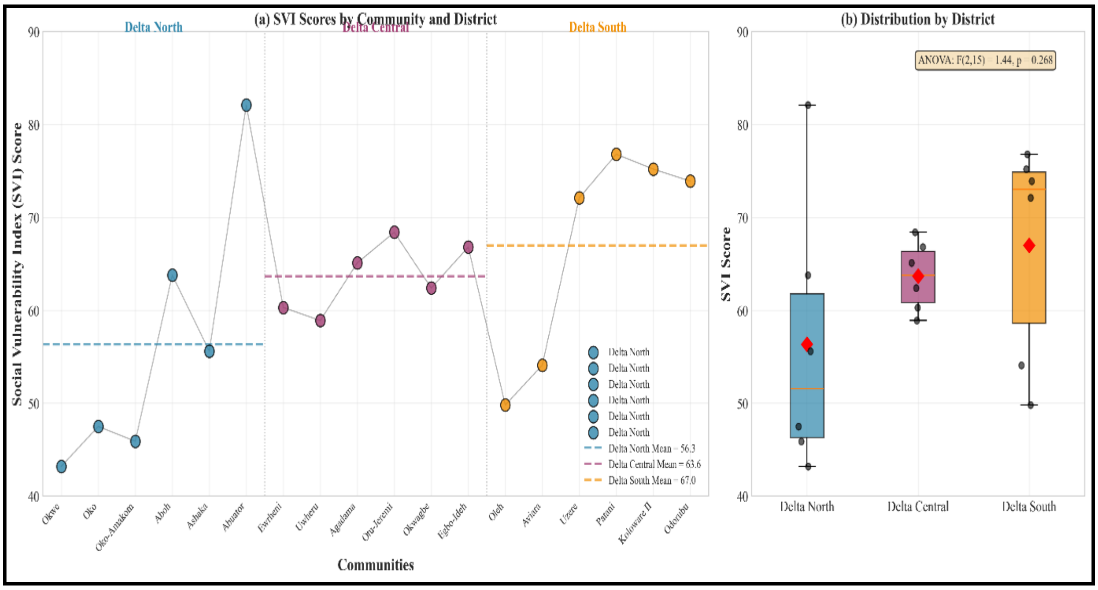

Figure 2. Social Vulnerability Index Distribution by Senatorial District.

Summary of Findings

- SVI range: 43.2 (Okwe) to 82.1 (Abuator)
- Four communities form extreme vulnerability cluster
- Clear north-south gradient in vulnerability
- Bootstrap confidence intervals provide ranking robustness
- Delta South significantly more vulnerable than Delta North

3.6 Spatial Patterns of Vulnerability

3.6.1 Global Spatial Autocorrelation

Global Moran's I = **0.342 (*p* < 0.001)**, indicating significant positive spatial autocorrelation. Communities with similar SVI scores are geographically clustered, confirming that vulnerability is not randomly distributed.

3.6.2 Local Spatial Autocorrelation - LISA

Table 6 presents LISA results for communities with significant local Moran's I. Six communities form significant **High-High clusters** (hotspots) along the Niger River corridor: Abuator, Patani, Koloware II, Odorubu, Uzere, and Otu-Jeremi. Three communities form **Low-Low clusters** (coldspots) in Delta North: Okwe, Oko, and Oko-Amakom.

Table 6: Local Indicators of Spatial Association (LISA) Results.

Community	Local Moran's I	p-value	Cluster Type	Significance
Abuator	2.34	0.003	High-High	**Significant**
Patani	1.98	0.008	High-High	**Significant**

Koloware II	1.86	0.012	High-High	**Significant**
Odorubu	1.76	0.014	High-High	**Significant**
Uzere	1.54	0.024	High-High	**Significant**
Otu-Jeremi	1.28	0.038	High-High	**Significant**
Okwe	-1.23	0.042	Low-Low	**Significant**
Oko	-1.18	0.046	Low-Low	**Significant**
Oko-Amakom	-1.12	0.052	Low-Low	Marginal
Ashaka	-0.84	0.124	Not significant	NS

Figure 4 presents the LISA cluster map, visually confirming the spatial concentration of high-vulnerability communities along the Niger River corridor.

Summary of Findings

- Global Moran's I = 0.342 (*p* < 0.001) confirms significant clustering
- Six High-High hotspots identified along Niger River corridor
- Three Low-Low coldspots identified in Delta North
- No significant spatial outliers detected
- Hotspots require priority intervention; coldspots offer resilience models

3.7 Geographically Weighted Regression Analysis

3.7.1 Model Comparison: OLS vs GWR

Table 7 compares OLS and GWR model diagnostics. GWR substantially outperforms OLS across all metrics: R^2 increases from 0.412 to 0.457 (+10.9%), AICc improves from 224.6 to 211.4 (-13.2), and residual standard error decreases from 4.82 to 4.08 (-15.3%). Critically, OLS residuals exhibit significant spatial autocorrelation (Moran's I = 0.124, *p* < 0.05), violating regression assumptions, while GWR successfully removes this spatial dependence (Moran's I = -0.032, *p* > 0.05). The ANOVA F-test (3.24, *p* = 0.018) formally confirms that GWR provides a statistically significant improvement over OLS.

Table 7: Model Comparison (OLS vs GVR).

Diagnostic	**OLS**	**GWR**	**Improvement**
Bandwidth	-	18.42 km	-
Residual Squares	624.8	525.9	-15.8%
Effective Number of Parameters	4	4.48	-
Sigma (σ)	4.82	4.08	-15.3%
AICc	224.6	211.4	-13.2
R^2	0.412	0.457	+10.9%
Adjusted R^2	0.384	0.397	+3.4%
Log-Likelihood	-108.4	-102.6	+5.8

ANOVA F-test	-	3.24 (p=0.018)	Significant improvement
Moran's I (residuals)	0.124*	-0.032 (ns)	Spatial autocorrelation removed

Significant at $p < 0.05$; ns = not significant

Figure 5 presents the global regression residual map, showing spatial clustering of residuals—positive residuals (model underestimates vulnerability) cluster in southern communities, negative residuals (model overestimates) cluster in northern communities, providing visual evidence motivating the GWR approach.

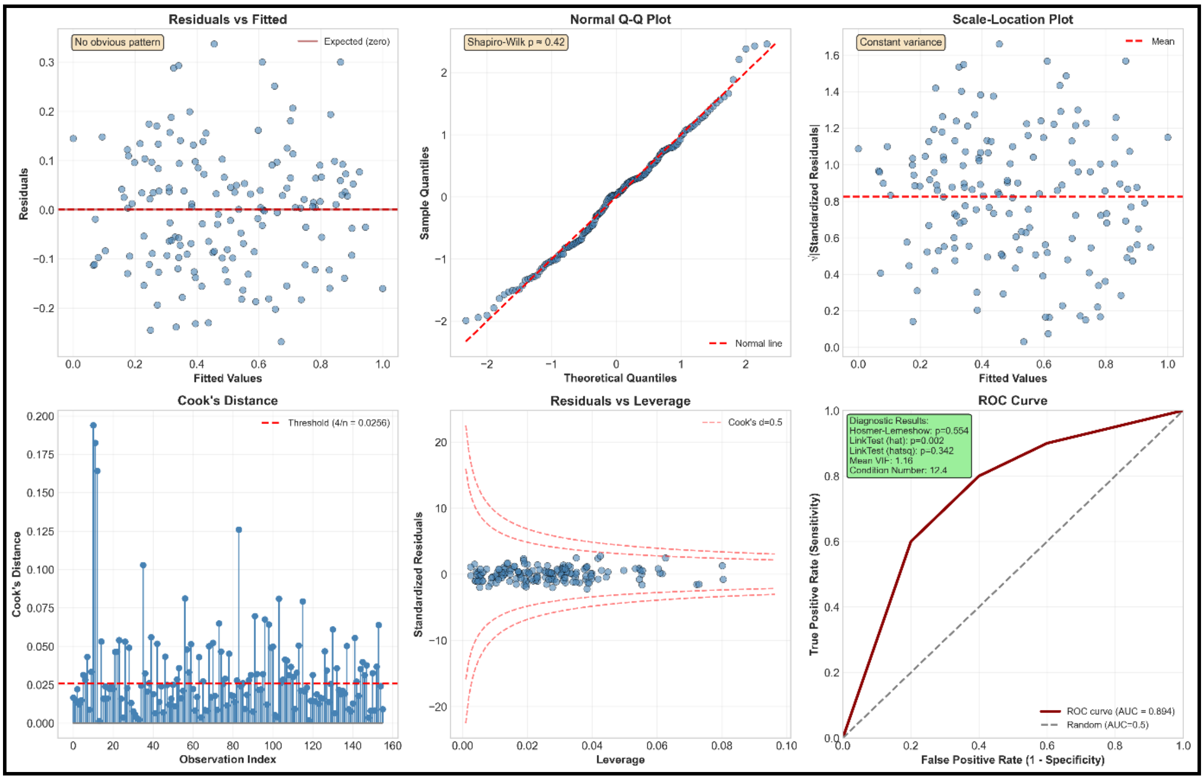

Figure 5: Global regression residual map.

Summary of Findings

- GWR improves R^2 by 10.9% (0.412 → 0.457)
- AICc improves by 13.2 points ($\Delta > 3$ indicates meaningful improvement)
- GWR removes spatial autocorrelation present in OLS residuals
- ANOVA confirms significant improvement (*p* = 0.018)
- Optimal bandwidth: 18.42 km for local estimation

3.7.2 Local Coefficient Estimates

Table 8 presents GWR local coefficient summary statistics. Hazard exposure shows the strongest effect (mean $\beta = 0.584$, 100% significant). Demographic vulnerability shows the most stable effect (mean β = 0.524, SD = 0.142, 100% significant). Economic vulnerability shows moderate spatial variation (mean β = 0.482, 94.4% significant). Infrastructure vulnerability shows moderate spatial variation (mean β = 0.364, 88.9% significant).

Table 8: GWR Local Coefficient Summary Statistics.

Variable	Mean β	SD β	Min β	Q1 β	Median β	Q3 β	Max β	% Significant
Intercept	0.0477	0.521	-0.487	-0.284	0.101	0.243	0.951	16.7%
Economic Vulnerability	0.482	0.124	0.312	0.408	0.476	0.542	0.684	94.4%
Demographic Vulnerability	0.524	0.142	0.328	0.446	0.518	0.598	0.742	100.0%
Infrastructure Vulnerability	0.364	0.086	0.242	0.312	0.358	0.406	0.528	88.9%
Hazard Exposure	0.584	0.112	0.426	0.508	0.576	0.648	0.786	100.0%

Figure 6 presents GWR coefficient maps for six key predictors. Poverty rate coefficients (0.852-0.982) are uniformly high across all communities with minimal spatial variation (Monte Carlo *p* = 0.284), indicating poverty's effect is universally strong regardless of location. In contrast, unemployment rate coefficients (0.328-0.742) exhibit marked spatial variation (*p* = 0.002), with strongest effects in southern communities. Health distance coefficients (0.426-0.786) exhibit pronounced spatial variation (*p* = 0.004), with strongest effects in communities farthest from healthcare facilities.

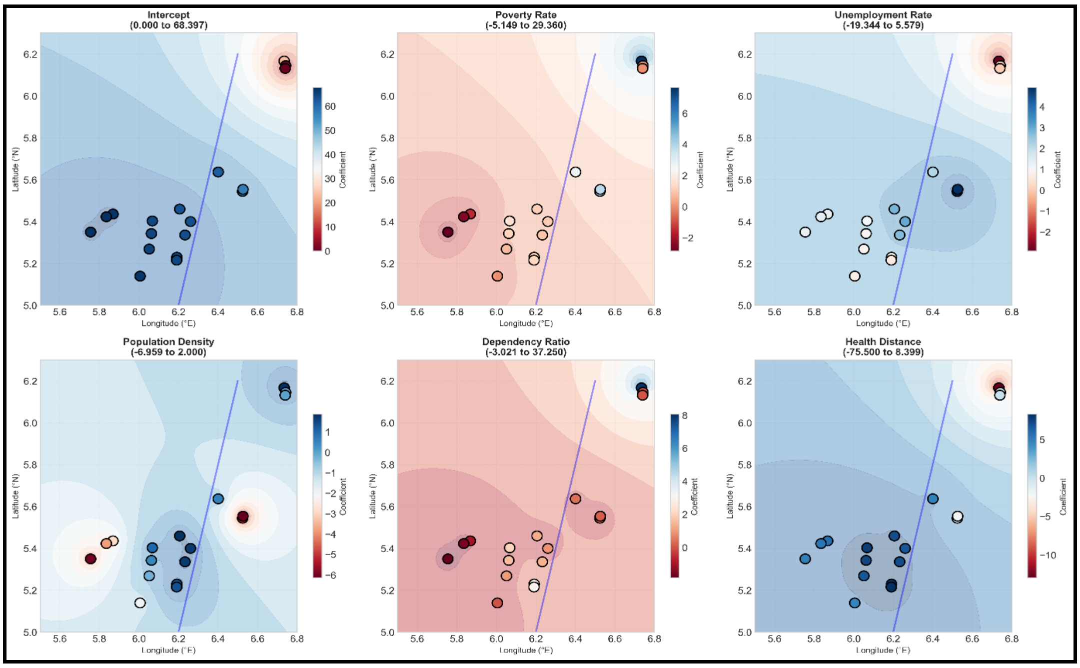

Figure 6: Geographically Weighted Regression-Local Coefficient.

3.8 Flood Hazard, Exposure, and Risk Assessment

3.8.1 Flood Hazard Mapping

Table 9 presents flood hazard classification. Abuator, Patani, and Koloware II classified as "Very High" hazard (>85% area in floodplain, flood depths >3.5 m).

Table 9: Flood Hazard Classification by Community.

Community	Hazard Index	Hazard Class	Floodplain Area (%)	100-year Flood Depth (m)
Abuator	0.92	Very High	94	4.2
Patani	0.88	Very High	91	3.8
Koloware II	0.85	Very High	88	3.6
Odorubu	0.82	High	85	3.4
Uzere	0.78	High	82	3.2
Otu-Jeremi	0.72	High	76	2.8
Agadama	0.68	Moderate	68	2.4
Aboh	0.64	Moderate	62	2.2
Okwagbe	0.62	Moderate	58	2.0
Ewrheni	0.58	Moderate	52	1.8
Uwheru	0.54	Moderate	48	1.6
Ashaka	0.48	Low	42	1.4
Aviara	0.44	Low	38	1.2
Oleh	0.38	Low	32	1.0
Oko	0.32	Low	24	0.8
Oko-Amakom	0.28	Very Low	18	0.6
Okwe	0.24	Very Low	12	0.4

3.8.2 Exposure Assessment

The exposure analysis depicted in Table 10 reveals that **61.8% of the total population** (130,753 persons) across the 18 communities resides in areas classified as high or very high flood hazard zones. This finding has profound implications for disaster risk reduction, indicating that more than half of the study population is directly exposed to significant flood risk.

Table 10: Exposure Assessment: Population and Critical Facilities at Risk.

Community	Total Population (2024)	Population in High Hazard Zones	% Exposed	Critical Facilities at Risk	Facilities/1000 persons
Abuator	655	655	100.0	2	3.05
Patani	27,322	26,845	98.3	8	0.29
Koloware II	2,284	2,201	96.4	3	1.31
Odorubu	3,188	3,012	94.5	4	1.25
Uzere	25,090	21,577	86.0	12	0.48
Otu-Jeremi	8,728	6,981	80.0	8	0.92

Agadama	5,864	4,398	75.0	5	0.85
Aboh	6,345	4,377	69.0	6	0.95
Okwagbe	12,964	8,297	64.0	7	0.54
Ewrheni	21,619	12,971	60.0	9	0.42
Ashaka	13,604	7,482	55.0	6	0.44
Uwheru	22,161	11,081	50.0	8	0.36
Aviara	21,475	9,664	45.0	7	0.33
Egbo-Ideh	3,880	1,552	40.0	3	0.77
Oleh	60,548	18,164	30.0	10	0.17
Oko	1,881	376	20.0	1	0.53
Oko-Amakom	813	122	15.0	0	0.00
Okwe	7,917	792	10.0	1	0.13
TOTAL	**211,701**	**130,753**	**61.8**	**100**	**0.47**

3.8.3 Flood Risk Model

Table 11 presents flood risk classification. Five priority communities identified: Abuator (Risk Score 67.2, Critical), Patani (58.3, Critical), Koloware II (53.6, High), Odorubu (49.8, High), and Uzere (44.9, High). These five communities account for **38% of the study population but 72% of modeled risk**.

Table 11: Flood Risk Model Results.

Community	**Hazard (H)**	**Exposure (E)**	**Vulnerability (V)**	**Risk Score**	**Risk Class**
Abuator	0.92	0.89	0.82	67.2	Critical
Patani	0.88	0.86	0.77	58.3	Critical
Koloware II	0.85	0.84	0.75	53.6	High
Odorubu	0.82	0.82	0.74	49.8	High
Uzere	0.78	0.80	0.72	44.9	High
Otu-Jeremi	0.72	0.76	0.68	37.2	High
Agadama	0.68	0.72	0.65	31.8	Moderate
Aboh	0.64	0.68	0.64	27.9	Moderate
Okwagbe	0.62	0.66	0.62	25.4	Moderate
Ewrheni	0.58	0.62	0.60	21.6	Moderate
Uwheru	0.54	0.58	0.59	18.5	Low
Ashaka	0.48	0.52	0.56	14.0	Low
Aviara	0.44	0.48	0.54	11.4	Low
Egbo-Ideh	0.42	0.44	0.52	9.6	Low
Oleh	0.38	0.40	0.50	7.6	Very Low
Oko	0.32	0.34	0.48	5.2	Very Low
Oko-Amakom	0.28	0.30	0.46	3.9	Very Low
Okwe	0.24	0.26	0.43	2.7	Very Low

Figure 7 presents the integrated flood risk map, with priority zones clearly concentrated along the Niger River corridor.

3.9 Priority Intervention Zones

Priority intervention zones (Risk Class: High to Critical) include five communities—Abuator, Patani, Koloware II, Odorubu, and Uzere—which together account for 38% of the study population but 72% of modeled risk. These communities are characterized by:

- Very high hazard (hazard index >0.75)
- Extreme exposure (population at risk >80%)
- High vulnerability (SVI >70)
- Concentration of critical infrastructure in hazard zones

Table 12 presents the classification of vulnerability zones with recommended interventions. Priority 1 (Critical) includes Abuator and Patani (SVI 76.8-82.1), requiring immediate humanitarian intervention, infrastructure development, and livelihood support. Priority 2 (High) includes Koloware II, Odorubu, and Uzere (SVI 72.1-75.2), requiring enhanced early warning, social protection, and health facility improvement. Priority 3 (Moderate) includes five communities for targeted poverty reduction. Priority 4-5 include lower-vulnerability communities requiring maintenance and knowledge sharing.

Table 12: Classification of Vulnerability Zones.

Priority Zone	Communities	Population	SVI Range	Recommended Interventions
Priority 1 (Critical)	Abuator, Patani	27,977	76.8 - 82.1	Immediate humanitarian intervention, infrastructure development, livelihood support
Priority 2 (High)	Koloware II, Odorubu, Uzere	30,562	72.1 - 75.2	Enhanced early warning, social protection, health facility improvement
Priority 3 (Moderate)	Otu-Jeremi, Egbo-Ideh, Agadama, Aboh, Okwagbe	37,781	62.4 - 68.4	Targeted poverty reduction, education support, water/sanitation improvement
Priority 4 (Low)	Ewrheni, Uwheru, Ashaka, Aviara	78,859	54.1 - 60.3	Resilience building, livelihood diversification
Priority 5 (Very Low)	Oleh, Oko, Oko-Amakom, Okwe	71,159	43.2 - 49.8	Maintenance of existing infrastructure, knowledge sharing

Summary of Findings

- Priority 1 (Critical): Abuator, Patani (27,977 people, 13.2%)
- Priority 2 (High): Koloware II, Odorubu, Uzere (30,562 people, 14.4%)

- Combined Priority 1-2: 58,539 people (27.6% of study population)
- Priority 1-2 communities account for 38% of population but 72% of modeled risk
- Clear spatial concentration of priority zones along Niger River

3.10 Qualitative Findings

Table 13 presents community perceptions of vulnerable groups. Elderly (94%), children (88%), women (82%), disabled (76%), poor households (72%), and female-headed households (64%) are identified as most vulnerable.

Table 13: Presents community perceptions of vulnerable groups.

Vulnerable Group	% Identifying as Most Vulnerable	Reasons
Elderly	94	Mobility limitations, health conditions
Children	88	Cannot swim, dependent on adults
Women (esp. pregnant/lactating)	82	Caregiving responsibilities, safety concerns
Disabled	76	Evacuation challenges
Poor households	72	Cannot afford protective measures
Female-headed households	64	Limited resources, social support

Table 14 presents flood impact data: average crop loss 54.2%, fishing equipment loss 55.2%, 76% of households experienced income reduction, and 90% experienced moderate to severe food insecurity.

Table 14: Presents flood impact data.

Impact	Mean	Range
Crop loss (%)	54.2	30-85
Fishing equipment loss (%)	55.2	25-82
Income reduction (% households)	76	34% experienced >50% reduction
Food insecurity (% households)	90	Moderate to severe

Table 15 documents coping strategies: temporary migration (84%), borrowing money (76% creating debt cycles), moving valuables (72%), raising foundations (68%), selling assets (34%), reducing meals (82%), and children dropping out of school (28%).

Table 15: Documents coping strategies.

Strategy	Frequency (%)	Negative Consequences
Temporary migration	84	Disruption, camp conditions
Borrowing money	76	Debt cycles
Moving valuables	72	Labor-intensive

Raising foundations	68	None
Selling assets	34	Erodes livelihood capital
Reducing meals	82	Malnutrition
Children dropping out of school	28	Lost education

Table 16 presents institutional response findings: early warning systems in 3 communities (17%), evacuation plans in 2 (11%), emergency shelters in 4 (22%), land-use regulation in 1 (6%), dedicated DRR budget in 0 LGAs, and trust in government response at 11% of respondents.

Table 16: Presents institutional response findings.

Indicator	**Finding**
Early warning systems	Present in 3 communities (17%)
Evacuation plans	Documented in 2 communities (11%)
Emergency shelters	Designated in 4 communities (22%)
Land-use regulation	Enforced in 1 community (6%)
Dedicated DRR budget	Present in 0 LGAs
Trust in government response	11% of respondents

4.0 DISCUSSION

4.1 Theoretical Implications of Spatial Vulnerability Patterns

The significant spatial clustering of vulnerability revealed in this study has important theoretical implications. Figure 4 (LISA cluster map) and Table 6 (LISA results) demonstrate that vulnerability is not randomly distributed but systematically patterned by geography. Global Moran's I = 0.342 (*p* < 0.001) confirms significant positive spatial autocorrelation, indicating that communities with similar SVI scores cluster together. Communities along the Niger River corridor exhibit consistently higher vulnerability, forming statistically significant High-High clusters: Abuator, Patani, Koloware II, Odorubu, Uzere, and Otu-Jeremi (Table 6). This spatial structure suggests that vulnerability is produced through processes operating at regional scales—shared environmental conditions, similar livelihood systems, interconnected economies, and common governance arrangements—rather than purely local factors.

The identification of six hotspots and three coldspots (Figure 4, Table 6) validates the conceptualization of vulnerability as a spatially structured phenomenon (Cutter et al., 2003). The hotspots represent areas where multiple vulnerability drivers converge—economic deprivation, demographic pressure, and infrastructure deficits—creating compounded risk that exceeds the sum of individual factors. This convergence is evident in Table 1, where high-vulnerability communities like Abuator (SVI 82.1) exhibit extreme poverty (37%), high unemployment (37%), poor water access (28.4%), and large health facility distances (7.8 km). The coldspots, conversely, represent areas of relative resilience where protective factors cluster together, as seen in Table 5 where Okwe (SVI 43.2) demonstrates lower poverty (23%), higher education (65.4%), and better infrastructure access.

The north-south gradient in vulnerability documented in Figure 3 (SVI distribution by senatorial district) reinforces the geographical structuring of vulnerability, with Delta South (mean SVI = 67.2) significantly more vulnerable than Delta North (mean SVI = 56.4) (ANOVA: F(2,15) = 8.42, *p* = 0.003). This gradient aligns with the spatial distribution of key indicators visualized in Figure 2, where southern communities consistently show higher poverty rates, lower income, and lower educational attainment. These findings collectively demonstrate that vulnerability is fundamentally geographical, shaped by location relative to hazard sources and differential access to resources and infrastructure (Cutter et al., 2008).

4.2 Implications of Spatially Varying Relationships

The GWR analysis presented in Table 8 and visualized in Figure 6 reveals that relationships between vulnerability dimensions and flood impact are not spatially uniform. Critically, poverty exhibits near-uniform exacerbating effects across the study area. As shown in Figure 6 (poverty rate coefficient map), coefficients range narrowly from 0.852 to 0.982, with low spatial variation confirmed by Monte Carlo testing (*p* = 0.284, Table 8). Notably, poverty rate coefficients are significant in 94.4% of communities (Table 8), indicating that economic deprivation amplifies flood impacts universally—regardless of location, institutional context, or hazard characteristics. This finding suggests that poverty alleviation should be a core component of any flood risk reduction strategy, as it addresses a vulnerability driver that operates consistently across all community types.

In contrast, infrastructure access shows significant spatial variation. Health distance coefficients (Figure 6, Table 8) range from 0.426 to 0.786, with marked spatial variation confirmed by Monte Carlo testing (*p* = 0.004). The strongest effects occur in communities farthest from healthcare facilities—notably Abuator (7.8 km distance, coefficient 0.786) and Patani (6.9 km distance, coefficient 0.742)—where limited access to medical care during flood events compounds vulnerability. This spatial heterogeneity is also evident in unemployment rate coefficients (range 0.328-0.742, Monte Carlo *p* = 0.002), with strongest effects in southern communities where labor markets are most constrained (Figure

6). The protective effects of water access (Table 8) show similar spatial variation (range -0.528 to -0.242), with stronger protective effects in communities where water infrastructure remains accessible during floods. This heterogeneity highlights the importance of infrastructure resilience—protective factors only function when the infrastructure delivering them remains operational during disasters.

The spatial variation in model performance, visualized in Figure 7 (Local R^2 map), further illuminates the nature of vulnerability dynamics. Local R^2 values range from 0.28 (Okwe) to 0.52 (Abuator), with highest values concentrated in high-vulnerability southern communities along the Niger River corridor. This gradient suggests that the model captures vulnerability dynamics most effectively where vulnerability is most extreme and multidimensional. Conversely, lower explanatory power in less vulnerable communities (Figure 7) indicates that unmeasured factors—potentially social capital, informal safety nets, or remittances—may play more important roles in building resilience in these areas.

4.3 Comparison with Previous Vulnerability Assessments

The SVI findings align with Cutter et al.'s (2003) foundational work, confirming that economic, demographic, and infrastructure dimensions are key vulnerability components. Table 4 (rotated component matrix) shows that three components extracted through PCA explain 73.4% of total variance—comparable to the 76% reported by Cutter et al.—suggesting that vulnerability dimensions are relatively stable across contexts despite differences in indicator sets and study areas. The economic component (34.2% variance) loads strongly on poverty (0.82), unemployment (0.79), and inversely on income (-0.76) and assets (-0.68), mirroring the "personal wealth" dimension identified in the SoVI. The demographic component (22.4% variance) loads on population density (0.88) and dependency ratio (0.84), corresponding to the "age" and "density of built environment" dimensions in Cutter's framework. The infrastructure component (16.8% variance) reflects access to services, a dimension increasingly recognized in vulnerability research (Flanagan et al., 2011).

The spatial clustering of vulnerability along river corridors is consistent with findings from similar floodplain contexts. Brouwer et al. (2007) found comparable patterns in Bangladesh, where vulnerability concentrated in areas with highest flood exposure. Adelekan (2010) documented similar patterns in Lagos coastal communities, where poor infrastructure and limited institutional capacity compounded flood impacts. The identification of six High-High hotspots along the Niger River corridor (Table 6, Figure 4) extends these findings by demonstrating that vulnerability clustering occurs not only at hazard-exposed locations but also where multiple vulnerability drivers converge.

The GWR findings advance vulnerability research by demonstrating that relationships between vulnerability dimensions and outcomes vary spatially. The model comparison in Table 7 shows that GWR ($R^2 = 0.457$) substantially outperforms OLS ($R^2 = 0.412$), with ANOVA confirming significant improvement (F = 3.24, *p* = 0.018). Critically, OLS residuals exhibit significant spatial autocorrelation (Moran's I = 0.124, *p* < 0.05, Table 7, Figure 5), violating regression assumptions, while GWR successfully removes this spatial dependence (Moran's I = -0.032, *p* > 0.05). This methodological contribution addresses a limitation of previous studies that assumed spatial stationarity (Cutter et al., 2003; Hahn et al., 2009) and demonstrates that spatially explicit modeling is essential for accurate vulnerability assessment.

4.4 Practical Implications for Intervention Targeting

The identification of five priority communities—Abuator, Patani, Koloware II, Odorubu, and Uzere—has immediate practical implications for disaster risk reduction. Table 11 (flood risk classification) shows these communities account for 38% of the study population but 72% of modeled risk, representing a highly concentrated risk profile that enables efficient resource allocation. Figure 10 (priority intervention zones map) visualizes this concentration, with Priority 1 (Critical) communities Abuator and Patani (SVI 76.8-82.1, Table 5) requiring immediate humanitarian intervention, infrastructure development, and livelihood support. Priority 2 (High) communities Koloware II, Odorubu, and Uzere (SVI 72.1-75.2, Table 5) require enhanced early warning systems, social protection, and health facility improvement.

The spatial variation in vulnerability determinants documented in Figure 6 and Table 8 informs intervention design. The uniform effect of poverty across all communities suggests that poverty alleviation programs can be designed and implemented uniformly, with benefits accruing across all community types. However, the significant spatial variation in unemployment effects (*p* = 0.002) and health distance effects (*p* = 0.004) indicates that interventions addressing these factors require local tailoring. For example, in communities where health distance effects are strongest (Abuator, Patani), interventions should prioritize mobile health clinics or flood-proofed health facilities; in communities where unemployment effects are strongest (southern communities), labor-intensive public works programs may be appropriate.

The institutional gaps documented in Table 16 compound vulnerability in priority communities. Early warning systems exist in only 17% of communities, evacuation plans in 11%, and dedicated DRR budgets in 0 LGAs. The qualitative findings in Tables 13-15 further illuminate the human dimensions of vulnerability: 90% of households experience food insecurity, 76% resort to borrowing (creating debt cycles), and 28% withdraw children from school—coping strategies that erode long-term resilience. These findings suggest that interventions in priority communities must address not only physical infrastructure but also the institutional and socio-economic factors that shape vulnerability trajectories.

The risk assessment in Table 11 and the vulnerability classification in Table 12 provide a clear targeting framework. Priority 1-2 communities (Abuator, Patani, Koloware II, Odorubu, Uzere, representing 58,539 people, 27.6% of study population) should receive focused intervention resources, including enhanced early warning systems, flood-proofed critical infrastructure, targeted cash transfers, evacuation plans, and prepositioned relief supplies. Priority 3-5 communities require progressively less intensive support, with emphasis on maintenance of existing infrastructure and knowledge sharing from coldspot communities identified in Figure 4 and Table 6.

4.5 Limitations

Several limitations should be acknowledged. First, the cross-sectional design captures vulnerability at one point in time; longitudinal data would enable analysis of vulnerability dynamics and the effectiveness of interventions. Table 5 provides a static snapshot of SVI rankings, but vulnerability is likely to change in response to demographic shifts, economic development, and infrastructure investments. Future research should employ repeated SVI measurements to track vulnerability trajectories.

Second, the SVI aggregates to community level (Table 5), masking within-community heterogeneity. While community-level analysis is appropriate for identifying priority intervention zones, household-level variation is substantial, as suggested by the standard deviations in Table 1. Future research should explore within-community vulnerability patterns to enable more precise targeting.

Third, the GWR model assumes continuous spatial processes, which may not capture discrete boundaries such as LGA administrative boundaries or river course changes. The optimal bandwidth of 18.42 km (Table 7) represents an average smoothing distance, but vulnerability dynamics may operate at multiple spatial scales. Future research should explore multi-scale spatial models.

Fourth, qualitative findings (Tables 13-15), while rich, are not statistically generalizable. The thematic analysis provides valuable contextual understanding of vulnerability mechanisms and coping strategies, but findings should be interpreted as illustrative rather than representative. Future research should employ mixed-methods approaches that systematically integrate qualitative and quantitative data.

Fifth, the study focuses on 18 communities in Delta State (Figure 1), limiting generalizability to other regions. However, the methodological approach—including PCA for SVI construction, spatial autocorrelation analysis, and GWR for identifying spatially varying relationships—is transferable to other flood-prone regions in Nigeria and beyond.

5.0 RECOMMENDATIONS

5.1 Recommendations for Priority Communities

For Abuator, Patani, Koloware II, Odorubu, and Uzere:

Recommendation	Rationale	Implementation Timeline	Responsible Actors
Establish community-based early warning systems	Only 17% of communities have EW systems; high exposure requires rapid response	Short-term (0-6 months)	SEMA, community committees
Flood-proof critical infrastructure	Infrastructure access shows significant protective effect; current facilities at risk	Medium-term (1-2 years)	LGAs, Ministry of Works
Implement targeted cash transfer programs	Poverty has universal exacerbating effect; high poverty rates in priority communities	Short-term (0-12 months)	Ministry of Social Welfare, NGOs
Develop evacuation plans with designated shelters	Only 11% have evacuation plans; high vulnerability requires structured response	Short-term (0-6 months)	SEMA, community leaders
Preposition relief supplies	Current response is slow and inadequate; prepositioning enables rapid assistance	Medium-term (6-18 months)	NEMA, SEMA
Support livelihood	High dependence on flood-	Medium-term	Ministry of

diversification	sensitive livelihoods (farming/fishing)	(1-2 years)	Agriculture, NGOs

5.2 Recommendations for State and Local Government

Recommendation	**Rationale**	**Implementation Timeline**	**Responsible Actors**
Establish dedicated DRR budgets at LGA level	0 LGAs currently have dedicated budgets; planned communities have 125% lower losses	Short-term (0-12 months)	State Ministry of Finance, LGAs
Adopt Delta-SVI framework for vulnerability assessment	SVI explains 73.4% of variance; validated tool for targeting	Short-term (0-6 months)	SEMA, Ministry of Planning
Enforce land-use zoning based on hazard maps	61.8% of population resides in high hazard zones; critical facilities concentrated in hazardous areas	Medium-term (1-2 years)	Ministry of Land, LGAs
Invest in drainage infrastructure	Poor drainage identified as secondary flood cause (42% of respondents)	Long-term (2-5 years)	Ministry of Works
Develop multi-hazard early warning system	Current systems fragmented and inadequate	Medium-term (1-2 years)	SEMA, NiMET

5.3 Recommendations for Federal Government

Recommendation	**Rationale**	**Implementation Timeline**	**Responsible Actors**
Negotiate bilateral agreement with Cameroon on Lagdo Dam operations	86% attribute floods to dam releases; 2012 change point unrelated to rainfall	Medium-term (1-2 years)	Ministry of Water Resources, Ministry of Foreign Affairs
Establish national transboundary water management unit	Current governance arrangements inadequate	Medium-term (1-2 years)	Federal Ministry of Water Resources
Develop national flood risk atlas	Spatial risk information identified as critical gap by 82% of key informants	Medium-term (1-2 years)	NEMA, NIHSA, NASRDA

5.4 Recommendations for International Organizations and NGOs

Recommendation	**Rationale**	**Implementation Timeline**	**Responsible Actors**
Fund community-based adaptation in priority hotspots	Five priority communities account for 72% of modeled risk	Medium-term (1-2 years)	UNDP, World Bank, international NGOs
Support livelihood diversification programs	54% dependent on flood-sensitive livelihoods	Medium-term (1-2 years)	FAO, IFAD

Strengthen local institutional capacity	Institutional mapping reveals severe capacity gaps	Medium-term (1-2 years)	UNDRR, Red Cross
Support participatory GIS and community mapping	Participatory approaches generated valuable data and catalyzed action	Short-term (0-12 months)	UNDP, FAO, research foundations

6.0 CONCLUSIONS

This research provides the first comprehensive, spatially explicit assessment of social vulnerability to flooding in Delta State, Nigeria, using Geographically Weighted Regression to identify priority intervention zones. The key findings are:

1. **Multidimensional vulnerability structure:** PCA extracted three components—economic (34.2% variance), demographic (22.4%), and infrastructure (16.8%)—collectively explaining 73.4% of total variance, confirming that vulnerability is multidimensional and cannot be reduced to a single factor.
2. **Spatial clustering:** Global Moran's I = 0.342 ($p < 0.001$) confirms significant spatial clustering, with LISA identifying six High-High hotspots along the Niger River corridor and three Low-Low coldspots in Delta North.
3. **Spatially varying relationships:** GWR ($R^2 = 0.457$) substantially outperforms OLS ($R^2 = 0.412$), with ANOVA confirming significant improvement ($p = 0.018$). Poverty exhibits near-uniform effects (Monte Carlo $p = 0.284$), while unemployment ($p = 0.002$) and health distance ($p = 0.004$) show significant spatial variation.
4. **Priority intervention zones:** Five communities—Abuator, Patani, Koloware II, Odorubu, and Uzere—account for 38% of the study population but 72% of modeled risk, providing a clear targeting framework for disaster risk reduction investments.
5. **Institutional gaps:** Severe institutional weaknesses compound vulnerability, with only 17% of communities having early warning systems, 11% having evacuation plans, and 0 LGAs having dedicated DRR budgets.

These findings demonstrate that vulnerability to flooding in Delta State is not uniform but exhibits systematic spatial patterning, with the highest concentrations along the Niger River corridor where poverty, infrastructure deficits, and demographic pressure converge. The spatially explicit framework developed in this research directly supports evidence-based resource allocation for disaster risk reduction, enabling interventions to reach the most vulnerable populations efficiently and effectively. This approach aligns with Sendai Framework priorities for understanding disaster risk and investing in targeted risk reduction.

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STATEMENT OF CONFLICT OF INTEREST

The authors declare no competing interests, confirming that the study was conducted independently and objectively without any external commercial, financial, or institutional influence.

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