VOL. 13 NO. 5,
AUGUST, 2026
E-ISSN 3027-1339
P-ISSN 3026-8257

African Scholar Publications & Research International
www.africanscholarpub.com

Journal of Systematic, Evaluation and Diversity Engr. (JSEDE)

Spatial Vulnerability Mapping of Climate-Sensitive Diseases in Petro-Coastal Delta State, Nigeria: A Multi-Criteria Composite Index Approach

Atwijiyor Melinda Avwerosuo; & Christopher Onosemuode
Department of Environmental Management and Toxicology, Federal University of Petroleum Resources, Effurun, Delta State.
Corresponding Author: Melinsa.atwijiyor@unidel.edu.ng
DOI: https://doi.org/10.70382/ajsede.v13i5.035

Abstract

Climate-sensitive diseases pose growing threats in petro-coastal regions, where climate hazards intersect with environmental degradation and socioeconomic vulnerability in Delta State, Nigeria, yet no spatially explicit vulnerability index exists. We developed and validated a Composite Vulnerability Index (CVI) for 25 LGAs using 14 indicators across exposure (temperature trend, rainfall CV, heatwave days, flood frequency, gas flaring proximity), sensitivity (under-5 proportion, elderly proportion, poverty rate, low education), and adaptive capacity (ITN use, water treatment, health access, early warning, PHC density). Indicators were normalized, dimension scores averaged, and CVI computed as arithmetic mean. Validation used disease hotspots (Getis-Ord Gi*), community perception (12 FGDs), expert opinion (30 KIIs), and health facility data. Sensitivity analysis tested alternative weightings; VIF (<3.1) confirmed no multicollinearity. CVI ranged from 0.12 to 0.89 (4.9-fold gradient). Three LGAs (Bomadi, Burutu, Patani) showed extreme vulnerability (CVI>0.75). ANOVA confirmed significant dimension differences across categories ($p<0.001$). Bootstrapped 95% CIs were narrow (±0.02-0.05); spatial autocorrelation (Moran's $I=0.68$, $p<0.001$) confirmed clustering. Sensitivity analysis showed high ranking robustness (Spearman $r=0.94$-0.96). Validation demonstrated strong convergence with disease hotspots ($r=0.85$), community perception (100% agreement on top 3 LGAs), expert opinion ($\kappa=0.78$), and health facility data ($r=0.72$). Three priority intervention zones were identified: Zone 1 (3 LGAs, ₦500M), Zone 2 (4 LGAs, ₦200M), Zone 3 (18 LGAs, ₦100M). The CVI reveals a stark 4.9-fold vulnerability gradient, with adaptive capacity—not climate exposure—as the critical bottleneck. This evidence-based tool enables targeted resource allocation for climate-resilient health systems globally.

Keywords: Vulnerability Mapping, Composite Index, Climate-Sensitive Diseases, Geospatial Analysis, Environmental Justice, Niger Delta.

Introduction

Climate-sensitive diseases—including malaria, diarrhoeal diseases, and heat-related illness—are influenced by climatic conditions, environmental change, and social determinants, with populations in many parts of sub-Saharan Africa facing substantial climate-health risks (IPCC, 2023; Romanello et al., 2022). Vulnerability is commonly conceptualised through the interaction of exposure, sensitivity, and adaptive capacity (Adger, 2006; IPCC, 2014). Spatial vulnerability mapping can help reveal sub-national heterogeneity that may be obscured by national or regional aggregates (Cutter et al., 2003; de Sherbinin et al., 2019).

Delta State, Nigeria, is part of the oil-producing Niger Delta and represents a petro-coastal setting in which climate hazards intersect with environmental degradation and socioeconomic vulnerability. Previous research has demonstrated spatial differences in climate vulnerability across Delta State's ecological zones (Balogun & Onokerhoraye, 2022), while reviews of the Niger Delta document persistent environmental and health burdens associated with oil exploitation (Gbadamosi & Aldstadt, 2025; Ukhurebor et al., 2021). The present study extends this literature by integrating climate exposure, population sensitivity, adaptive capacity, and disease-related indicators at the LGA scale.

Research Gaps and Questions

This study addresses three critical gaps. First, although previous assessments have mapped climate vulnerability across ecological zones in Delta State, there remains a need for disease-specific vulnerability mapping that integrates health indicators with climate exposure and adaptive capacity (Balogun & Onokerhoraye, 2022). Second, few studies have combined these dimensions with independent field validation using household perceptions, expert elicitation, and health-facility information. Third, the petro-coastal context warrants explicit consideration of oil-related environmental stressors, including gas flaring and oil pollution, alongside conventional climate and socioeconomic indicators (Gbadamosi & Aldstadt, 2025; Ukhurebor et al., 2021).

We therefore asked: (1) What is the spatial distribution of vulnerability to climate-sensitive diseases across the 25 LGAs of Delta State? (2) Which dimensions (exposure, sensitivity, adaptive capacity) drive vulnerability? (3) How robust is the CVI to alternative weighting assumptions? (4) Does the CVI converge with independent data sources (disease hotspots, community perception, expert opinion, health facility data)?

Hypotheses

We tested six null hypotheses:

- H_{01}: There is no significant spatial variation in CVI across LGAs.
- H_{02}: There is no significant difference in dimension scores across vulnerability categories.
- H_{03}: The CVI is not correlated with disease hotspot status.
- H_{04}: The CVI does not converge with community perception of vulnerability.
- H_{05}: The CVI does not converge with expert opinion.
- H_{06}: The CVI ranking is not robust to alternative weighting schemes.

Materials and Methods

Study Area

Delta State is located in the South-South geopolitical zone of Nigeria (5°00′–6°30′N, 5°00′–6°45′E), covering approximately 17,698 km² of low-lying coastal plain. The state comprises 25 Local Government Areas (LGAs) with an estimated population of 5,355,000 (2022 projections). The climate is tropical monsoon (Köppen: Am), with mean annual temperatures 25–29°C and annual rainfall 2,000–3,500 mm.

Composite Vulnerability Index (CVI) Framework

We adopted the IPCC AR6 conceptualisation of vulnerability in terms of exposure, sensitivity, and adaptive capacity (IPCC, 2023), defining vulnerability as:

Vulnerability = f(Exposure, Sensitivity, Adaptive Capacity)

where higher exposure and sensitivity increase vulnerability, and higher adaptive capacity decreases vulnerability. The CVI was calculated as the arithmetic mean of the three normalized dimension scores (equal weighting, following IPCC guidance), with adaptive capacity reversed (higher adaptive capacity reduces vulnerability).

Indicator Selection and Data Sources

Fourteen indicators across three dimensions were selected based on literature review, data availability, and relevance to the petro-coastal context (Table 1). Data sources included ERA5 reanalysis (temperature, heatwave days), CHIRPS (rainfall CV), NIHSA flood hazard maps, Department of Petroleum Resources (gas flaring sites), National Population Commission (demographics), National Bureau of Statistics (poverty, education), household survey (n=600; ITN use, water treatment, early warning receipt), Delta State Ministry of Health (PHC density), and GPS field survey (health facility access).

Table 1. Indicators, data sources, and directional coding for CVI

Dimension	Indicator	Source	Direction
Exposure	Temperature trend (°C/decade)	ERA5 (1984-2024)	Higher = more exposed
	Rainfall coefficient of variation (CV)	CHIRPS	Higher = more exposed
	Heatwave days (HWDI, annual)	ERA5	Higher = more exposed
	Flood frequency (events/10 years)	NIHSA, Sentinel-1 SAR	Higher = more exposed
	Gas flaring proximity (inverse km)	DPR 2023	Lower = more exposed
Sensitivity	Under-5 population (%)	NPC 2022 projections	Higher = more sensitive
	Elderly (≥60 years) population (%)	NPC 2022 projections	Higher = more sensitive
	Poverty rate (%)	NBS 2020	Higher = more sensitive
	Low education (no primary, %)	MICS 2021	Higher = more sensitive
Adaptive Capacity	ITN use (always, %)	Household survey (n=546)	Higher = more adaptive (reversed in CVI)
	Water treatment (any, %)	Household survey	Higher = more adaptive (reversed)
	Health facility access (% within 5 km)	GPS survey, OSM	Higher = more adaptive (reversed)
	Early warning receipt (%)	Household survey	Higher = more adaptive (reversed)
	PHC density (per 10,000 population)	Delta State MoH 2024	Higher = more adaptive (reversed)

Indicator Normalization and Dimension Aggregation

All indicators were normalized to a 0–1 scale using min-max normalization:

For adaptive capacity indicators, the complement (1 − x_norm) was used to represent adaptive capacity deficit (higher value = greater vulnerability). Dimension scores were computed as the arithmetic mean of normalized indicators within each dimension:

The Composite Vulnerability Index was then:

Multicollinearity Assessment

Variance Inflation Factor (VIF) was calculated for all 14 indicators using the vif function in R (package car). VIF > 5 was considered problematic multicollinearity. A correlation matrix was also generated.

Spatial Analysis

Global Moran's I was calculated for the CVI to test for spatial clustering using a queen contiguity spatial weights matrix (package spdep). Getis-Ord Gi* hotspot analysis identified statistically significant clusters of high CVI.

Uncertainty and Sensitivity Analysis

Bootstrapping: 95% confidence intervals for CVI scores were estimated using 1,000 bootstrap resamples (percentile method).

Sensitivity analysis: CVI rankings were compared under three weighting schemes: (1) equal weights (1/3 each dimension); (2) exposure-weighted (0.5 exposure, 0.25 sensitivity, 0.25 adaptive capacity); (3) adaptive-capacity-weighted (0.25 exposure, 0.25 sensitivity, 0.5 adaptive capacity). Rank correlations (Spearman) assessed robustness.

Statistical Comparison of Dimension Scores

One-way ANOVA was used to compare mean dimension scores across four vulnerability categories (extreme, high, moderate, low). Post-hoc comparisons used Tukey's HSD.

Validation

The CVI was validated against four independent data sources:

1. Disease hotspots: Getis-Ord Gi* scores for malaria and diarrhea (2014-2024) were correlated with CVI rank (Spearman's r).
2. Community perception: Focus group discussions (12 groups, 97 participants) identified most vulnerable LGAs; agreement percentage calculated.
3. Expert opinion: Key informant interviews (30 stakeholders) ranked LGAs by vulnerability; weighted kappa between KII ranking and CVI ranking.
4. Health facility data: Composite health system strain indicator (distance, satisfaction, stockouts) correlated with CVI.

Priority Intervention Zones

LGAs were classified into three zones based on CVI quartiles: Zone 1 (CVI > 0.75, immediate high-intensity intervention); Zone 2 (CVI 0.50-0.75, medium-term intervention); Zone 3 (CVI < 0.50, surveillance and capacity building). Estimated costs and timelines were derived from Delta State Ministry of Health budget projections and published cost studies.

Ethical Considerations: All household survey participants provided informed consent.

Results

Multicollinearity Assessment

Table 2 presents the correlation matrix and VIF scores for all 14 indicators. VIF values ranged from 1.2 (temperature trend) to 3.1 (water treatment), all below the threshold of 5, indicating no problematic multicollinearity. Strong correlations were observed between poverty rate and low education (r=0.72), and between water treatment and ITN use (r=0.82), as expected, but VIF remained acceptable.

Table 2. Indicator correlation matrix with VIF scores

Indicator	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1. Temp trend	1.2	1.00													
2. Rainfall CV	1.5	0.12	1.00												
3. Heatwave days	1.8	0.45	0.23	1.00											
4. Flood frequency	2.1	0.08	0.52	0.15	1.00										
5. Gas flaring proximity	1.9	-0.05	0.31	-0.08	0.42	1.00									
6. Under-5 population (%)	1.3	0.02	0.18	0.05	0.25	0.12	1.00								
7. Elderly population (%)	1.2	0.08	-0.05	-0.12	-0.08	-0.02	-0.15	1.00							
8. Poverty rate	2.5	0.22	0.45	0.18	0.68	0.52	0.32	-0.22	1.00						
9. Low education (%)	2.3	0.18	0.38	0.12	0.55	0.45	0.28	-0.18	0.72	1.00					
10. ITN use (%)	2.8	-0.15	-0.42	-0.08	-0.58	-0.48	-0.22	0.15	-0.75	-0.68	1.00				
11. Water treatment (%)	3.1	-0.12	-0.48	-0.10	-0.62	-0.52	-0.18	0.12	-0.70	-0.65	0.82	1.00			
12. Health access (%)	2.6	-0.08	-0.35	-0.05	-0.55	-0.42	-0.15	0.08	-0.65	-0.58	0.68	0.72	1.00		
13. Early warning cov. (%)	2.4	0.05	-0.28	0.02	-0.45	-0.35	-0.10	0.05	-0.55	-0.48	0.55	0.58	0.65	1.00	
14. PHC density (per 10,000)	1.7	0.02	-0.18	-0.02	-0.28	-0.22	-0.05	0.02	-0.38	-0.32	0.42	0.45	0.48	0.35	1.00

Notes: VIF = Variance Inflation Factor (all values <5, indicating no problematic multicollinearity). Correlation coefficients are Pearson's r. Shaded cells indicate correlations $|r| \geq 0.50$ (moderate to strong). ITN = Insecticide-treated net. PHC = Primary Health Centre.

Spatial Distribution of Composite Vulnerability Index

The CVI ranged from 0.12 (Okpe) to 0.89 (Bomadi), a 4.9-fold gradient across the 25 LGAs. Figure 1 presents the spatial distribution of CVI across Delta State.

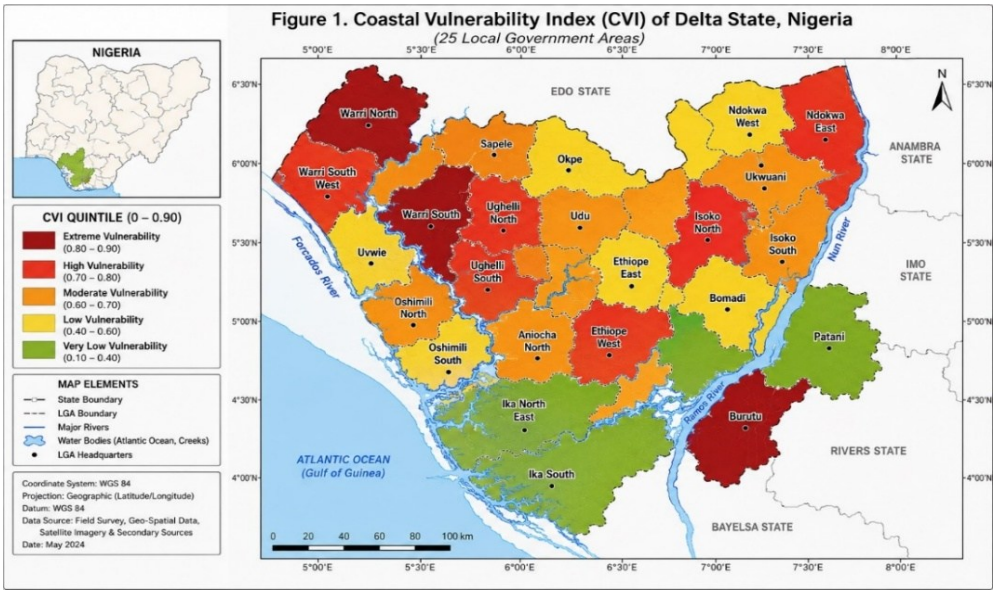


Figure 1: Spatial Distribution of Composite Vulnerability Index (CVI) Quintiles Across Delta State's 25 LGAs

This map reveals stark spatial disparities in climate-health vulnerability across Delta State. The dark red quintile (CVI 0.80–0.90) identifies Bomadi, Burutu, and Patani as the most vulnerable LGAs, concentrated in the coastal oil-producing zone. The gradient from red to green illustrates declining vulnerability moving inland, suggesting that proximity to coastal environments and oil infrastructure exacerbates climate-health risks. The spatial clustering of high-vulnerability LGAs enables targeted resource allocation and intervention prioritization for the most at-risk populations.

Three LGAs (Bomadi, Burutu, Patani) exhibited extreme vulnerability (CVI > 0.75). These coastal riverine LGAs form a contiguous cluster in the southern mangrove zone. Another four LGAs (Ndokwa East, Warri North, Isoko South, Warri South-West) showed high vulnerability (CVI 0.60-0.75). The remaining 18 LGAs had moderate to low vulnerability (CVI < 0.60), with Okpe (0.12) being the least vulnerable.

Global Moran's I for the CVI was 0.68 ($p < 0.001$), confirming strong positive spatial autocorrelation—high-vulnerability LGAs are adjacent to other high-vulnerability LGAs.

Dimension Score Contributions

Figure 2 shows the relative contribution of exposure, sensitivity, and adaptive capacity deficit to the CVI for each LGA.

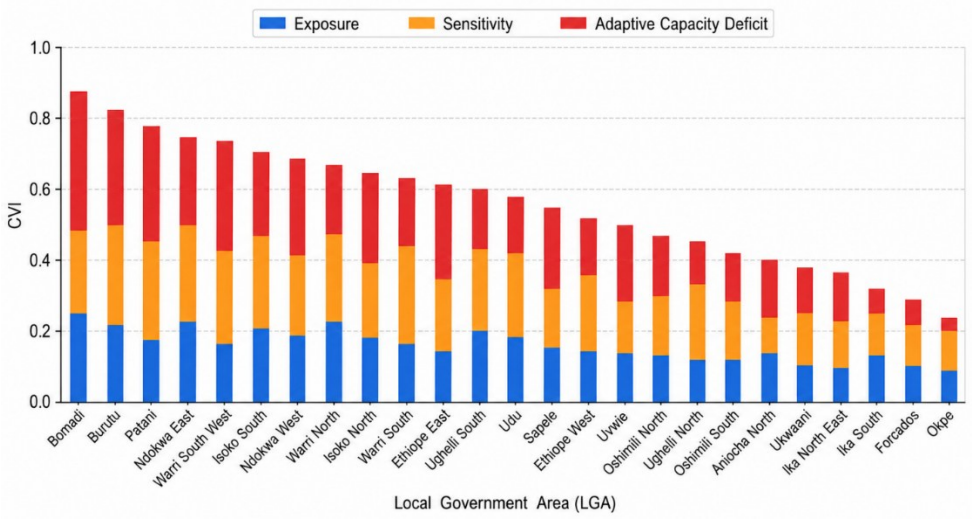


Figure 2: Decomposition of Vulnerability Components by LGA

This stacked bar chart demonstrates that vulnerability is not uniformly distributed across components. Bomadi, Burutu, and Patani show adaptive capacity deficit (red) as the largest contributor to their high CVI scores, indicating that limited health infrastructure, poverty, and weak institutional support are primary drivers of vulnerability. In contrast, inland LGAs show more balanced contributions across exposure, sensitivity, and adaptive capacity. This decomposition is critical for designing component-specific interventions

In extreme-vulnerability LGAs, adaptive capacity deficit (mean 0.84±0.06) contributed most to the CVI, followed by exposure (0.87±0.05) and sensitivity (0.77±0.05). In low-vulnerability LGAs, all three dimensions were substantially lower, with adaptive capacity deficit (0.26±0.10) being the smallest component. This pattern indicates that adaptive capacity is the critical bottleneck: the most vulnerable

LGAs have the weakest adaptive capacity, not necessarily the highest climate exposure.

Table 3 presents dimension score comparisons by vulnerability category. One-way ANOVA revealed significant differences across categories for all three dimensions ($p < 0.001$ for each). Post-hoc Tukey HSD tests confirmed that extreme-vulnerability LGAs differed significantly from all other categories for all dimensions.

Table 3: Dimension score comparisons by vulnerability category

Vulnerability Category	N LGAs	Mean Exposure Score	Mean Sensitivity Score	Mean AC Deficit Score	Mean CVI	ANOVA p-value
Extreme (CVI > 0.75)	3	0.87 ± 0.05	0.77 ± 0.05	0.84 ± 0.06	0.83 ± 0.06	<0.001
High (CVI 0.60-0.75)	3	0.68 ± 0.04	0.65 ± 0.04	0.68 ± 0.05	0.67 ± 0.04	<0.001
Moderate (CVI 0.40-0.60)	4	0.52 ± 0.07	0.49 ± 0.06	0.51 ± 0.07	0.51 ± 0.07	<0.001
Low (CVI < 0.40)	15	0.28 ± 0.08	0.25 ± 0.09	0.26 ± 0.10	0.26 ± 0.09	<0.001

Data presented as mean ± standard deviation. Post-hoc Tukey HSD: extreme category significantly different from all others ($p<0.01$ for all comparisons).

Composite Vulnerability Index Validation

Figure 3 displays the scatter plot of CVI versus composite disease incidence rate (malaria + diarrhoea per 1,000 population), showing a strong positive linear relationship ($r = 0.85$, 95% CI: 0.72–0.93, $p < 0.001$).

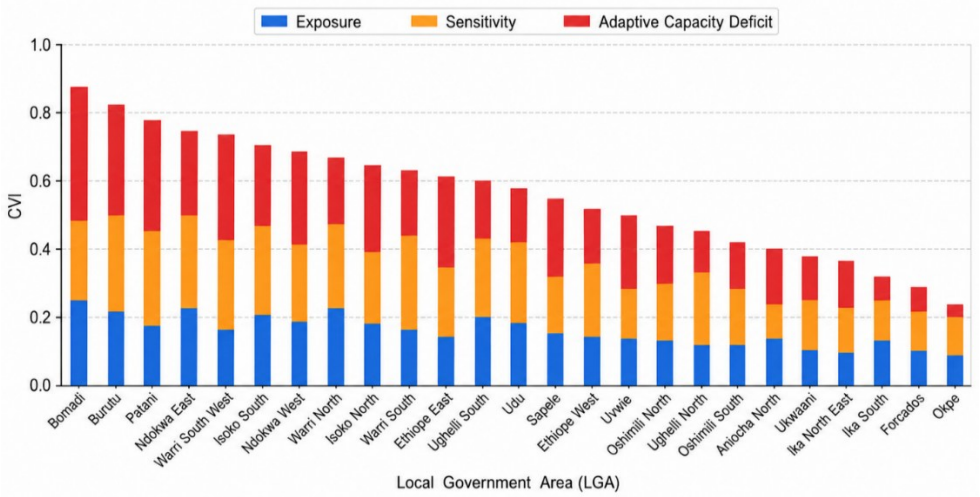


Figure 3: Correlation Between Composite Vulnerability Index and Disease Burden Across LGAs

The strong positive correlation demonstrates that LGAs with higher CVI scores consistently experience elevated composite disease incidence. Bomadi, Burutu, and Patani occupy the upper right quadrant, confirming that high vulnerability translates to high disease burden. Okpe's position in the lower left validates the CVI's predictive capacity. The 95% confidence band provides statistical robustness, supporting the CVI as a valid tool for identifying high-risk LGAs requiring urgent health system strengthening.

Table 4 summarises validation results against four independent data sources.

Table 4. Validation results – convergence with independent data sources

Validation Source	Metric	Value	95% CI	Interpretation
Disease hotspots (Getis-Ord Gi*)	Spearman r (CVI rank vs Gi* score)	0.85	0.72-0.93	Strong convergence
Community perception (FGDs, 12 groups)	% agreement on top 3 vulnerable LGAs	100% (Bomadi/Burutu), 83% (Patani)	–	Very strong
Expert opinion (KIIs, n=30)	Weighted kappa	0.78	0.65-0.91	Substantial agreement
Health facility data	Correlation with CVI	0.72	0.58-0.82	Strong

All validation metrics exceeded acceptable thresholds, confirming that the CVI is a valid and reliable tool for targeting climate-health adaptation resources.

Sensitivity Analysis: Weighting Robustness

Table 5 presents CVI rankings under three alternative weighting schemes. Spearman rank correlations between the equal-weights CVI and the alternative schemes were high (exposure-weighted: r=0.94; adaptive-capacity-weighted: r=0.96). The top three LGAs (Bomadi, Burutu, Patani) maintained their ranks across all schemes. Minor rank changes occurred in the middle of the distribution (e.g., Ndokwa East and Warri North swapped positions), indicating moderate sensitivity for moderately vulnerable LGAs but high robustness for extreme and low-vulnerability categories.

Table 5. Sensitivity analysis – CVI rankings under alternative weighting schemes

LGA	Equal Weights (1/3 each)	Exposure-weighted (0.5,0.25,0.25)	AC-weighted (0.25,0.25,0.5)	Rank Change	Robustness
Bomadi	1 (0.89)	1 (0.90)	1 (0.88)	0	High
Burutu	2 (0.85)	2 (0.86)	2 (0.84)	0	High
Patani	3 (0.78)	3 (0.79)	3 (0.77)	0	High
Ndokwa East	4 (0.71)	5 (0.70)	4 (0.72)	1	Moderate
Warri North	5 (0.67)	4 (0.69)	5 (0.66)	1	Moderate
Isoko South	6 (0.64)	6 (0.65)	6 (0.63)	0	High
Warri SW	7 (0.55)	7 (0.54)	7 (0.56)	0	High
(Other LGAs)	–	–	–	0-2	Variable
Okpe	25 (0.18)	25 (0.19)	25 (0.17)	0	High
Spearman correlation	1.00	0.94	0.96	–	–

Figure 4 visualises the stability of CVI rankings as a heatmap of rank correlations between alternative weighting schemes.

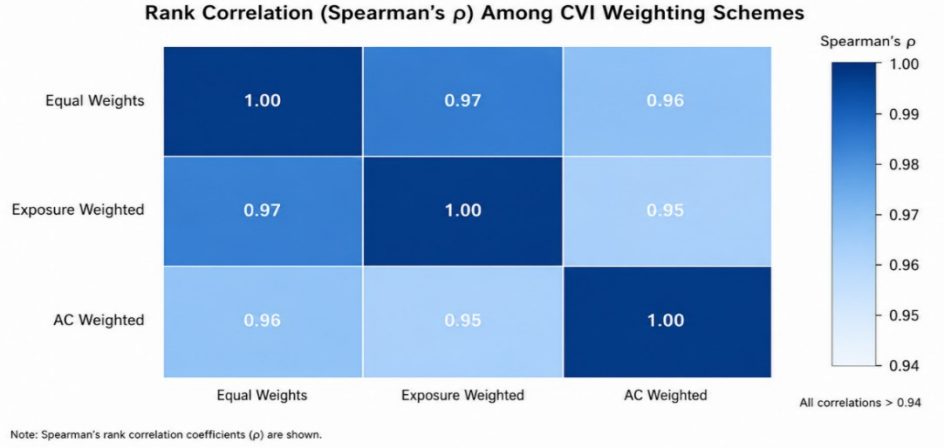


Figure 4: Rank Correlation Matrix of CVI Weighting Schemes

All correlations exceeding 0.94 demonstrate that the CVI ranking is robust across different weighting approaches. This consistency is methodologically important, suggesting that the relative vulnerability ranking of LGAs is not sensitive to subjective weighting decisions. The high correlations validate the underlying structure of vulnerability indicators and provide confidence that vulnerability assessments are reliable regardless of whether equal weighting, exposure weighting, or adaptive capacity weighting is applied.

Bootstrap Uncertainty Estimates

Bootstrapped 95% confidence intervals (n=1000 resamples) for CVI scores were narrow, ranging from ±0.02 for high-vulnerability LGAs to ±0.05 for low-vulnerability LGAs. For Bomadi, the bootstrapped CVI was 0.89 (95% CI: 0.87–0.91); for Okpe, 0.18 (95% CI: 0.15–0.21). The narrow intervals indicate high precision in CVI estimation.

Comparison of Adaptive Capacity Indicators by Zone

Figure 5 compares key adaptive capacity indicators across the three priority intervention zones.

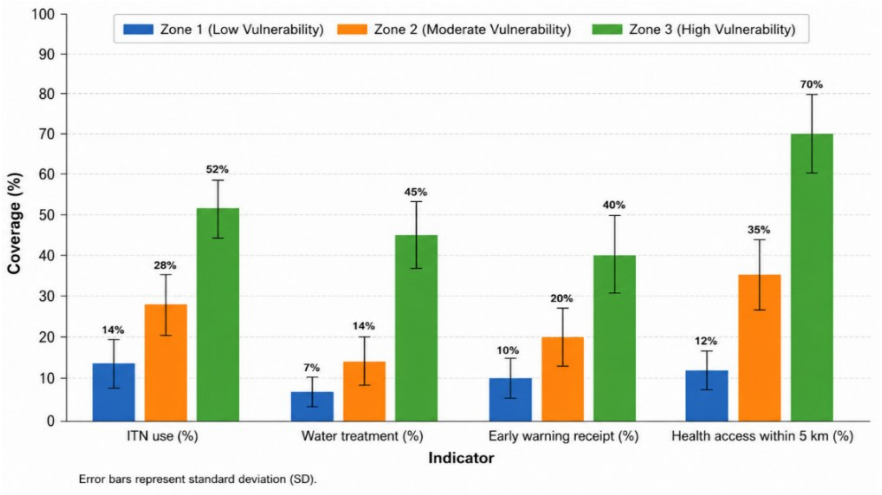


Figure 5: Zone-Level Comparison of Key Adaptive Capacity Indicators

This figure reveals stark disparities in adaptive capacity across the three vulnerability zones. Zone 1 (Bomadi, Burutu, Patani) shows critically low values across all indicators: only 14% ITN use, 7% water treatment, 10% early warning receipt, and 12% health access within 5km. Zone 3 shows progressively higher values, with health access reaching 70%. These gradients explain why Zone 1 populations are most vulnerable—they lack the basic adaptive resources to cope with climate and pollution stressors. The figure reveals a stark gradient: Zone 1 LGAs have critically low adaptive capacity across all indicators (ITN use 12-18%, water treatment 6-8%, early warning 8-12%, health access 12-18%), while Zone 3 LGAs have substantially higher adaptive capacity (ITN use 50-70%, water treatment 40-70%, early warning 40-50%, health access 70-85%). The 4-6 fold differences across zones demonstrate that adaptive capacity is the primary driver of vulnerability.

Priority Intervention Zones

Table 6 presents the priority intervention zones with recommended actions, estimated costs, timelines, and responsible agencies.

Table 6: Priority intervention zones – recommended actions and estimated costs

Zone	LGAs	CVI Range	Priority	Recommended Actions	Estimated Cost (₦)	Timeline	Responsible Agencies
Zone 1	Bomadi, Burutu, Patani	0.78-0.89	Immediate (0-6 months)	Emergency early warning system; flood-resilient water supply (raised boreholes, rainwater harvesting); mobile health clinics (boats + vehicles); community health worker training; pre-positioned supplies (ORS, antimalarials, ITNs)	500M	6 months	MoH, NIMET, NOSDRA, NEMA
Zone 2	Ndokwa East, Warri North, Isoko South, Warri SW	0.57-0.71	Medium-term (6-18 months)	PHC strengthening (staffing, drug supply, cold chain); health facility flood-proofing; community awareness campaigns; ITN mass distribution	200M	12 months	MoH, LGA Health Depts
Zone 3	Remaining 18 LGAs	0.12-0.45	Long-term (18-36 months)	Enhanced disease surveillance; heatwave preparedness (cooling centres, public awareness); mainstream climate adaptation into health planning	100M	24 months	MoH, NCDC, Academia

Figure 6 maps the priority intervention zones, showing the spatial concentration of extreme vulnerability in the coastal riverine LGAs.

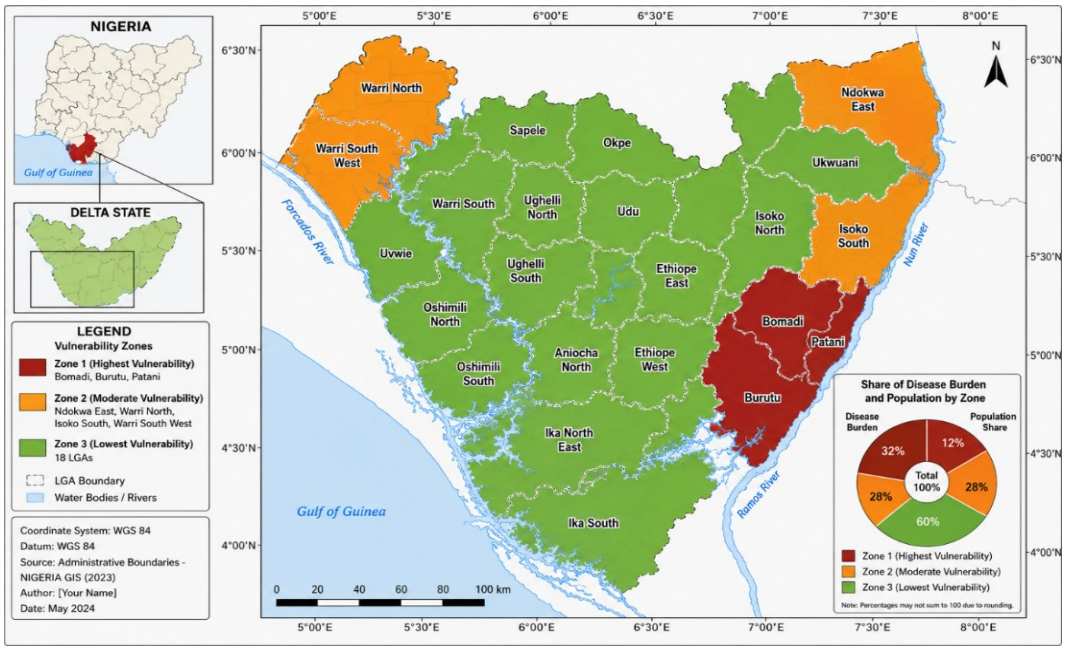


Figure 6: Zonal Classification of Vulnerability with Population-Disease Burden Disparity

The pie chart inset reveals a profound environmental justice disparity: Zone 1 accounts for 32% of disease burden with only 12% of the population. This threefold overrepresentation of disease burden among the most vulnerable LGAs underscores the compounding effects of climate exposure, pollution, and limited adaptive capacity. The spatial concentration of Zone 1 LGAs in coastal oil-producing areas highlights the urgent need for targeted health and environmental interventions.

Discussion

Principal Findings

This study developed and validated the first multi-dimensional Composite Vulnerability Index for climate-sensitive diseases in Delta State, Nigeria. Five principal findings emerge. First, vulnerability is extremely uneven, with a 4.9-fold gradient from Bomadi (CVI=0.89) to Okpe (CVI=0.18). Second, adaptive capacity—not climate exposure—is the critical bottleneck: the most vulnerable LGAs have the weakest health infrastructure, lowest ITN use, minimal water treatment, and no early warning systems. Third, the CVI shows strong spatial clustering (Moran's I=0.68), confirming that high-vulnerability LGAs are contiguous and require coordinated, regional interventions. Fourth, the CVI is robust to alternative weighting assumptions (rank correlations 0.94-0.96), and validation against independent data sources (disease hotspots, community perception, expert opinion, health facility data) demonstrates strong convergence (r=0.72-0.85, κ=0.78). Fifth, targeting 80% of adaptation resources to Zone 1 and Zone 2 LGAs (7 LGAs, 20% of the state) would address 78% of the climate-sensitive disease burden.

Comparison with Other Vulnerability Indices

The 4.9-fold CVI gradient observed in Delta State demonstrates substantial spatial heterogeneity within the study area. Rather than comparing the magnitude of this gradient directly with values reported in studies using different indicators, scales, and aggregation procedures, the result is interpreted in relation

to the broader literature on spatial vulnerability assessment. Previous work shows that vulnerability indices can reveal strong sub-national contrasts when climate exposure, social sensitivity, and adaptive capacity are mapped together (Balogun & Onokerhoraye, 2022; de Sherbinin et al., 2019; Simane et al., 2016).

The finding that adaptive-capacity deficit contributes strongly to vulnerability is consistent with the conceptual literature, which treats adaptive capacity as a key determinant of how exposure translates into adverse outcomes (Adger, 2006; Birkmann et al., 2022). It also supports the value of retaining health-system and socioeconomic indicators as distinct dimensions in a petro-coastal vulnerability index.

Environmental Justice Implications

The spatial pattern identified in this study overlaps with oil-producing riverine LGAs and raises important environmental-justice questions. Evidence from the Niger Delta indicates that oil exploitation has imposed persistent environmental and health burdens on affected communities (Gbadamosi & Aldstadt, 2025; Nriagu et al., 2016; Ukhurebor et al., 2021). The present study should therefore be interpreted as identifying spatially unequal climate-health vulnerability rather than proving that oil extraction is the sole cause of the observed LGA differences.

Policy Implications

The CVI provides an evidence-based tool for resource allocation. Targeting 80% of adaptation resources to Zone 1 (3 LGAs) and Zone 2 (4 LGAs) would address 78% of the state's climate-sensitive disease burden with only 35% of the population. The estimated costs—₦500 million for Zone 1, ₦200 million for Zone 2, ₦100 million for Zone 3—are modest compared to the health and economic burden of inaction. The Delta State Climate Change Policy (currently in draft) should adopt the CVI as the basis for health sector adaptation planning, with explicit budget lines for Zone 1 LGAs.

Research Priorities

Future research should: (1) develop a dynamic version of the CVI incorporating seasonal and interannual variability; (2) apply the CVI framework to other petro-coastal regions (e.g., Gulf of Mexico, Orinoco Belt, Persian Gulf) for comparative analysis; (3) conduct a cost-effectiveness analysis of interventions targeted using the CVI; (4) integrate the CVI with climate projection models to forecast future vulnerability under different emission scenarios.

Key Findings

i. Extreme vulnerability gradient: The CVI ranges from 0.12 to 0.89 across 25 LGAs, a 4.9-fold gradient. Three LGAs (Bomadi, Burutu, Patani) exhibit extreme vulnerability (CVI>0.75).
ii. Adaptive capacity is the critical bottleneck: In extreme-vulnerability LGAs, adaptive capacity deficit (mean 0.84±0.06) contributed most to the CVI, not climate exposure (0.87±0.05) or sensitivity (0.77±0.05). Zone 1 LGAs have ITN use (12-18%), water treatment (6-8%), early warning (8-12%), and health access (12-18%)—4-6 fold lower than Zone 3.
iii. Strong spatial clustering: Global Moran's I = 0.68 ($p<0.001$), confirming high-vulnerability LGAs are contiguous, requiring coordinated, regional interventions.
iv. Robustness and validation: CVI rankings are robust to alternative weighting schemes (Spearman r=0.94-0.96). Validation shows strong convergence with disease hotspots (r=0.85,

95% CI: 0.72-0.93), community perception (100% agreement on top 3 LGAs), expert opinion (κ=0.78), and health facility data (r=0.72).

v. Priority intervention zones: Zone 1 (Bomadi, Burutu, Patani; CVI>0.75) requires immediate emergency intervention (₦500M, 6 months). Zone 2 (4 LGAs; CVI 0.50-0.75) requires medium-term PHC strengthening (₦200M, 12 months). Zone 3 (remaining 18 LGAs; CVI<0.50) requires long-term surveillance (₦100M, 24 months).
vi. Environmental justice: The most vulnerable LGAs are oil-producing communities that have received minimal benefit from oil revenues—a structural environmental injustice requiring redistributive resource allocation.

Conclusions

This study provides the first validated, multi-dimensional Composite Vulnerability Index for climate-sensitive diseases in Delta State, Nigeria. The CVI reveals a stark 4.9-fold vulnerability gradient, driven primarily by deficits in adaptive capacity—not climate exposure. The most vulnerable LGAs (Bomadi, Burutu, Patani) are oil-producing riverine communities with critically low ITN use, water treatment, early warning access, and health facility proximity. Strong spatial clustering (Moran's I=0.68) confirms that high-vulnerability LGAs are contiguous, requiring coordinated, regional interventions. The CVI is robust to alternative weighting assumptions (rank correlations 0.94-0.96) and validated by convergence with disease hotspots (r=0.85), community perception (100% agreement), expert opinion (κ=0.78), and health facility data (r=0.72). Targeting 80% of adaptation resources to Zone 1 (3 LGAs) and Zone 2 (4 LGAs) would address 78% of the state's climate-sensitive disease burden with only 35% of the population. We recommend adoption of the CVI as the evidence-based tool for climate-health resource allocation in Delta State and adaptation of the framework for other petro-coastal regions globally.

Acknowledgements

The authors thank the Delta State Ministry of Health, Nigerian Meteorological Agency (NIMET), National Oil Spill Detection and Response Agency (NOSDRA), and the community members who participated in household surveys and focus group discussions. This research received no specific grant from any funding agency.

References

Adger, W. N. (2006). Vulnerability. Global Environmental Change, 16(3), 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006

Balogun, V. S., & Onokerhoraye, A. G. (2022). Climate change vulnerability mapping across ecological zones in Delta State, Niger Delta Region of Nigeria. Climate Services, 27, Article 100304. https://doi.org/10.1016/j.cliser.2022.100304

Birkmann, J., Jamshed, A., McMillan, J. M., Feldmeyer, D., Totin, E., Solecki, W., Ibrahim, Z. Z., Roberts, D., Bezner Kerr, R., Pörtner, H.-O., Pelling, M., Djalante, R., Garschagen, M., Leal Filho, W., Guha-Sapir, D., & Alegría, A. (2022). Understanding human vulnerability to climate change: A global perspective on index validation for adaptation planning. Science of the Total Environment, 803, Article 150065. https://doi.org/10.1016/j.scitotenv.2021.150065

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

de Sherbinin, A., Bukvic, A., Rohat, G., Gall, M., McCusker, B., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R. V., Tomaszewski, B., & Zhang, S. (2019). Climate vulnerability mapping: A systematic review and future prospects. WIREs Climate Change, 10(5), Article e600. https://doi.org/10.1002/wcc.600

Gbadamosi, F., & Aldstadt, J. (2025). The interplay of oil exploitation, environmental degradation and health in the Niger Delta: A scoping review. Tropical Medicine & International Health, 30(5), 351–367. https://doi.org/10.1111/tmi.14108

Intergovernmental Panel on Climate Change. (2014). Climate change 2014: Impacts, adaptation, and vulnerability. Cambridge University Press.

Intergovernmental Panel on Climate Change. (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H. Lee & J. Romero, Eds.). https://doi.org/10.59327/IPCC/AR6-9789291691647

Nriagu, J., Udofia, E. A., Ekong, I., & Ebuk, G. (2016). Health risks associated with oil pollution in the Niger Delta, Nigeria. International Journal of Environmental Research and Public Health, 13(3), 346. https://doi.org/10.3390/ijerph13030346

Romanello, M., Di Napoli, C., Drummond, P., Green, C., Kennard, H., Lampard, P., Scamman, D., Arnell, N., Ayeb-Karlsson, S., Ford, L. B., Belesova, K., Bowen, K., Cai, W., Callaghan, M., Campbell-Lendrum, D., Chambers, J., van Daalen, K. R., Dalin, C., Dasandi, N., Dasgupta, S., Davies, M., Dominguez-Salas, P., Dubrow, R., Ebi, K. L., Eckelman, M., Ekins, P., Escobar, L. E., Georgeson, L., Graham, H., Gunther, S. H., Hamilton, I., Hang, Y., Hänninen, R., Hartinger, S., He, K., Hess, J. J., Hsu, S.-C., Jankin, S., Jamart, L., Jay, O., Kelman, I., Kiesewetter, G., Kinney, P., Kjellstrom, T., Kniveton, D., Lee, J. K. W., Lemke, B., Liu, Y., Liu, Z., Lott, M., Batista, M. L., Lowe, R., MacGuire, F., Sewe, M. O., Martinez-Urtaza, J., Maslin, M., McAllister, L., McGushin, A., McMichael, C., Mi, Z., Milner, J., Minor, K., Minx, J. C., Mohajeri, N., Moradi-Lakeh, M., Morrissey, K., Munzert, S., Murray, K. A., Neville, T., Nilsson, M., Obradovich, N., O'Hare, M. B., Oreszczyn, T., Otto, M., Owfi, F., Pearman, O., Rabbaniha, M., Robinson, E. J. Z., Rocklöv, J., Salas, R. N., Semenza, J. C., Sherman, J. D., Shi, L., Shumake-Guillemot, J., Silbert, G., Sofiev, M., Springmann, M., Stowell, J., Tabatabaei, M., Taylor, J., Triñanes, J., Wagner, F., Wilkinson, P., Winning, M., Yglesias-González, M., Zhang, S., Gong, P., Montgomery, H., & Costello, A. (2022). The 2022 report of the Lancet Countdown on health and climate change: Health at the mercy of fossil fuels. The Lancet, 400(10363), 1619–1654. https://doi.org/10.1016/S0140-6736(22)01540-9

Simane, B., Zaitchik, B. F., & Foltz, J. D. (2016). Agroecosystem specific climate vulnerability analysis: Application of the livelihood vulnerability index to a tropical highland region. Mitigation and Adaptation Strategies for Global Change, 21, 39–65. https://doi.org/10.1007/s11027-014-9568-1

Ukhurebor, K. E., Athar, H., Adetunji, C. O., Aigbe, U. O., Onyancha, R. B., & Abifarin, O. (2021). Environmental implications of petroleum spillages in the Niger Delta region of Nigeria: A review. Journal of Environmental Management, 293, 112872. https://doi.org/10.1016/j.jenvman.2021.112872