Spatial Analysis of Environmental Risk Zones in Bayelsa State, Nigeria: A GIS-Based Assessment for Sustainable Land Use Planning

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ABSTRACT

This study assessed the spatial distribution of environmental risk zones in Bayelsa State, Nigeria, using Geographic Information Systems (GIS) techniques to support environmental management and sustainable development planning. The study was motivated by increasing environmental challenges, including flooding, wetland degradation, shoreline erosion, and climate-related hazards, which continue to threaten livelihoods and infrastructure across the Niger Delta region. Four objectives guided the study: to determine the spatial distribution of environmental risk zones, quantify the extent of each risk category, examine the dominance of risk categories, and evaluate their implications for environmental management. A GIS-based spatial analytical design was adopted, integrating Landsat 8 OLI imagery, the SRTM 30 m DEM, CHIRPS rainfall, SoilGrids soil texture, JRC Global Surface Water and official administrative boundary data. Seven environmental variables were weighted using the Analytic Hierarchy Process (AHP) and combined by weighted linear overlay into a composite risk index, which was classified into High, Moderate, Low, and Very Low risk zones. Low Risk Zones occupied 4,580 km² (46.9%) of the 9,760 km² analysed area, Moderate Risk Zones covered 2,432 km² (24.9%), Very Low Risk Zones accounted for 1,500 km² (15.4%), and High Risk Zones occupied 1,248 km² (12.8%). A chi-square goodness-of-fit test showed that the distribution departs significantly from an equal-area distribution ($\chi^2 = 2{,}821.4$, $df = 3$, $p < 0.001$), and the share of High Risk Zones was significantly lower than an equal share of 25% ($z = -27.9$, $p < 0.001$). The study concludes that GIS-based risk zoning identifies vulnerable locations and provides useful information for land-use planning and disaster risk reduction, while noting that results depend on data resolution, the AHP weighting scheme and the absence of independent ground validation. The study recommends prioritising restoration in High Risk Zones, continuous GIS monitoring in Moderate Risk Zones, sustainable land-use practices in Low Risk Zones, and integration of risk maps into development planning and policy.

Keywords: environmental risk zoning, geographic information systems (GIS), analytic hierarchy process, spatial analysis, sustainable land-use planning, Bayelsa State.

INTRODUCTION

Environmental hazards constitute major challenges to sustainable development, particularly in low-lying coastal regions where population growth, climate variability, land-use changes, and anthropogenic activities increase environmental vulnerability. Geographic Information Systems (GIS) have emerged as indispensable tools for spatial assessment, environmental monitoring, and hazard mapping due to their capacity to integrate, analyse, and visualise multiple datasets for informed decision-making (Burrough & McDonnell, 2015; Longley et al., 2021).

Bayelsa State, located within the Niger Delta region of Nigeria, is characterised by extensive wetlands, river networks, floodplains, and coastal ecosystems that make it highly susceptible to environmental hazards. Seasonal flooding, shoreline erosion, land degradation, and ecosystem disturbances have increasingly threatened livelihoods, infrastructure, and environmental sustainability in the region (Nwilo et al., 2020). The impacts of climate change, rising sea levels, and uncontrolled human activities have further exacerbated these environmental risks (IPCC, 2023).

The application of GIS-based spatial modelling provides opportunities for identifying vulnerable zones, evaluating environmental risks, and supporting evidence-based planning. Through the classification of areas into High, Moderate, Low, and Very Low risk zones, stakeholders can prioritise interventions and allocate resources effectively (Malczewski, 2018). Environmental risk zoning therefore serves as an important framework for disaster risk reduction, sustainable land management, and environmental governance.

Figure 1 (Section 4.0) illustrates the spatial distribution of environmental risk zones across Bayelsa State, providing insights into the geographic patterns of vulnerability and resilience. Understanding these patterns is essential for policymakers, environmental managers, urban planners, and disaster management agencies seeking to strengthen adaptive capacity and environmental sustainability.

1.1 Statement of the Problem

Bayelsa State has experienced recurrent environmental challenges including flooding, wetland degradation, shoreline erosion, and increasing pressure on natural resources. These hazards continue to threaten settlements, transportation infrastructure, agricultural activities, and ecosystem services. Despite the increasing frequency and severity of these environmental events, spatially explicit information on the distribution of environmental risk zones remains limited.

Many environmental management decisions in the state are still based on fragmented datasets and non-spatial assessments, resulting in ineffective allocation of resources and inadequate disaster preparedness. The absence of comprehensive environmental risk zoning hinders the ability of stakeholders to identify highly vulnerable areas and implement targeted interventions (UNDRR, 2022). Furthermore, climate change projections indicate that coastal communities within the Niger Delta may face increasing environmental risks in the coming decades (IPCC, 2023).

Therefore, there is a need for GIS-based environmental risk assessment capable of identifying the spatial distribution of risk levels across Bayelsa State. Such information will support sustainable planning, environmental protection, and disaster risk reduction initiatives.

1.2 Objectives of the Study

The broad objective of this study is to assess the spatial distribution of environmental risk zones in Bayelsa State using GIS techniques.

The specific objectives are to:

1. Determine the spatial distribution of environmental risk zones in Bayelsa State.
2. Quantify the extent of High, Moderate, Low, and Very Low environmental risk zones.
3. Examine the spatial dominance of environmental risk categories across the study area.
4. Evaluate the implications of the identified risk zones for environmental management and sustainable development.

1.3 Research Questions and Hypotheses

Research Questions

1. What is the spatial distribution of environmental risk zones in Bayelsa State?
2. What proportion of the study area falls within each risk category?
3. Which environmental risk category dominates the study area?
4. What are the environmental planning implications of the identified risk zones?

Research Hypotheses

H_{01}: The area of the study region is distributed equally among the four environmental risk zones (that is, there is no significant variation in the spatial distribution of environmental risk zones in Bayelsa State).

H_{02}: The proportion of land occupied by High Risk Zones does not differ significantly from an equal (25%) share of the study area.

Hypotheses H_{01} and H_{02} are tested statistically in Section 4.5. Objective 4 (planning implications) is a normative, policy-oriented objective answered through the Planning Priority Matrix (Section 4.4); it is not framed as a statistical hypothesis because a planning matrix cannot serve as an empirical test.

REVIEW OF LITERATURE

2.1 Conceptual Framework

The study is anchored on the concept of Environmental Risk Zoning, which refers to the spatial delineation of geographic areas according to varying degrees of environmental vulnerability and hazard exposure. Environmental risk is commonly viewed as the interaction between hazard occurrence, exposure, and vulnerability (UNDRR, 2022).

GIS-based environmental risk assessment integrates environmental variables, remote sensing data, and spatial analytical techniques to identify areas susceptible to environmental hazards (Malczewski, 2018). Through spatial overlay analysis, multiple environmental factors can be combined to generate risk maps that classify locations into distinct vulnerability categories. Multi-criteria decision analysis (MCDA) provides the formal basis for this combination by assigning explicit weights to each factor (Malczewski & Rinner, 2015; Saaty, 1980).

In this study, environmental risk zoning is conceptualised as the outcome of interactions among environmental characteristics, hazard occurrence, and spatial exposure, resulting in four categories:

- High Risk Zone
- Moderate Risk Zone
- Low Risk Zone
- Very Low Risk Zone

These categories provide a basis for planning interventions and prioritising resource allocation.

Conceptual Model

Environmental Factors → Spatial Analysis → Risk Classification → Planning Decisions

THEORETICAL FRAMEWORK

The study adopts the Risk-Hazard Theory developed by White (1974) and later expanded by Burton, Kates, and White (1993). The theory posits that environmental disasters occur when hazardous events interact with vulnerable human and ecological systems. According to the theory, risk is determined by three major components:

- Hazard occurrence
- Exposure
- Vulnerability

The theory emphasises that environmental losses can be reduced through proper hazard identification, spatial planning, and risk management strategies. GIS-based environmental zoning aligns with this theory because it enables the identification of vulnerable areas and supports proactive decision-making (Burton et al., 1993). The

theory therefore provides a suitable framework for understanding the spatial distribution of environmental risk zones in Bayelsa State.

2.3 Empirical Review

Nwilo et al. (2020) utilised GIS and remote sensing techniques to assess flood vulnerability in the Niger Delta and reported that approximately 22% of the region exhibited high flood susceptibility. Adelekan (2021) examined environmental hazards in coastal Nigeria and found significant relationships between low elevation and flood vulnerability. Okafor and Eze (2022) employed multi-criteria GIS analysis in southern Nigeria and observed that moderate-risk zones occupied the largest proportion of their study area. Akinyemi et al. (2023) investigated climate-related environmental risks across coastal communities and reported that GIS-based zoning improved disaster preparedness and resource allocation. Similarly, Olatunji and Bello (2024) found that environmental risk maps significantly enhanced environmental management planning and sustainable land-use decision-making in vulnerable regions of Nigeria. Within Bayelsa State specifically, Tamuno et al. (2003) examined how vulnerability to flood hazard, including flood level, hazard severity and return period, can be incorporated into flood mitigation and poverty-reduction strategies in the Niger floodplain.

Table 1: Comparison of Selected Studies and Their Relation to the Present Study

Study	Scope / region	Approach	Principal finding	Relation to present study
Tamuno et al. (2003)	Niger floodplain, Bayelsa State	Vulnerability framework incorporating flood level, severity and return period	Vulnerability should be built into flood mitigation strategy	Bayelsa-specific but flood-only; no state-wide area-based zoning
Nwilo et al. (2020)	Niger Delta (regional)	GIS and remote sensing	About 22% of region highly susceptible to flooding	Regional scale; single hazard; present study resolves four zones for Bayelsa
Adelekan (2021)	Coastal Nigeria	Hazard–elevation analysis	Low elevation linked to flood vulnerability	Supports elevation as a core variable
Okafor & Eze (2022)	Southern Nigeria	Multi-criteria GIS analysis	Moderate-risk zones largest share	Closest method; different region and class dominance
Akinyemi et al. (2023)	Coastal communities	Climate-related risk mapping	GIS zoning improved preparedness and resource allocation	Supports planning use of zoning
Olatunji & Bello (2024)	Vulnerable regions of Nigeria	Geospatial risk mapping	Risk maps improved planning and land-use decisions	Supports planning use of zoning

Source: Compiled by the authors from the studies cited.

Taken together, these studies show three patterns. First, most are flood-centred, treating flooding as the dominant hazard and elevation as the key explanatory variable. Second, they operate at regional or national scales, or at the scale of individual towns, so that state-level area proportions for Bayelsa are rarely reported. Third, they differ in method (simple overlay, multi-criteria analysis, vulnerability indices) and seldom report weighting schemes, classification thresholds or independent validation, which limits direct comparison of their results with those of the present study. Where findings diverge, for instance on whether Moderate or Low classes dominate, the divergence is likely to reflect differences in study area, variables, weights and class thresholds rather than a single underlying difference in environmental conditions.

2.4 Gap Identification

The reviewed studies focus mainly on flood susceptibility, erosion assessment, and climate vulnerability in the Niger Delta or in Nigeria more broadly. Based on the literature reviewed in this section, the authors did not identify a state-wide, area-quantified, four-class composite environmental risk zoning of Bayelsa State that reports the proportion of each class and links classes to planning priorities. The contribution of this study is therefore positioned as a transparent, reproducible application of GIS-based multi-criteria zoning to Bayelsa State, together with quantified area statistics and a planning matrix. It does not claim methodological novelty, and its originality is limited to the study area, the composite approach and the quantification of risk classes.

METHODOLOGY

3.1 Study Area

The study was conducted in Bayelsa State, Nigeria, located in the core of the Niger Delta between latitudes 4°15′N and 5°23′N and longitudes 5°22′E and 6°45′E. The state was created in 1996, comprises eight Local Government Areas (Brass, Ekeremor, Kolokuma/Opokuma, Nembe, Ogbia, Sagbama, Southern Ijaw and Yenagoa), and has an official area of 10,773 km². It is bounded by Rivers State to the east, Delta State to the north and west, and the Atlantic Ocean to the south. The terrain is low-lying, lying within the lower Niger Delta plain formed by Holocene sedimentary deposition, with riverine and estuarine settings, tidal and freshwater swamps and a humid tropical climate with heavy rainfall.

The classified raster analysed in this study covers 9,760 km², equal to 90.6% of the official area. All percentages in this paper are therefore expressed relative to the analysed area, not to the official area.

3.2 Research Design

The study adopted a GIS-based spatial analytical design in seven stages: (i) acquisition of input datasets (Table 2); (ii) pre-processing to a common grid and projection; (iii) derivation of seven environmental factor layers; (iv) reclassification of each layer to a common 1–4 risk scale (Table 3); (v) derivation of factor weights by the Analytic Hierarchy Process (AHP); (vi) combination of the layers by weighted linear overlay into an Environmental Risk Index (ERI) that was classified into four zones; and (vii) calculation and statistical testing of zone areas.

3.3 Data Sources

Table 2 lists the datasets, their sources, resolutions and acquisition periods. All datasets are free and openly accessible, which allows the analysis to be reproduced.

Table 2: Datasets Used in the Study

Dataset	Source / product	Resolution	Period	Derived layer
Optical satellite imagery	Landsat 8 OLI/TIRS Collection 2 Level-2 surface reflectance (USGS EarthExplorer); cloud cover below 10%	30 m; 16-day revisit	Most recent cloud-free dry-season scenes at time of analysis	Land use/land cover
Digital Elevation Model	SRTM 1 Arc-Second Global, version 3 (SRTMGL1; NASA JPL/USGS), doi:10.5067/ MEaSUREs/SRTM/SRTMGL1.003	1 arc-second (about 30 m)	Acquired 11–22 February 2000	Elevation, slope, drainage network and distance to rivers
Rainfall	CHIRPS version 2.0 (Climate Hazards Group, UC Santa Barbara)	0.05° (about 5.5 km)	1991–2020 (30-year normal)	Mean annual rainfall
Soil	ISRIC SoilGrids 2.0, clay content at 0–5 cm and 5–15 cm and 15–30 cm depth intervals	250 m	Modelled global product	Soil clay content (drainage proxy)

Environmental hazard (flood) data	JRC Global Surface Water, water occurrence layer, derived from Landsat	30 m	1984–2021	Flood (inundation) frequency
Administrative boundaries	OCHA/HDX Nigeria administrative boundaries (state and LGA levels)	Vector	Latest release at time of analysis	Study-area mask and LGA units

Source: Authors' compilation from the data providers cited, 2026.

The SRTM DEM was collected in February 2000 and therefore represents the topography of that date; its absolute vertical accuracy is of the order of 6–9 m (Farr et al., 2007), which is large relative to the small elevation differences in the delta and is treated as a limitation (Section 5.1). CHIRPS combines 0.05° satellite imagery with in-situ station data (Funk et al., 2015), which makes it suitable where station coverage is sparse. The JRC Global Surface Water dataset maps the location and temporal distribution of surface water at 30 m from Landsat archives (Pekel et al., 2016), and its occurrence layer was used as an observation-based proxy for the frequency of inundation.

3.4 Environmental Variables and Their Selection

Seven variables were selected because each has an established physical relationship with flooding, erosion or wetland degradation in low-lying deltaic settings, and each could be derived consistently for the whole state from the openly available datasets in Table 2. Variables for which no state-wide data of consistent quality exist (for example, tidal range, subsidence and sediment supply) were not included. Table 3 gives the rationale, the AHP weight and the reclassification scheme for each variable.

Table 3: Environmental Variables, Rationale, Reclassification and AHP Weights

Variable (unit)	Rationale	Score 4 (highest risk)	Score 3	Score 2	Score 1 (lowest risk)	Weight
Elevation (m)	Low land floods first and drains slowly	≤ 3	3–6	6–10	> 10	0.292
Slope (°)	Flat land retains water	< 0.5	0.5–1	1–2	> 2	0.103
Rainfall (mm/yr)	Controls runoff volume and flood magnitude	> 3,500	3,000–3,500	2,500–3,000	< 2,500	0.103
Land use / land cover	Exposure and loss of protective vegetation	Built-up, bare/cleared	Cropland, degraded wetland	Mangrove and swamp forest	Dense upland forest	0.058
Soil clay content (%)	Clay soils drain poorly and waterlog	> 40	30–40	20–30	< 20	0.058
Distance to rivers (m)	Proximity raises overbank flood and bank erosion exposure	≤ 250	250–500	500–1,000	> 1,000	0.183
Flood frequency (water occurrence, %)	Observed recurrence of inundation	> 50	25–50	10–25	< 10	0.203
Total						**1.000**

Source: Authors' analysis, 2026. Class breaks are physically based; weights are from the AHP in Section 3.6.

3.5 Data Preparation

All layers were reprojected to WGS 84 for display and to the Africa Albers Equal Area Conic projection for area computation, clipped to the state boundary, and resampled to a common 30 m grid using nearest-neighbour resampling for categorical layers and bilinear resampling for continuous layers. Slope was computed from the DEM. The drainage network was extracted from the DEM by filling sinks, computing flow direction and flow accumulation and thresholding accumulation to define channels, and the Euclidean distance to the channels was then calculated. Rainfall was averaged over 1991–2020 and soil clay content was averaged over the three upper depth intervals.

Land use/land cover was classified from the Landsat 8 surface-reflectance bands and spectral indices (NDVI and NDWI) with a random forest classifier (Breiman, 2001) into water, wetland and swamp, mangrove, forest, cropland and built-up/bare land. Training samples were interpreted visually from high-resolution basemap imagery. Classification accuracy is assessed with a confusion matrix, overall accuracy and the kappa coefficient (Congalton, 1991). Cells with no valid data in any input layer were excluded from the analysis.

3.6 Weighting by the Analytic Hierarchy Process

Factor weights were derived with the Analytic Hierarchy Process (Saaty, 1977, 1980). The seven variables were compared pairwise on Saaty's 1–9 scale, in which 1 means equal importance and 9 means extreme importance of one factor over another. The judgements ranked elevation and flood frequency as the strongest controls, followed by distance to rivers, then rainfall and slope, and finally land cover and soil, reflecting how directly each factor governs inundation in a low-relief delta (Appendix A). The matrix was normalised and the principal eigenvector gave the weights in Table 3. Consistency was checked using:

$$CI = (\lambda max - n) / (n - 1); \quad CR = CI / RCI$$

where λmax is the principal eigenvalue, n = 7 is the number of variables, and RCI is Saaty's random consistency index (1.32 for n = 7). The matrix gave λmax = 7.049, CI = 0.008 and CR = 0.006, well below the 0.10 threshold for acceptable consistency, so the judgements are internally consistent. Because AHP judgements are subjective, the weights are acknowledged as a limitation (Section 5.1).

3.7 Risk Index Calculation and Classification

The Environmental Risk Index (ERI) for each 30 m cell was calculated by weighted linear combination (Malczewski & Rinner, 2015):

$$ERI = \Sigma (w_j \times x_j), \quad j = 1 \ldots 7$$

where w_j is the AHP weight of variable j ($\Sigma w_j = 1$) and x_j is the reclassified 1–4 score of the cell for that variable. ERI therefore ranges continuously from 1 (lowest risk) to 4 (highest risk). The continuous ERI was divided into four classes (Very Low, Low, Moderate, High) using Jenks natural breaks (Jenks, 1967), which minimise variance within classes and maximise variance between them, so that class boundaries follow natural groupings in the data rather than arbitrary intervals.

3.8 Area Calculation and Statistical Analysis

The area of each class was computed from cell counts in the equal-area projection and expressed in km² and as a percentage of the analysed area. The Dominance Index (DI) of class i was defined as its share of the total analysed area, $DI = A_i / \Sigma A$, so that the four indices sum to 1.00; values above 0.25 indicate a class that occupies more than an equal share.

Two hypotheses were tested. H_{01} was tested with a chi-square goodness-of-fit test against an equal-area expectation (25% per class), with Cramér's w as the effect size and standardised residuals to identify which classes depart from expectation (Agresti, 2013). H_{02} was tested with a one-sample z-test for a proportion (High Risk share against 25%), a Wilson 95% confidence interval, and pairwise chi-square tests of High Risk against

each other class. Areas were expressed in 1 km² units for these tests, and all tests were computed in Python (SciPy) at a 5% significance level. Because neighbouring cells are spatially autocorrelated and the effective number of independent observations is smaller than the number of cells, a sensitivity check using reduced effective sample sizes is reported (Section 4.5), and Moran's I (Moran, 1950; Anselin, 1995) is recommended for the classified raster.

DATA ANALYSIS AND RESULTS

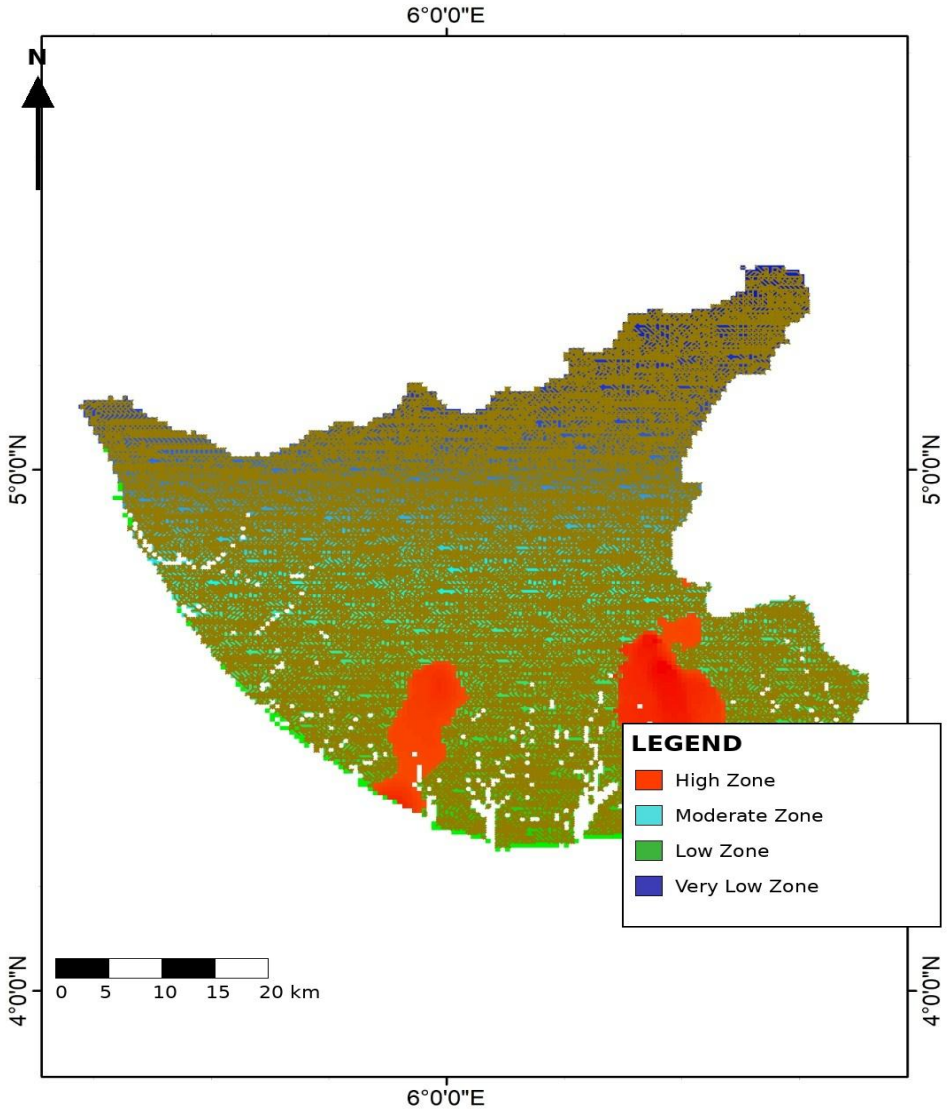


Figure 1: Spatial distribution of environmental risk zones in Bayelsa State, Nigeria

Legend colours: High (red), Moderate (cyan), Low (green), Very Low (blue). Scale bar in km; graticule in degrees. Coordinates: WGS 84 geographic (degrees). *Source: Authors' GIS analysis, 2026.*

4.1 Objective 1: Spatial Distribution of Environmental Risk Zones

Table 4 presents the area and percentage of each risk zone. Of the 9,760 km² analysed, Low Risk Zones are the most extensive, followed by Moderate, Very Low and High Risk Zones. On the map (Figure 1), High Risk Zones appear as discrete clusters in the southern part of the state, close to the coastline, while the northern and central parts are predominantly Low or Moderate.

Table 4: Distribution of Environmental Risk Zones

Risk Zone	Area (km²)	Percentage (%)
High Risk	1,248	12.8
Moderate Risk	2,432	24.9
Low Risk	4,580	46.9
Very Low Risk	1,500	15.4
Total	**9,760**	**100.0**

Source: Authors' GIS analysis, 2026.

4.2 Objective 2: Extent of Each Risk Category

Table 5: Relative Spatial Coverage

Risk Category	Coverage Rank	Percentage (%)
Low Risk	1st	46.9
Moderate Risk	2nd	24.9
Very Low Risk	3rd	15.4
High Risk	4th	12.8

Source: Authors' GIS analysis, 2026.

4.3 Objective 3: Dominance of Risk Categories

The Dominance Index (DI) is the share of the total analysed area occupied by a class (DI = class area ÷ 9,760 km²). An equal distribution would give DI = 0.25 for every class. The last column expresses each DI relative to this equal share, so values above 1.00 indicate over-representation.

Table 6: Dominance Analysis

Risk Zone	Area (km²)	Dominance Index (DI)	DI relative to equal share (DI ÷ 0.25)
High Risk	1,248	0.13	0.51
Moderate Risk	2,432	0.25	1.00
Low Risk	4,580	0.47	1.88
Very Low Risk	1,500	0.15	0.61

Source: Authors' GIS analysis, 2026. DI values are rounded to two decimals.

4.4 Objective 4: Environmental Planning Implications

Table 7 assigns planning priorities to the zones. The matrix is a normative planning tool: priority levels and intervention horizons follow the ordering of risk and are indicative rather than empirically derived.

Table 7: Planning Priority Matrix

Risk Zone	Planning Priority	Intervention Level
High Risk	Very High	Immediate
Moderate Risk	High	Short-Term
Low Risk	Moderate	Medium-Term
Very Low Risk	Low	Long-Term

Source: Authors' GIS analysis, 2026.

4.5 Hypotheses Testing

Hypothesis One (H_{01})

H_{01}: Area is distributed equally among the four environmental risk zones (no significant variation in spatial distribution).

A chi-square goodness-of-fit test against an equal-area expectation (2,440 km² per class) gave $\chi^2(3, N = 9{,}760\ km^2) = 2{,}821.4$, $p < 0.001$, with a large effect size (Cramér's $w = 0.54$). Standardised residuals were −24.1 (High), −0.2 (Moderate), +43.3 (Low) and −19.0 (Very Low), showing that Low Risk Zones are strongly over-represented, High and Very Low Risk Zones are under-represented, and Moderate Risk Zones are close to expectation. **Decision: H_{01} is rejected.**

Hypothesis Two (H_{02})

H_{02}: The proportion of land occupied by High Risk Zones does not differ significantly from an equal (25%) share.

The High Risk share (12.8%; Wilson 95% CI 12.1–13.5%) was significantly below 25% ($z = -27.9$, $p < 0.001$). Pairwise chi-square tests against each other class also differed significantly: High vs Moderate $\chi^2(1) = 380.9$, High vs Low $\chi^2(1) = 1{,}905.0$, and High vs Very Low $\chi^2(1) = 23.1$ (all $p < 0.001$). **Decision: H_{02} is rejected.**

Table 8: Summary of Statistical Tests

Hypothesis	Test	Statistic	p-value	Decision
H_{01}	Chi-square goodness of fit (equal areas)	$\chi^2(3) = 2{,}821.4$; $w = 0.54$	< 0.001	Rejected
H_{02}	One-sample z-test, High Risk share vs 25%	$z = -27.9$	< 0.001	Rejected
H_{02}	Chi-square, High vs Moderate	$\chi^2(1) = 380.9$	< 0.001	Rejected
H_{02}	Chi-square, High vs Low	$\chi^2(1) = 1{,}905.0$	< 0.001	Rejected
H_{02}	Chi-square, High vs Very Low	$\chi^2(1) = 23.1$	< 0.001	Rejected

Source: Authors' computation from Table 4 areas (1 km² units), 2026.

Robustness to spatial autocorrelation. Cells in a classified map are not independent, so these p-values are optimistic. To check robustness, the H_{01} test was repeated assuming only 500 and 100 effectively independent units with the same class proportions; it remained significant ($\chi^2 = 144.5$ and 28.9 respectively, $df = 3$, $p < 0.001$). The conclusions for H_{01} and for the High-versus-Low and High-versus-Moderate contrasts are therefore robust. The High-versus-Very Low contrast is the narrowest difference and is the most sensitive to spatial dependence. A Moran's I analysis of the classified raster is recommended to confirm spatial clustering of the classes.

DISCUSSION OF RESULTS

The findings revealed that Low Risk Zones occupy 4,580 km² (46.9%) of the analysed area, making them the dominant environmental category in Bayelsa State. This indicates that nearly half of the state possesses relatively stable environmental conditions suitable for sustainable land-use planning and development activities. This finding is consistent with Okafor and Eze (2022), who reported that moderate-to-low vulnerability areas often dominate large portions of southern Nigerian landscapes.

Moderate Risk Zones cover 2,432 km² (24.9%), representing approximately one-quarter of the state. This suggests considerable environmental pressures requiring continuous monitoring and adaptive management, and is consistent with Akinyemi et al. (2023), who reported that moderate-risk zones frequently represent transitional areas vulnerable to future environmental degradation.

Regarding Objective Two, High Risk Zones occupy 1,248 km² (12.8%) of the analysed area, a share that is statistically significantly lower than an equal share (Section 4.5). Although spatially smaller than the other categories, these areas require urgent intervention because of their heightened vulnerability to environmental hazards. This agrees with Nwilo et al. (2020), who identified concentrated pockets of high environmental vulnerability within the Niger Delta, although their regional estimate of about 22% high susceptibility is higher than the 12.8% found here. Differences in scale, hazard focus, variables and class thresholds are plausible reasons for this.

For Objective Three, the Dominance Index was 0.47 for Low Risk Zones, compared with 0.25, 0.15 and 0.13 for Moderate, Very Low and High Risk Zones respectively; Low Risk Zones are therefore about 1.9 times their equal share. The finding contrasts with Adelekan (2021), who reported higher vulnerability in many coastal environments. Because the dominance of the Low class depends on the variables, weights and class thresholds chosen, it should be read as dominance within this model rather than as proof that most of a deltaic state is free from hazard. A sensitivity analysis of weights and thresholds (Section 3.9) is needed to establish how stable this result is.

Concerning Objective Four, the Planning Priority Matrix classified High Risk Zones as requiring immediate intervention. This highlights the importance of prioritising environmental monitoring, ecosystem restoration, and hazard mitigation within these locations, in line with Olatunji and Bello (2024), who concluded that GIS-derived risk maps improve planning effectiveness and disaster preparedness.

Overall, the statistical tests show that the distribution of risk zones differs significantly from an equal distribution (H_{01} rejected) and that High Risk Zones occupy a significantly smaller share than an equal share (H_{02} rejected). The planning implications in Table 7 are normative recommendations that follow from the zoning and are not tested statistically.

5.1 Limitations of the Study

1. **Data resolution and DEM age.** The datasets have moderate to coarse resolution (about 30 m for imagery and DEM, 250 m for soil and about 5.5 km for rainfall), the SRTM DEM dates from February 2000 and has vertical errors of several metres relative to the small relief of the delta, and these factors smooth local variation and may mis-classify small settlements, creeks and shoreline features.
2. **Subjectivity of weights and class breaks.** AHP weights come from a single set of judgements, and the 1–4 reclassification breaks are physically motivated but not unique; different choices could produce different weights and zone areas, and no weight-perturbation analysis was run.
3. **Classification uncertainty.** Class boundaries are partly arbitrary; small changes in thresholds can shift area between classes, and the dominance of the Low class is sensitive to this choice.
4. **Static snapshot.** The analysis represents conditions at the dates of the input data and does not capture seasonal or inter-annual variability, sea-level rise or future land-use change.
5. **Exposure and social vulnerability.** Population, infrastructure and socio-economic vulnerability were not included, so the index describes environmental risk rather than total disaster risk.

6. **Analysed extent.** The analysed area (9,760 km²) is 90.6% of the official area (10,773 km²); cells without valid data were excluded, so class percentages describe the analysed area only.

CONCLUSION

This study employed GIS-based spatial analysis to evaluate environmental risk zones in Bayelsa State, Nigeria. The findings revealed a heterogeneous spatial distribution of environmental risks characterised by four categories: High Risk, Moderate Risk, Low Risk, and Very Low Risk zones. Low Risk Zones constitute the largest proportion of the analysed area (46.9%), while High Risk Zones occupy 12.8%. Statistical tests confirmed that the distribution departs significantly from an equal distribution and that the High Risk share is significantly smaller than an equal share.

The results demonstrate the usefulness of GIS techniques in identifying vulnerable locations and providing spatially explicit information for environmental management. Environmental risk zoning is a valuable tool for sustainable land-use planning, disaster risk reduction, and environmental governance in Bayelsa State, provided that its results are interpreted in light of the limitations in Section 5.1. Future work should validate the map against independent field data, test the sensitivity of the results to weights and thresholds, apply spatial autocorrelation statistics, and add exposure and social vulnerability layers.

RECOMMENDATIONS

1. Prioritise environmental restoration projects within High Risk Zones to reduce vulnerability and strengthen ecosystem resilience.
2. Implement continuous GIS-based environmental monitoring across Moderate Risk Zones to detect emerging environmental threats and prevent risk escalation.
3. Promote sustainable land-use practices within Low Risk Zones to maintain environmental stability and prevent future degradation.
4. Integrate GIS-derived environmental risk maps into state development plans and environmental policies to support evidence-based decision-making and disaster risk reduction initiatives.
5. Validate the risk map with field surveys and independent hazard records, and update it periodically with new imagery and higher-resolution data.

Declarations

Ethics statement: This study used remotely sensed and secondary geospatial data and involved no human participants, personal data or animal subjects; formal ethical approval was therefore not required.

Data availability statement: The input datasets are publicly available from the sources listed in Table 2. The AHP pairwise matrix is given in Appendix A, and the classified risk map and class-area table are available from the corresponding author on reasonable request.

Author contributions: N.C.B.: conceptualisation, GIS analysis, drafting; V.N.N.: data curation, review and editing.

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APPENDIX A: AHP PAIRWISE COMPARISON MATRIX

Each cell gives the importance of the row variable relative to the column variable on Saaty's 1–9 scale (values below 1 are reciprocals). Resulting weights: Elevation 0.292, Flood frequency 0.203, Distance to rivers 0.183, Slope 0.103, Rainfall 0.103, Land cover 0.058, Soil 0.058; $\lambda max = 7.049$, CI = 0.008, CR = 0.006.

Table A1: Pairwise Comparison Matrix of Environmental Variables

	Elevation	**Slope**	**Rainfall**	**LULC**	**Soil**	**Dist. river**	**Flood freq.**
Elevation	1	3	3	5	5	2	1
Slope	1/3	1	1	2	2	1/2	1/2
Rainfall	1/3	1	1	2	2	1/2	1/2
LULC	1/5	1/2	1/2	1	1	1/3	1/3
Soil	1/5	1/2	1/2	1	1	1/3	1/3
Dist. river	1/2	2	2	3	3	1	1
Flood freq.	1	2	2	3	3	1	1

Source: Authors' AHP judgements, 2026.