

Spatial Assessment of Climate-Induced Disaster Risk in the Niger Delta Using GIS and Remote Sensing

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ABSTRACT

The Niger Delta combines extremely low relief, dense drainage, high rainfall and one of Africa's largest concentrations of people and petroleum infrastructure, yet spatially explicit, reproducible risk information for the whole delta remains scarce. This study develops a fully open-data geospatial assessment of climate-induced disaster risk for the nine Niger Delta states of Nigeria, integrating satellite topography, a remotely sensed drainage network, gridded population and 44 years of reanalysis rainfall in a GIS-based multi-criteria decision analysis (MCDA). Seven conditioning factors — elevation, slope, topographic wetness index (TWI), distance to drainage channel, drainage density, mean annual rainfall and distance to the coast — were derived on a common 15 arc-second grid (89,832 km² of land, 34.2 million people), reclassified on a five-point susceptibility scale, and combined by weighted linear combination using Analytic Hierarchy Process (AHP) weights (consistency ratio CR = 0.012). Hazard was integrated with a population-based exposure surface to produce a composite risk index; results were validated against a hydrologically connected inundation model and tested with one-factor-removed and Monte Carlo sensitivity analyses. High and very-high flood-hazard classes cover 31,820 km² (35.4% of the study area) and contain 13.0 million people (38.1%).

Hazard is strongly concentrated: 72.6% of Bayelsa and 71.1% of Rivers State land falls in these classes, against 11.0% in Edo, and 78.0% of the population of Rivers State living within the study window is exposed. Very-high composite risk (upper quintile) contains 13.79 million people, 40.3% of the delta population, and the highest-risk local government areas (Port-Harcourt, Ogu Bolo, Asari-Toru, Andoni, Obio/Akpor, Okrika) are urban, coastal and estuarine units in Rivers State. A 5 m connected water-level increment would inundate 1,668 km² and directly expose about 603,000 people, 73% of them in Rivers State alone. Rainfall records for 1981–2024 show no coherent intensification (Theil–Sen slopes from –183 to +145 mm decade⁻¹; significant change only for heavy-rain-day counts at Port Harcourt and Eket), confirming that delta flood risk is governed primarily by terrain, drainage and coastal setting rather than by local rainfall trends. The hazard model reproduces connected inundation with an area under the ROC curve of 0.936 and is highly robust to weight perturbation (mean Spearman ρ = 0.998). The resulting maps provide a transferable, reproducible screening layer for land-use control, drainage investment, early warning and disaster-risk reduction planning in the Niger Delta.

Keywords: Disaster Risk Reduction; Flood Hazard Mapping; GIS Multi-criteria decision analysis; analytic hierarchy process; Remote Sensing; Niger Delta; Climate Change Adaptation; Population exposure

Highlights

Open-data GIS and remote-sensing workflow maps climate-induced disaster risk across all nine Niger Delta states at 15 arc-second resolutions.

Seven AHP-weighted conditioning factors (CR = 0.012) yield a flood-hazard surface validated at AUC =

0.936 against connected inundation modelling.

35.4% of the delta land surface and 38.1% of its 34.2 million residents fall in high or very-high hazard classes.

Bayelsa (72.6%) and Rivers (71.1%) States dominate hazard area; 40.3% of the delta population lies in the highest composite-risk quintile. 1981–2024 rainfall trends are weak and inconsistent, so risk reduction must target terrain, drainage and coastal exposure rather than rainfall alone.

INTRODUCTION

Climate-induced disasters in low-lying tropical deltas are the product of interacting physical and human systems: terrain that offers almost no gradient for drainage, dense distributary networks that transmit both fluvial and tidal water, intense seasonal rainfall, subsiding and sediment-starved surfaces, and rapidly urbanizing populations concentrated on the most flood-prone land. The Niger Delta is the archetype of this configuration in Africa. It is Nigeria's oil and gas heartland, hosts more than 30 million people, and has experienced two catastrophic flood seasons within a decade — 2012 and 2022 — each displacing well over a million people nationally and inundating settlements, farmland, roads and industrial facilities across the delta states.

Disaster-risk reduction in this environment depends on knowing where risk is concentrated, at a resolution and coverage that supports planning decisions. Geographic information systems (GIS) and remote sensing have become the standard instruments for producing that information, because they allow physically meaningful conditioning factors to be derived consistently over large areas from satellite data, and combined with socio-economic layers into indices that can be mapped, audited and updated (Malczewski, 2006; Musa et al., 2015).

Among the available approaches, GIS-based multi-criteria decision analysis using the Analytic Hierarchy Process (AHP) has proved particularly durable for regional flood-hazard screening: it is transparent, it requires no inventory of past flood events, its weights can be tested for logical consistency, and it performs comparably to data-hungry statistical and machine-learning methods at the screening scale (Saaty, 1977; Kazakis et al., 2015; Tehrany et al., 2014; Darwish, 2023). Nigerian applications have advanced substantially over the past two decades, from early vulnerability zonation of the delta (Ologunorisa, 2004) to geospatial risk mapping along the Niger–Benue corridor (Nkeki et al., 2013), coastline change detection (Obowu & Abam, 2014), mangrove and land-cover dynamics (Nababa et al., 2020) and critical reviews of urban flood modelling capacity in developing countries (Nkwunonwo et al., 2020).

Three gaps nevertheless persist. First, most studies treat a single state, city or watershed, so results are not comparable across the delta and cannot support federal or regional prioritisation. Second, exposure is often described qualitatively or with state-level totals, rather than with gridded population data that resolve where people actually live relative to hazard. Third, published assessments rarely report the validation and sensitivity diagnostics — consistency ratios, receiver-operating-characteristic (ROC) statistics, weight-perturbation experiments — that determine whether a hazard map is decision-grade, and rarely release a reproducible workflow.

This paper addresses those gaps with a delta-wide, fully reproducible assessment built only from openly available datasets. The objectives are to (i) derive a consistent set of terrain, hydrological, climatic and coastal conditioning factors for the nine Niger Delta states from satellite topography and remotely sensed drainage data; (ii) integrate them into an AHP-weighted flood-hazard surface and test its internal consistency; (iii) combine hazard with gridded population to produce a composite disaster-risk index and quantify exposure at state and local-government-area (LGA) level; (iv) evaluate plausible coastal-fluvial inundation scenarios; (v) place the results in the context of observed 1981–2024 rainfall behaviour; and (vi) assess robustness through validation and sensitivity analysis. The intended contribution is both substantive — a delta-wide, population-weighted risk geography — and methodological: a documented, low-cost

workflow that state agencies can rerun as new data become available.

Study area

The study area comprises the nine states of Nigeria's Niger Delta region — Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo and Rivers — within a geographic window of 4.0–7.2°N and 4.8–8.6°E (Figure 1). Land within the window that falls inside these states covers 89,832 km² and, using WorldPop 2020 gridded counts, 34.2 million people. Physically the region is a wave- and tide-influenced arcuate delta built by the Niger–Benue system, with four broad eco-zones arranged roughly parallel to the coast: barrier-island beach ridges, saline mangrove swamp, freshwater swamp forest, and lowland rain forest on slightly higher terrain inland. Relief is minimal — median elevation within the study area is 35 m but the coastal belt lies within a few metres of sea level, and the median terrain slope is 0.42°, so surface-water gradients are extremely low.

The distributary network is exceptionally dense, and the tidal prism reaches tens of kilometres inland along the major creeks, allowing marine water levels to modulate drainage far from the shoreline. Mean annual rainfall interpolated from reanalysis records ranges from about 1,770 mm at the northern margin of the window to nearly 2,690 mm in the central and eastern coastal belt, delivered in a single long wet season peaking July–October. These conditions produce a compound flood regime. Fluvial flood waves generated by rainfall over the upstream Niger and Benue basins arrive in the delta with a lag of weeks and are occasionally amplified by reservoir releases (Abam, 2001); local convective rainfall generates rapid pluvial flooding in urbanised areas with limited drainage capacity; and high coastal water levels, storm surge and tidal blocking raise base levels in the distributaries, obstructing gravity drainage.

Human modification intensifies each pathway. Canalisation, dredging and road embankments have altered conveyance; wetland reclamation has reduced flood storage; mangrove clearance and *Nypa fruticans* invasion have degraded natural buffers (Nababa et al., 2020); and unplanned urban growth in Port Harcourt, Warri, Yenagoa, Aba, Uyo, Calabar and Eket has placed dense populations on floodplains and reclaimed swamp. The delta is also subsiding and sediment-starved, so relative sea-level rise exceeds the global mean rate, a mechanism documented for delta's worldwide (Syvitski et al., 2009; Tessler et al., 2015; Nicholls et al., 2021). Disaster consequences are therefore not limited to inundation. Floods interact with the region's petroleum infrastructure and its legacy of oil pollution, mobilizing hydrocarbons from spill sites and artisanal refining points across farmland, fishponds and drinking-water sources, and compounding the loss of livelihoods (Fentiman & Zabbey, 2015; Sam & Zabbey, 2018; Adekola & Mitchell, 2011). This makes spatially explicit risk information a prerequisite not only for emergency management but also for pollution control, land-use regulation and infrastructure design.

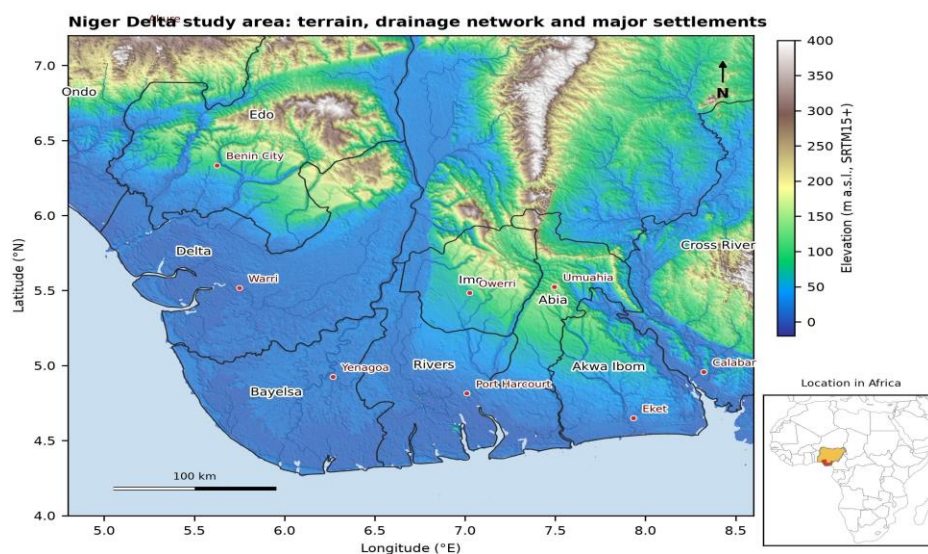


Figure 1 Study area: the nine Niger Delta states of Nigeria. (a) Shaded-relief topography from SRTM15+

with state boundaries, major cities and the drainage network; (b) inset showing the location of the delta within Africa.

DATA AND METHODS

Overall Design

The assessment follows the standard hazard–exposure–vulnerability formulation used in disaster-risk science, implemented as a five-stage geospatial workflow: (1) acquisition and harmonisation of open satellite and gridded datasets on a common grid; (2) derivation of seven flood-conditioning factors, including hydrological terrain analysis; (3) reclassification and AHP-weighted combination into a flood-hazard index and five susceptibility classes; (4) integration with gridded population to yield a composite disaster-risk index, followed by zonal statistics at state and LGA level and connected-inundation scenario analysis; and (5) validation and sensitivity analysis. All processing was scripted in Python and is documented in Appendix A.

Data Sources

All input datasets are openly licensed and globally consistent, which makes the workflow transferable to other deltas (Table 1). Analysis was performed on the native 15 arc-second grid of the elevation dataset (769 × 913 cells; nominal cell area 0.214 km² at the latitude of the delta).

Dataset	Variable used	Native resolution	Role in this study	Source
SRTM15+ v2	Elevation and bathymetry	15 arc-sec (~450 m)	Elevation, slope, sink-filled hydrological terrain analysis, coastline definition	Tozer et al. (2019)
Natural Earth Rivers (10 m) plus derived channel network	Surface drainage	Vector / derived raster	Drainage network, distance to channel, drainage density	Natural Earth (public domain); this study
WorldPop Global 2020, 1 km unconstrained	Population count	1 km	Exposure surface, population in hazard and risk classes	Tatem (2017)
NASA POWER (MERRA-2) daily precipitation, 1981–2024	Daily rainfall at 13 points	0.5° × 0.625°	Mean annual rainfall surface; trend analysis of rainfall indices	Gelaro et al. (2017)
geoBoundaries v6 (gbOpen)	Nigeria ADM1 and ADM2 polygons	Vector, 2022	Zonal statistics by state and local government area	Runfola et al. (2020)

Note. SRTM15+ was accessed through the NOAA ERDDAP griddap service; POWER data through the NASA POWER daily point API; boundaries through the geoBoundaries API.

Terrain and Hydrological Factor Derivation

Elevation was extracted for the study window and ocean cells (elevation ≤ -0.5 m, after morphological opening to remove isolated pixels) were masked. Slope was computed from the elevation gradient in metric units. The elevation surface was then sink-filled with a priority-flood algorithm, D8 flow directions and flow accumulation were computed on the filled surface, and the channel network was extracted with an accumulation threshold of 200 cells, merged with the ocean mask to represent tidal water bodies. From these products three hydrological factors were derived:

Topographic wetness index (TWI), $TWI = \ln(a / \tan\beta)$, where a is the upslope contributing area per unit contour length and β is the local slope, with slope floored at 0.02° to avoid singularities on flat deltaic terrain (Beven & Kirkby, 1979; Tarboton, 1997). TWI within the study area ranges from 5.44 to 13.95 (median 10.76).

Euclidean distance to the nearest channel or tidal water body, computed with a metric distance transform (median 52.4 km across the window, but under 2 km throughout the swamp belt).

Drainage density, the channel length per unit area within a moving 13×13 -cell window.

Two further factors capture the coastal and climatic setting: **distance to the coast**, computed as the metric distance to the nearest ocean cell, and **mean annual rainfall**, interpolated by inverse-distance weighting (power 2) from 13 NASA POWER points — four delta locations (Port Harcourt, Yenagoa, Warri, Eket/Qua Iboe) and the nine state representative points — using the 1981–2024 mean of annual totals.

Rainfall Trend Analysis

For the four delta locations, daily precipitation for 1981–2024 was aggregated into six annual indices: annual total, wet-season (July–October) total, maximum 1-day (Rx1day) and 5-day (Rx5day) totals, counts of days ≥ 20 mm and ≥ 50 mm, and R95pTOT (rainfall from days above the 1981–2010 95th percentile of wet days). Monotonic trends were tested with the two-sided Mann–Kendall test and quantified with the Theil–Sen slope estimator (Sen, 1968); significance was assessed at $\alpha = 0.05$.

Reclassification of Conditioning Factors

Each factor was reclassified onto a common five-point ordinal susceptibility scale (1 = very low, 5 = very high contribution to flood hazard), using physically interpretable thresholds for elevation, slope, distance to channel and distance to coast, and quintile breaks of the observed distribution for TWI, drainage density and rainfall (Table 2). Directionality was set so that a rating of 5 always denotes the most hazard-prone condition.

Factor	Rating 5 (very high)	4	3	2	Rating 1 (very low)	Rationale / break type
Elevation (m)	≤ 5	5–10	10–20	20–50	> 50	Physical thresholds;

Factor	Rating 5 (very high)	4	3	2	Rating 1 (very low)	Rationale / break type
						deltaic flood levels
Slope (°)	≤ 0.2	0.2–0.5	0.5–1.0	1.0–3.0	> 3.0	Ponding potential on near-flat terrain
TWI (dimensionless)	> 13.76	12.16–13.76	11.36–12.16	10.53–11.36	≤ 10.53	Quintiles of study-area distribution
Distance to channel (km)	≤ 0.5	0.5–1.5	1.5–3.0	3.0–6.0	> 6.0	Fluvial and tidal overbank proximity
Drainage density (km km ⁻²)	> 0.179	0.115–0.179	0.038–0.115	0–0.038	0	Quintiles of study-area distribution
Mean annual rainfall (mm)	$> 2,454$	2,215–2,454	2,082–2,215	1,986–2,082	$\leq 1,986$	Quintiles of study-area distribution
Distance to coast (km)	≤ 10	10–25	25–50	50–100	> 100	Surge, tidal blocking and salinity influence

AHP weighting

Relative factor importance was established with a Saaty pairwise comparison matrix (Table 3) constructed from the published Niger Delta flood literature and from the physical reasoning that, in an extremely low-relief delta, absolute elevation and micro-relief control inundation more strongly than rainfall amount (Saaty, 1977; Kazakis et al., 2015). Weights were computed as the normalised principal eigenvector of the matrix, and logical consistency was verified through the consistency index $CI = (\lambda_{\max} - n)/(n - 1)$ and the consistency ratio $CR = CI/RI$, with $RI = 1.32$ for $n = 7$.

Factor	Elev.	Slope	TWI	Dist. channel	Drainage dens.	Rainfall	Dist. coast
Elevation	1	2	2	3	4	3	5
Slope	1/2	1	1	2	3	2	4
TWI	1/2	1	1	2	3	2	4
Distance to channel	1/3	1/2	1/2	1	2	2	3
Drainage density	1/4	1/3	1/3	1/2	1	1	2
Rainfall	1/3	1/2	1/2	1/2	1	1	2
Distance to coast	1/5	1/4	1/4	1/3	1/2	1/2	1

The resulting weights (Table 4) satisfy the conventional acceptability criterion by a wide margin ($CR = 0.012 \ll 0.10$). The flood-hazard index was then computed by weighted linear combination, $H = \sum w_i r_i$, where r_i is the reclassified rating of factor i , giving a continuous index on the 1–5 scale, which was divided into five susceptibility classes at fixed breaks of 2.0, 2.6, 3.2 and 3.8.

Rank	Factor	AHP weight	Interpretation
1	Elevation	0.306	Dominant control on inundation depth and extent
2	Slope	0.187	Governs ponding and drainage velocity
3	Topographic wetness index	0.187	Integrates contributing area and gradient

Rank	Factor	AHP weight	Interpretation
4	Distance to channel	0.120	Fluvial and tidal overbank exposure
5	Mean annual rainfall	0.084	Regional pluvial forcing

6	Drainage density	0.071	Network concentration and conveyance
7	Distance to coast	0.045	Surge, tide and backwater influence

Note. $\lambda_{\max} = 7.096$, CI = 0.016, RI = 1.32, CR = 0.012.

Exposure and Composite Risk

WorldPop 2020 population counts were resampled by area-weighted averaging to the analysis grid, giving population density (persons km⁻²) and population per cell. Because population density is heavily right-skewed, the exposure rating E was derived from log₁₀(1 + density), linearly rescaled by its 99th percentile onto the same 1–5 scale. Hazard and exposure were normalised to [0, 1] and combined geometrically:

$$\text{RISK} = \sqrt{(H_n \cdot E_n)}$$

The geometric mean was preferred to an arithmetic average because disaster risk requires both hazard and exposure to be non-trivial: uninhabited swamp of very high hazard and dense urban land of negligible hazard should both score low. Risk was classified into quintiles of its own distribution, so that risk classes describe the relative geography of risk within the delta.

Inundation Scenarios

To complement the index-based hazard surface with an explicitly hydraulic (if simplified) view, connected "bathtub" inundation was computed for water-level increments of 1, 2, 3 and 5 m above present mean sea level. Cells below each level were retained only where they were hydrologically connected to the ocean or to the tidal channel network through eight-connectivity labelling, which removes the well-known overestimation of naive bathtub mapping in topographically isolated depressions. Inundated area and exposed population were then summarised by state

Validation and Sensitivity Analysis

Because no delta-wide, openly available inventory of historically flooded points exists at sufficient positional accuracy, the hazard index was validated against the independently computed 5 m connected inundation surface, which uses only sink-filled elevation and connectivity and is not an input to the weighted combination. A receiver-operating-characteristic (ROC) curve was constructed by thresholding the hazard index across its full range, and the area under the curve (AUC) was computed by trapezoidal integration (Fawcett, 2006).

Robustness was tested in two ways. First, a one-factor-removed analysis recomputed the hazard index with each factor in turn given zero weight (remaining weights renormalised), reporting the Spearman rank correlation with the baseline index, the change in mean index value and the percentage of cells retaining their original hazard class. Second, a Monte Carlo experiment drew 200 weight vectors by perturbing every AHP weight by up to $\pm 25\%$ and recorded the resulting rank correlation with the baseline surface.

RESULTS

Conditioning Factors and Criterion Weights

The reclassified conditioning factors (Figure 2) reproduce the expected physiographic organisation of the delta. Very high ratings for elevation, slope and TWI coincide in the mangrove and freshwater swamp belt from the western Delta State coast through Bayelsa to the Rivers State estuaries, and extend inland along the

Orashi, Nun, Forcados and Cross River corridors. Distance-to-channel ratings show that the swamp belt is almost everywhere within 1.5 km of a channel, whereas the inland margins of Edo, Imo and Abia lie several kilometres from any modelled watercourse. Drainage density peaks in the central delta where the distributary network fans out. Rainfall increases south-eastward, with the highest ratings over Rivers, Bayelsa and Akwa Ibom. Distance-to-coast ratings isolate the barrier-island and estuarine fringe within 10 km of open water. The AHP weights (Table 4, Figure 2h) place 68% of the total weight on the three terrain-derived factors (elevation, slope, TWI), 19% on the drainage factors, 8.4% on rainfall and 4.5% on coastal proximity, with an excellent consistency ratio of 0.012.

Reclassified conditioning factors and AHP criterion weights

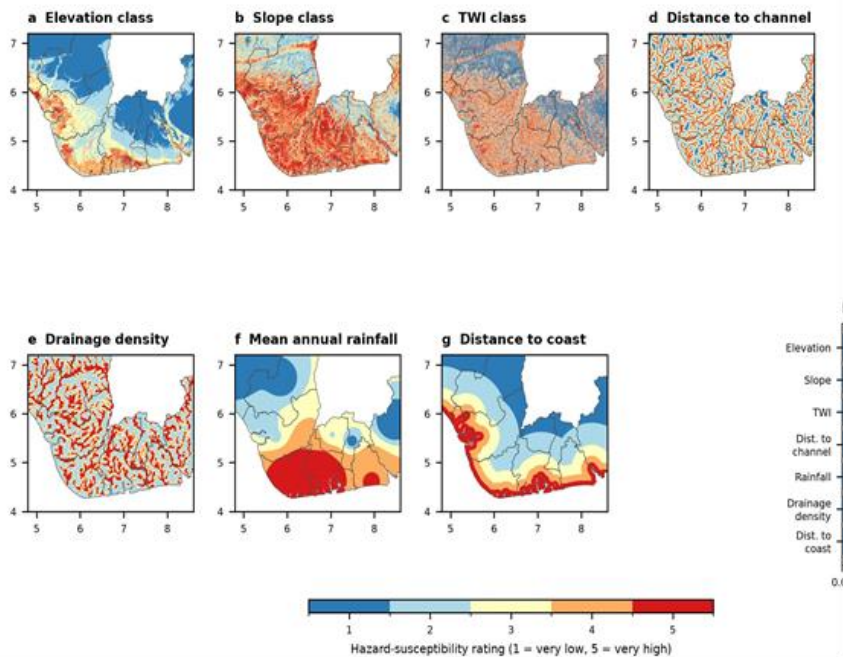


Figure 2 Reclassified flood-conditioning factors on the five-point susceptibility scale (a–g) and the AHP criterion weights with the consistency ratio (h).

Flood-Hazard Index and Susceptibility Classes

The weighted hazard index ranges from 1.07 to 5.00 across the study area, with a mean of 2.83 and a median of 2.87 (Figure 3a). Its spatial pattern is strongly zonal: values above 3.8 form an almost continuous coast-parallel band 30–80 km wide from the Benin River mouth in Ondo and Delta States, through the whole of Bayelsa, into the Rivers State estuaries and the Akwa Ibom and Cross River coastal margins, with inland extensions along the major distributaries. Values below 2.0 are restricted to the northern uplands of Edo, Imo, Abia and northern Cross River.

High and very-high hazard classes together cover 31,820 km², 35.4% of the delta land surface analysed, and contain 13.01 million people, 38.1% of the resident population (Table 5, Figure 3b). The very-high class alone — 13.3% of the area — holds 5.25 million people, indicating that the most hazard-prone terrain in the delta is not empty swamp but is settled at above-average density.

Hazard class	Index range	Area (km ²)	Area (%)	Population (millions)	Population (%)
Very low	1.00–2.00	19,003	21.2	5.94	17.4

Low	2.00–2.60	16,297	18.1	6.21	18.2
Moderate	2.60–3.20	22,713	25.3	9.03	26.4
High	3.20–3.80	19,833	22.1	7.76	22.7
Very high	3.80–5.00	11,987	13.3	5.25	15.4
High + very high	**> 3.20**	**31,820**	**35.4**	**13.01**	**38.1**

Note. Population from WorldPop 2020 gridded counts. Totals refer to the 89,832 km² of land and 34.2 million people inside the study window

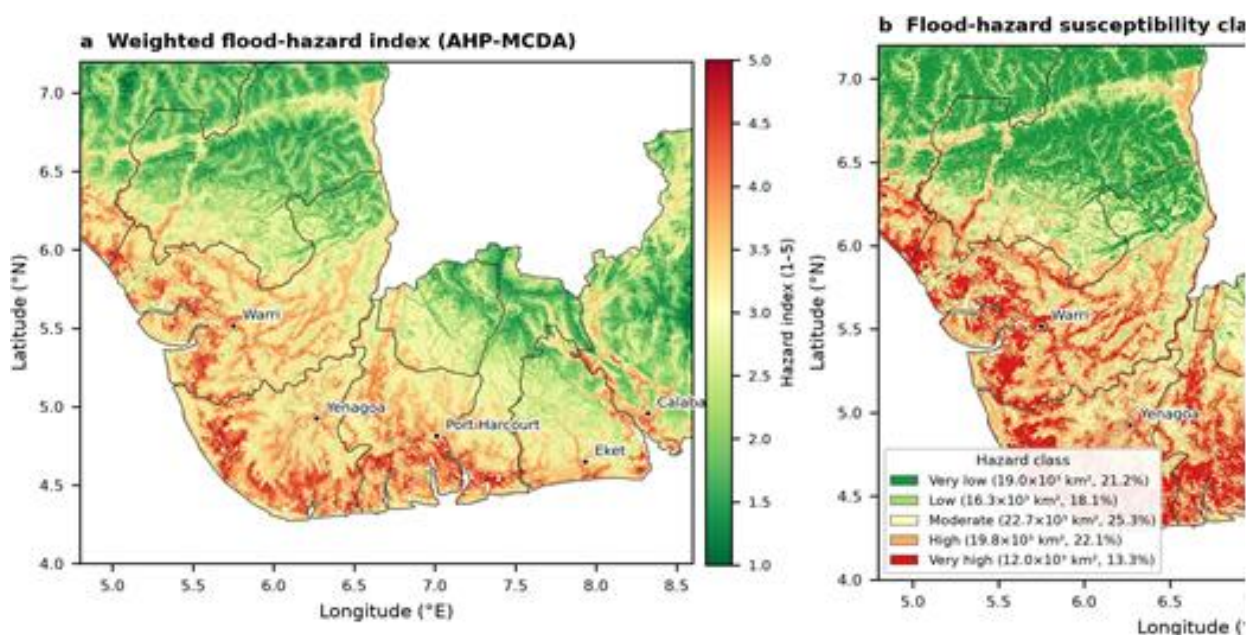


Figure 3 AHP-weighted flood-hazard assessment: (a) continuous hazard index; (b) five susceptibility classes with class areas and area shares.

Hazard and Risk by State

Zonal statistics reveal a pronounced concentration of hazard in three states (Table 6). Bayelsa has the highest mean hazard index (3.59) and the largest share of its land in high or very-high classes (72.6%), closely followed by Rivers (3.54; 71.1%) and Delta (3.21; 53.6%). At the other extreme, Edo (2.29; 11.0%), Ondo (2.30; 16.0% — restricted to its small delta fringe within the window) and Abia (2.34; 11.4%) have limited exposure.

When population is taken into account the ranking shifts in an important way. Rivers State combines high hazard with the largest population in the window: 5.21 million people, 78.0% of its residents, live in high or very-high hazard terrain, and it has both the highest mean risk index (0.684) and the largest share of area in the top two risk classes (84.5%). Akwa Ibom illustrates the divergence between hazard and risk most clearly: only 35.4% of its area is high-hazard and 30.8% of its population is hazard-exposed, yet its mean risk index (0.616) approaches that of Bayelsa (0.622) because population density is much higher. Imo shows the same effect in weaker form (13.8% of area high-hazard but 36.2% of area in the top two risk classes).

State	Land area in window (km ²)	Mean hazard index	Area in high/very-high hazard (%)	Population 2020	Population in high/very-high hazard	Population exposed (%)	Mean risk index	Area in high/very-high risk (%)
Bayelsa	9,396	3.59	72.6	2,073,278	1,448,993	69.9	0.622	68.3
Rivers	10,104	3.54	71.1	6,686,123	5,212,753	78.0	0.684	84.5
Delta	16,977	3.21	53.6	5,102,010	2,994,565	58.7	0.580	51.4
Akwa Ibom	6,868	2.97	35.4	5,037,667	1,552,358	30.8	0.616	65.6
Imo	5,134	2.55	13.8	4,905,29	282,419	5.8	0.535	36.2

State	Land area in window (km ²)	Mean hazard index	Area in high/very-high hazard (%)	Population 2020	Population in high/very-high hazard	Population exposed (%)	Mean risk index	Area in high/very-high risk (%)
				9				
Cross River	10,924	2.43	16.6	1,937,945	489,848	25.3	0.428	17.3
Abia	4,826	2.34	11.4	3,428,385	499,035	14.6	0.487	27.7
Ondo	7,913	2.30	16.0	1,532,008	248,583	16.2	0.414	14.7
Edo	17,692	2.29	11.0	3,499,303	283,553	8.1	0.406	8.4

Note. Values refer only to the portion of each state inside the 4.0–7.2°N, 4.8–8.6°E analysis window; states extending north of the window (notably Edo, Ondo, Cross River) are therefore partially represented.

Composite Disaster Risk and Local Hotspots

The composite risk surface (Figure 4b) is markedly more clustered than the hazard surface, because it superimposes the urban population pattern on the physiographic hazard band. Although risk classes are quintiles of area by construction, they are highly unequal in population: the very-high risk quintile contains 13.79 million people (40.3% of the delta population) against 3.40 million (9.9%) in the very-low quintile (Figure 4e). Risk therefore concentrates approximately four times more people per unit area at the top of the distribution than at the bottom.

Of the 176 local government areas analysed, the twenty highest-ranking by mean composite risk are dominated by Rivers State (Table 7): Port-Harcourt (mean risk 0.849, with 92.3% of its area in high or very-high hazard and 394,507 of its 436,665 residents hazard-exposed), Ogu Bolo (0.801), Asari-Toru (0.797), Andoni (0.786), Obio/Akpor (0.775) and Okrika (0.769). Delta State contributes Uvwie (0.763) and Udu (0.736), the industrial and urban core of the Warri conurbation; Akwa Ibom contributes Eastern Obolo (0.731) and Eket (0.727); Cross River contributes Calabar South (0.750); and Abia contributes Aba South (0.729), a dense inland city where high population weight rather than extreme terrain hazard drives risk.

Rank	LGA	State	Area (km ²)	Mean hazard index	Area in high hazard (%)	Population	Population in high hazard	Mean risk index
1	Port-Harcourt	Rivers	72	3.91	92.3	436,665	394,507	0.849
2	Ogu Bolo	Rivers	171	4.05	95.9	216,433	206,956	0.801
3	Asari-Toru	Rivers	218	4.03	90.9	321,073	286,041	0.797
4	Andoni	Rivers	327	3.98	89.5	321,156	288,640	0.786
5	Obio/Akpor	Rivers	265	3.64	88.3	513,422	448,351	0.775
6	Okrika	Rivers	586	4.01	92.2	517,537	487,611	0.769
7	Uvwie	Delta	84	3.55	68.9	183,982	159,762	0.763
8	Gokana	Rivers	133	3.55	75.5	327,116	212,982	0.761
9	Opobo/Nkoro	Rivers	101	3.74	75.7	104,064	78,267	0.758
10	Calabar South	Cross River	143	3.70	78.7	194,326	127,265	0.750
11	Eleme	Rivers	138	3.40	67.0	268,029	197,137	0.737
12	Udu	Delta	153	3.50	72.5	197,643	150,688	0.736
13	Eastern Obolo	Akwa Ibom	158	3.71	88.4	96,953	86,309	0.731

Rank	LGA	State	Area (km ²)	Mean hazard index	Area in high hazard (%)	Population	Population in high hazard	Mean risk index
14	Aba South	Abia	38	3.15	51.1	408,322	191,027	0.729
15	Eket	Akwa Ibom	189	3.53	73.8	221,603	139,241	0.727

Note. "Area in high hazard" is the percentage of LGA cells in hazard class 4 or 5. LGAs with fewer than 15 analysis cells inside the window were excluded.

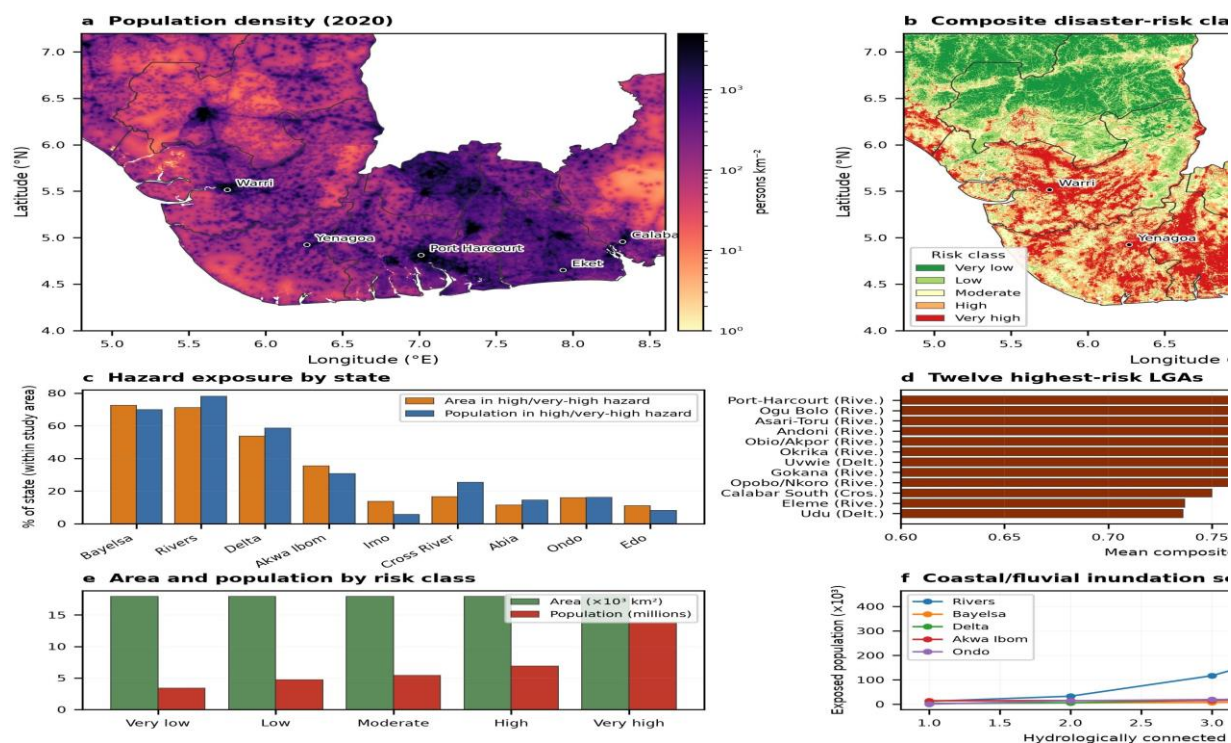


Figure 4 Composite disaster risk: (a) gridded population density; (b) risk classes; (c) hazard exposure of area and population by state; (d) twelve highest-risk LGAs; (e) area and population per risk class; (f) population exposed under connected inundation scenarios

Connected Inundation Scenarios

Water-level increments applied to the sink-filled, connectivity-constrained elevation surface produce a strongly non-linear escalation of exposure (Table 8, Figure 5d). A 1 m increment inundates 131 km² and directly affects about 38,400 people; 2 m raises this to 324 km² and 81,800 people; 3 m to 579 km² and 185,700 people; and 5 m to 1,668 km² and 602,900 people. Between the 3 m and 5 m cases the exposed population more than triples, because the additional area drawn in includes the densely settled estuarine fringe of Port Harcourt, Bonny, Okrika and Andoni.

Exposure is heavily concentrated. At the 5 m level, Rivers State accounts for 723 km² and 442,600 exposed residents (73.4% of the total), Delta State for 545 km² and 68,200 residents, and Ondo, Bayelsa, Akwa Ibom and Cross River for the remainder; Abia and Imo have no connected exposure at any level, and Edo effectively none. In relative terms, 7.15% of the Rivers State land area in the window is exposed at 5 m, against 3.21% in Delta and 2.08% in Ondo.

State	1 m: area (km ²) / population	2 m: area / population	3 m: area / population	5 m: area / population	5 m as % of state area
Rivers	47.5 / 11,807	103.2 / 32,724	232.5 / 116,465	722.9 / 442,609	7.15
Delta	29.1 / 3,018	53.3 / 5,849	132.3 / 16,626	544.5 / 68,195	3.21
Ondo	5.4 / 488	95.5 / 14,128	125.7 / 19,116	164.9 / 26,174	2.08
Bayelsa	25.3 / 3,608	38.8 / 5,499	50.3 / 7,145	163.4 / 17,436	1.74
Akwa Ibom	14.6 / 14,173	16.5 / 14,824	17.8 / 15,205	42.4 / 32,891	0.62
Cross River	7.9 / 5,322	15.0 / 8,773	19.1 / 11,087	28.0 / 15,523	0.26
Edo	1.1 / 16	1.3 / 18	1.7 / 25	1.7 / 25	0.01
Abia, Imo	0 / 0	0 / 0	0 / 0	0 / 0	0.00
Total	**130.8 / 38,435**	**323.5 / 81,818**	**579.4 / 185,673**	**1,667.7 / 602,856**	**1.86**

Note. Scenarios are hydrologically connected static water-level increments above present mean sea level, representing the combined effect of relative sea-level rise, storm surge and fluvial backwater; they are screening constructs, not hydrodynamic simulations, and exclude wave setup, subsidence and defence failure

Observed rainfall behaviour, 1981–2024

Rainfall records provide important context for interpreting the hazard map (Table 9, Figure 6). Mean annual totals over 1981–2024 range from 2,053 mm at Warri to 2,689 mm at Yenagoa, with July–October contributing 51–55% of the annual total. Trends, however, are weak and spatially inconsistent.

Annual totals decline at Port Harcourt (−161 mm decade^{−1}), Yenagoa (−183 mm decade^{−1}) and Warri (−38 mm decade^{−1}) and increase at Eket (+145 mm decade^{−1}), but none of these trends is significant at $\alpha = 0.05$ ($p = 0.055$ – 0.571). Only two of the 24 index–site combinations tested are significant: the count of days ≥ 20 mm at Port Harcourt declines (−4.3 days decade^{−1}; $\tau = -0.220$, $p = 0.037$) and the count of days ≥ 50 mm at Eket increases (+0.7 days decade^{−1}; $\tau = 0.225$, $p = 0.041$). Extreme-intensity indices (Rx1day, Rx5day) show no significant change anywhere.

Index		Port Harcourt	Yenagoa	Warri	Eket / Qua Iboe
Annual mean (mm)	total,	2,624	2,689	2,053	2,497
Annual total, Sen slope decade ^{−1}	(mm	−161.4 ($p = 0.110$)	−182.6 ($p = 0.115$)	−37.7 ($p = 0.571$)	+144.7 ($p = 0.055$)
Jul–Oct total, Sen slope decade ^{−1}	(mm	−114.4 ($p = 0.110$)	−127.4 ($p = 0.075$)	−29.3 ($p = 0.531$)	+63.8 ($p = 0.134$)
Rx1day,	mea	85.9	91.8	71.9	90.7

(mm)	n				
Rx5day, Sen slope (mm decade ⁻¹)		-12.5 (p = 0.241)	-7.4 (p = 0.544)	-5.8 (p = 0.430)	+6.7 (p = 0.418)
Days ≥ 20 mm, Sen slope (days decade ⁻¹)	** -4.26 (p = 0.037) **	(p =)	-4.00 (p = 0.064)	-1.41 (p = 0.390)	+1.97 (p = 0.112)
Days ≥ 50 mm, Sen slope (days decade ⁻¹)	0.00 (p = 0.500)		-0.62 (p = 0.207)	0.00 (p = 0.290)	** +0.71 (p =)

Index	Port Harcourt	Yenagoa	Warri	Eket / Qua Iboe
decade ⁻¹)				0.041) **
R95pTOT, Sen slope (mm decade ⁻¹)	-61.1 (p = 0.279)	-76.7 (p = 0.185)	-21.5 (p = 0.642)	+84.8 (p = 0.069)

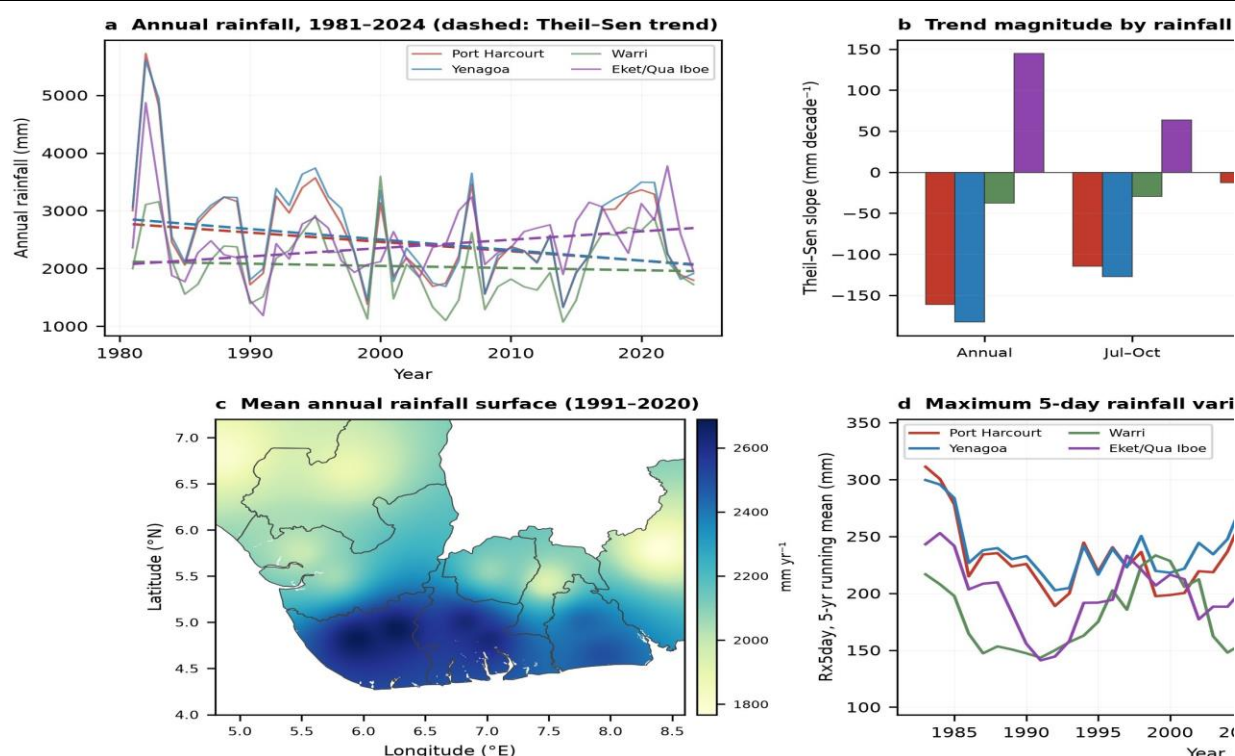


Figure 5 Rainfall context, 1981–2024: (a) annual totals with Theil–Sen trends at four delta stations; (b) trend magnitude by index and station; (c) interpolated mean annual rainfall surface; (d) five-year running mean of Rx5day.

Validation and Sensitivity

The hazard index discriminates connected inundation well, with an AUC of 0.936 against the 5 m connected-inundation surface (Figure 5a) — comparable to values normally regarded as "excellent" in flood-susceptibility validation and obtained despite the fact that the inundation surface uses connectivity information not available to the weighted combination. Sensitivity analysis (Table 10, Figure 5b) shows the model to be stable. Removing any single factor leaves the spatial ranking essentially intact (Spearman ρ = 0.937–0.998). Elevation is the most influential factor by a clear margin: its removal lowers ρ to 0.937, shifts

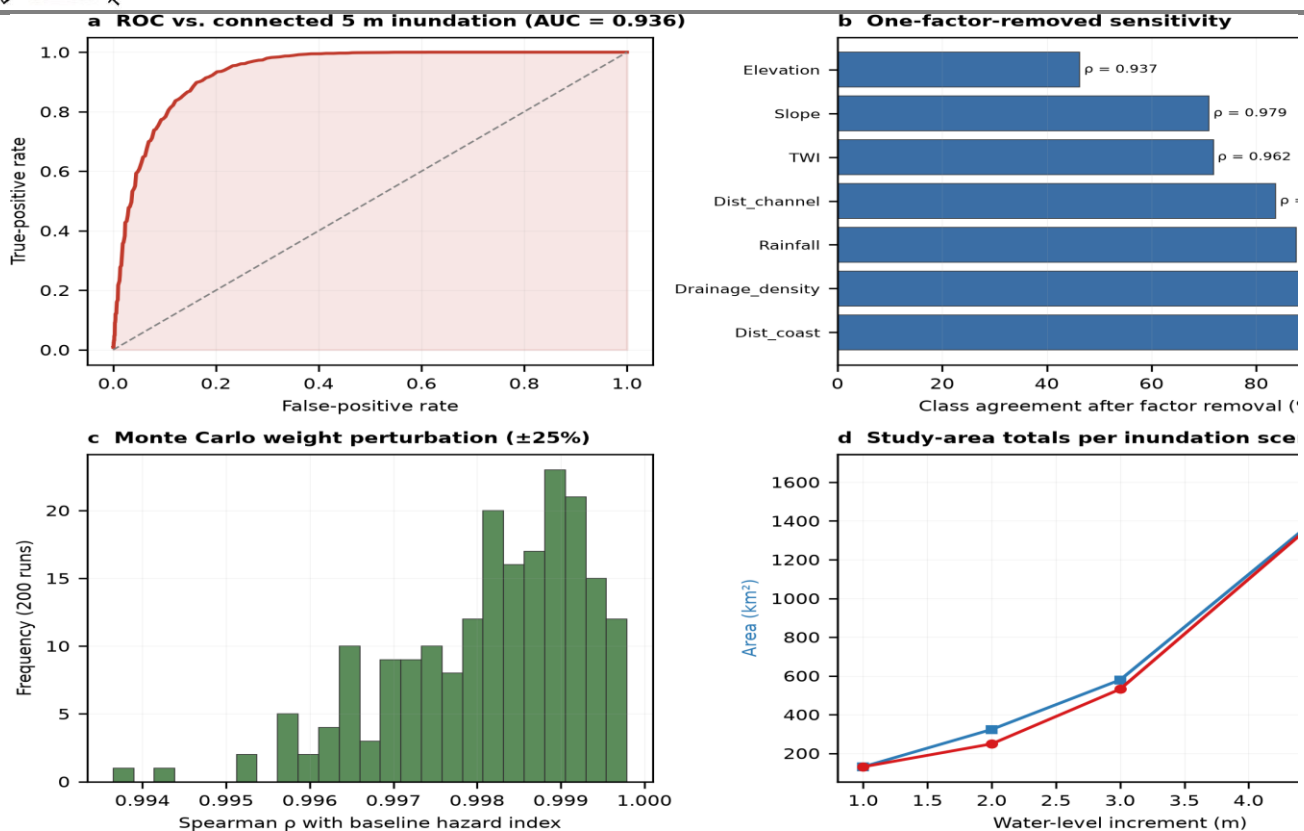
the mean index by +0.339 and changes the assigned class of 53.7% of cells.

Slope and TWI removal each retain 71% class agreement, while removing the three lowest-weighted factors (rainfall, drainage density, distance to coast) changes fewer than 13% of class assignments. The Monte Carlo experiment, in which all seven weights were perturbed randomly by up to $\pm 25\%$, produced rank correlations with the baseline of 0.994–0.999 (mean 0.998; Figure 5c), confirming that conclusions do not hinge on the precise pairwise judgements.

Factor removed	Weight	Spearman ρ with baseline	Change in mean index	Cells retaining class (%)
Elevation	0.306	0.937	+0.339	46.3
Slope	0.187	0.979	−0.171	71.0
TWI	0.187	0.962	−0.043	71.8
Distance to channel	0.120	0.987	−0.032	83.7
Mean annual rainfall	0.084	0.992	−0.016	87.6
Drainage density	0.071	0.995	−0.035	89.1
Distance to coast	0.045	0.998	+0.014	94.6

Note. Weights renormalised after each removal. Monte Carlo perturbation of all weights by $\pm 25\%$ (200 realisations): $\rho = 0.994\text{--}0.999$, mean 0.998.

Figure 6 Validation and robustness: (a) ROC curve of the hazard index against connected 5 m inundation; (b) one-factor-removed sensitivity; (c) Monte Carlo weight-perturbation results; (d) study-area totals per inundn scerio.



DISCUSSION

The geography of Climate-Induced Disaster Risk in the Delta

The results define a coherent risk geography that is more specific than the conventional description of the Niger Delta as uniformly flood-prone. Hazard is organised as a coast-parallel band, widest in Bayelsa and the western Rivers estuaries, with inland fingers following the Nun, Forcados, Orashi and Cross River corridors; it is controlled first by absolute elevation and micro-relief, then by drainage configuration, and only marginally by rainfall gradient. This is consistent with earlier zonation of the delta (Ologunorisa, 2004) and with basin-scale mapping along the Niger–Benue corridor (Nkeki et al., 2013), but it quantifies the pattern consistently across all nine states for the first time in an openly reproducible form, and it resolves it at a grain (0.214 km² cells) usable for LGA-level planning. The more consequential finding is the divergence between hazard and risk.

Because the composite index requires both hazard and population to be non-trivial, it identifies the specific places where climate-induced hazard meets dense settlement: the Port Harcourt–Obio/Akpor–Okrika–Eleme conurbation, the Kalabari and Andoni estuarine belt, the Warri–Uvwie–Udu industrial axis, Calabar South, and the Eket–Eastern Obolo coastal strip.

Bayelsa has the highest physical hazard of any state but, with 2.07 million people over 9,396 km², a lower composite risk than Rivers State, whose 6.69 million residents occupy comparably hazardous terrain. Conversely, Akwa Ibom and Imo carry appreciable risk despite moderate hazard because their populations are concentrated. Risk-reduction budgets allocated on hazard area alone would therefore misallocate resources relative to lives and assets at stake; allocation on population alone would ignore the physical determinants that make protection expensive in the swamp belt.

Why Local Rainfall Trends Do Not Drive the Hazard Pattern

The rainfall analysis produced an important null result: over 44 years, annual totals, wet-season totals and extreme-intensity indices show no coherent, significant intensification anywhere in the delta, and the two

significant signals point in opposite directions at sites only 150 km apart. Two implications follow. First, the flood problem in the delta is not primarily a local-rainfall problem.

Delta flood stage integrates upstream discharge generated over a catchment of continental extent, reservoir operation, tidal and surge water levels, subsidence, and progressive loss of conveyance and storage — drivers that operate largely independently of rainfall measured within the delta itself. This is why the catastrophic 2012 and 2022 seasons occurred within a period of statistically flat local rainfall, and why compound-flood framing is essential for deltas (Syvitski et al., 2009; Tessler et al., 2015; Nicholls et al., 2021; Wahl et al., 2015; Edmonds et al., 2020), with extreme coastal water levels now mapped globally as a first-order driver of overtopping (Almar et al., 2021).

Second, this null result validates the weighting structure adopted here. Assigning only 8.4% of the criterion weight to rainfall, and 68% to terrain and wetness, is not an arbitrary preference; it reflects the observed fact that spatial variation in flood susceptibility across the delta is governed by elevation and drainage, while rainfall varies comparatively little (1,770–2,690 mm) and shows no trend that would reorder the spatial pattern.

It also implies that projected rainfall change, however uncertain, is unlikely to shift the location of the highest-hazard zones, though it may change their frequency of inundation — an important distinction for adaptation planning, since it means the maps presented here have a longer useful life than rainfall-driven hazard maps would.

Methodological Implications

Three methodological points merit emphasis. First, the AHP-MCDA approach performed strongly on internal diagnostics: CR = 0.012 and an AUC of 0.936 against an independently derived connected-inundation surface, with the spatial ranking essentially invariant to $\pm 25\%$ perturbation of all weights ($\rho \geq 0.994$). This corroborates findings from other regions that index-based MCDA is adequate for regional screening when no flood inventory exists (Kazakis et al., 2015; Darwish, 2023; Samanta et al., 2018), and it means that debate over the exact pairwise judgements is less consequential than the choice of which factors to include.

Second, the dominance of elevation in the sensitivity analysis (removal changes the class of 53.7% of cells) shows that the quality of the digital elevation model, not the weighting scheme, is the binding constraint on accuracy. At 15 arc-second resolution with metre-scale vertical error and vegetation-contaminated returns over mangrove, the elevation surface is adequate for regional zonation but not for site design — a limitation shared by most published DEM-based flood mapping in tropical deltas (Musa et al., 2015).

Third, using connectivity-constrained inundation both as a scenario tool and as a validation target is a pragmatic response to the absence of an open, positionally accurate flood inventory for the delta. It is an internal-consistency test rather than an external validation, and future work should replace it with satellite-observed flood extents, for example from the Global Flood Database or Sentinel-1 SAR compositing for the 2012, 2018 and 2022 events (Tellman et al., 2021; Gebremichael et al., 2020), and complement the terrain factors with optical water indices such as NDWI for seasonal surface-water mapping (Gao, 1996). Coupling the hazard surface with a coastal-vulnerability component of the kind used elsewhere in tropical deltaic and island settings (Hastuti et al., 2022) would extend the framework to shoreline erosion and salinisation.

Implications for Disaster-Risk Reduction and Adaptation

The maps translate into a differentiated intervention agenda rather than a single delta-wide programme (Table 11). In the very-high hazard, high-population units — Port-Harcourt, Obio/Akpor, Okrika, Ogu Bolo, Asari-Toru, Andoni, Uvwie, Udu, Calabar South — the binding constraints are urban drainage capacity, unregulated construction on reclaimed swamp, and evacuation logistics in creek-side communities; these

demand drainage rehabilitation, enforcement of flood-plain zoning, elevation standards for new construction, and community early-warning systems tied to upstream gauges and dam-release notifications.

In high-hazard, low-population units across Bayelsa and the western Delta swamp, the priorities are protecting natural conveyance and buffers — mangrove restoration, control of canalisation and dredging, and wetland conservation — rather than hard defences that would be economically unjustifiable and ecologically damaging. In moderate-hazard, high-population inland cities such as Aba South, Owerri and Uyo, pluvial flooding from rainfall on impervious surfaces dominates, so storm-water design standards and solid-waste management in drains matter more than coastal or fluvial defence.

Across all categories, four cross-cutting measures follow directly from the results: (i) incorporate the hazard and risk layers into state physical development plans and building-permit review, so that new construction in classes 4–5 requires elevated floor levels and verified drainage; (ii) prioritise the 22 LGAs whose mean risk index exceeds 0.70 (11 in Rivers, 5 in Akwa Ibom, 3 in Delta, and one each in Cross River and Abia) for investment sequencing; (iii) integrate the population-weighted exposure figures into contingency planning, since 13.0 million residents in high-hazard terrain implies shelter, health and logistics requirements an order of magnitude above current provision; and (iv) institutionalise annual updating of the layers, reporting progress against the Sendai Framework's targets on critical-infrastructure resilience and disaster-risk information (UNDRR, 2015), as new WorldPop, elevation and satellite flood products are released, which the open workflow makes inexpensive.

Risk–hazard category	Representative LGAs / areas	Dominant flood pathway	Priority interventions
Very high hazard, very high population	Port-Harcourt, Obio/Akpor, Okrika, Uvwie, Calabar South	Pluvial + tidal backwater	Drainage rehabilitation and pumping, flood-plain zoning enforcement, elevated construction standards, urban early warning
Very high hazard, dispersed creek-side population	Ogu Bolo, Asari-Toru, Andoni, Opobo/Nkoro, Eastern Obolo	Tidal, surge, fluvial overbank	Community early warning and evacuation routes, elevated public buildings, jetty and shelter provision, mangrove buffer restoration
High hazard, low population (swamp belt)	Southern Bayelsa, western Delta swamp	Fluvial and tidal inundation	Wetland and mangrove conservation, control of canalisation/dredging, no-build designation, ecosystem-based flood storage
Moderate hazard, high population (inland cities)	Aba South, Owerri, Uyo, Warri north	Pluvial (drainage capacity)	Storm-water design standards, drain maintenance and waste management, permeable surfaces, retention basins
Low hazard	Northern Edo, Imo, Abia uplands	Localized pluvial	Routine drainage maintenance; preferred sites for relocation and new development

LIMITATIONS

Six limitations bound the interpretation of these results. **Elevation accuracy.** SRTM15+ has a nominal 450 m cell and metre-scale vertical uncertainty, and its surface includes vegetation returns over mangrove and swamp forest, which biases elevations upward in precisely the most hazardous terrain; the resulting hazard classes are regional screening products, and site-level decisions require LiDAR or high-accuracy GNSS

survey referenced to a defined vertical datum.

Rainfall representation. POWER precipitation derives from the MERRA-2 reanalysis (Gelaro et al., 2017), which is known to misrepresent convective extremes over tropical West Africa; the trend results should be corroborated with Nigerian Meteorological Agency gauge records and satellite–gauge products such as CHIRPS before use in design.

No hydrodynamic simulation. Neither the hazard index nor the connected-inundation scenarios simulate depth, velocity, duration or timing. Static connected inundation ignores hydraulic gradients, wave setup, defence failure, subsidence and the temporal coincidence of drivers, and therefore cannot substitute for calibrated 1D/2D modelling of the distributary network.

Absence of an independent flood inventory. Validation used an internally derived inundation surface rather than observed flood extents; AUC = 0.936 should therefore be read as internal consistency, not as verified predictive skill against historical events.

Exposure and vulnerability are incompletely represented. Exposure is proxied by residential population density alone. Critical infrastructure, petroleum facilities, roads, health and education facilities, agricultural assets and economic activity are not included, and social vulnerability — poverty, age structure, disability, tenure security, coping capacity — is omitted for lack of consistent open sub-state data. The composite index is therefore a hazard–population risk screen, not a full risk assessment.

Index and weighting subjectivity. AHP weights encode expert judgement; although the sensitivity analysis shows the spatial pattern is robust to $\pm 25\%$ perturbation, a fundamentally different factor set (for example including land cover, imperviousness, soil hydraulic properties or river gauge statistics) could yield a different result. Class breaks likewise involve choices, and risk quintiles describe relative rather than absolute risk within the delta.

CONCLUSIONS

This study produced the first openly reproducible, delta-wide spatial assessment of climate-induced disaster risk for the nine Niger Delta states, combining satellite topography, a remotely sensed drainage network, gridded population and 44 years of reanalysis rainfall in a GIS-based AHP multi-criteria framework. Four conclusions stand out.

First, hazard is extensive and highly organized: 35.4% of the 89,832 km² analysed falls in high or very-high flood-hazard classes, forming a coast-parallel band that covers 72.6% of Bayelsa and 71.1% of Rivers State but only 11.0% of Edo. Second, exposure is greater than area statistics suggest, because the most hazardous terrain is settled: 13.0 million people (38.1% of the delta population within the study window) live in high or very-high hazard classes, and 78.0% of Rivers State residents are so exposed.

Third, composite risk concentrates sharply — 40.3% of the population lies in the highest risk quintile, and the 20 highest-risk LGAs are dominated by urban and estuarine units of Rivers State, led by Port-Harcourt, Ogu Bolo, Asari-Toru, Andoni, Obio/Akpor and Okrika — so that risk reduction can be geographically targeted with precision.

Fourth, observed 1981–2024 rainfall shows no coherent intensification, which means the delta's escalating flood losses are driven by terrain, drainage, coastal water levels, subsidence, land-use change and population growth rather than by local rainfall trends; adaptation must therefore target the physical and institutional configuration of the delta, not rainfall alone.

Methodologically, the workflow achieved excellent internal diagnostics (CR = 0.012; AUC = 0.936; $\rho \geq 0.994$ under $\pm 25\%$ weight perturbation) using only free global datasets and open-source software, making it directly repeatable by Nigerian state agencies and transferable to other tropical deltas.

Priorities for subsequent work are calibrated hydrodynamic modelling of the distributary network, validation against satellite-observed flood extents for 2012, 2018 and 2022, incorporation of critical-infrastructure and social-vulnerability layers, and acquisition of bare-earth LiDAR elevation for the urbanised and industrial belt. With those extensions, the framework presented here can evolve from a screening layer into an operational risk-management system for one of Africa's most exposed populated deltas.

Declarations

Funding. This research received no external funding.

Conflicts of interest. The author declares no competing interests.

Data availability. All input datasets are openly available: SRTM15+ v2 topography (NOAA ERDDAP griddap), WorldPop Global 2020 1 km population counts (<https://www.worldpop.org>), NASA POWER daily meteorology (<https://power.larc.nasa.gov>), geoBoundaries administrative boundaries (<https://www.geoboundaries.org>) and Natural Earth 10 m rivers (<https://www.naturalearthdata.com>). Derived raster layers, zonal statistics tables and the processing scripts described in Appendix A are available from the author on request

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