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Research article

BEYOND FLOOD SUSCEPTIBILITY MAPPING: INTEGRATING GIS, REMOTE SENSING AND MACHINE LEARNING FOR FLOOD-RISK ASSESSMENT IN NIGERIA

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ABSTRACT
Flooding is a persistent environmental hazard in Nigeria, affecting settlements, infrastructure, agriculture, and livelihoods. Geographic Information Systems (GIS), remote sensing, and Machine Learning (ML) have improved the identification of flood-prone locations and the prediction of spatial flood patterns, yet a recurrent conceptual problem remains: a flood-susceptibility map is not, by itself, a flood-risk assessment. This paper presents a structured critical review of Nigerian flood studies published principally between 2016 and 2026, evaluating conceptual framing, data sources, modelling methods, and treatment of hazard, exposure, vulnerability, and uncertainty. The review finds that the literature has evolved from GIS-based multi-criteria mapping through statistical and ML modelling to event-scale satellite mapping and emerging integrated GeoAI approaches, with technical capability advancing faster than risk integration: many studies still estimate relative spatial propensity while omitting inundation depth, exposed assets, social vulnerability, and consequence. The review's main contribution is an operational framework in which dominant flood processes are diagnosed before modelling, hazard is characterised from satellite and hydrodynamic evidence, and susceptibility is explicitly linked to exposure, vulnerability, and future climate and land-use change. Future Nigerian flood studies should be judged not only by predictive accuracy, but also by physical plausibility, generalisability, uncertainty communication, and usefulness for planning.

KEYWORDS
Flood susceptibility, Flood-risk assessment, Geographic Information Systems (GIS), Remote sensing, Machine learning, GeoAI, Vulnerability assessment, Nigeria

INTRODUCTION

Flooding is recurrent across Nigeria's urban, riverine, and coastal landscapes. Its consequences are intensified by rapid urbanisation, limited drainage capacity, development on floodplains, wetland alteration, variable rainfall, river discharge, and rising concentrations of people and assets. The 2022 flood disaster reinforced the scale of national vulnerability and the importance of reliable monitoring, prediction, and risk management. GIS, remote sensing, and machine learning have become central to these tasks because they can integrate topographic, hydro-climatic, land-cover, and socioeconomic information while repeatedly observing landscape change and flood events (Komolafe et al., 2020;Eneyo, 2026a; Ighile et al., 2022; Bello et al., 2024).

Nevertheless, the sophistication of a modelling technique should not be confused with the comprehensiveness of its output. A model can report a high classification accuracy while estimating only the relative propensity of places to flood. Such an output is valuable for screening and prioritisation, but it is not equivalent to an assessment of risk unless it is connected to physical flood hazard, the people and assets that lie within the hazard footprint, their vulnerability, and the consequences likely to follow. This is a methodological distinction rather than a matter of terminology (Chukwuma et al., 2021; Chinedu et al., 2024; Eneyo, 2026b; Tique et al., 2026).

The problem is especially important in Nigeria because flood mechanisms and risk contexts differ sharply between locations. Riverine flooding along the Niger–Benue system, pluvial flooding in rapidly urbanising cities, coastal and tidal flooding around Lagos, and compound flooding in the Niger Delta cannot be adequately represented by a single generic set of static conditioning factors. The same susceptibility category can imply very different planning priorities where flood depth, exposure density, housing quality, drainage performance, and institutional capacity differ.

These differences are not merely academic. A susceptibility map that classifies a neighbourhood as "high risk" without specifying expected depth, likely duration, or the number and type of assets exposed gives a planning authority very little basis on which to choose between competing interventions — raising road levels, upgrading drainage, relocating vulnerable households, or simply issuing early warnings. As Nigerian cities continue to expand onto floodplains and wetlands under population pressure, the cost of relying on incomplete risk information rises correspondingly, which is precisely why a critical, synthesising review of how the literature has approached this problem is timely.

This review therefore examines the transition in Nigerian flood research from susceptibility mapping toward integrated flood-risk assessment. It evaluates the contributions and limitations of GIS-MCDA, remote sensing, ML, and GeoAI; identifies critical gaps in hazard magnitude, exposure, vulnerability, validation, and uncertainty; and proposes a decision-oriented framework for future work.

The contribution of this review is therefore conceptual and synthetic rather than empirical: it does not generate new flood maps or models, but instead draws together a fragmented body of Nigerian flood literature into a single evaluative framework, so that researchers, reviewers, and disaster-management agencies can judge more consistently what a given flood study does and does not demonstrate. This is particularly important in a policy environment where susceptibility maps are frequently, and sometimes uncritically, treated as ready-made risk products for evacuation planning, insurance pricing, or infrastructure siting.

LITERATURE REVIEW

Conceptual Framework: Susceptibility, Hazard, and Risk

Conceptual clarity is essential for evaluating the development of flood research. Flood susceptibility, hazard, exposure, vulnerability, and risk are closely related, but they describe different aspects of the flood-risk problem and should not be used interchangeably. This review therefore distinguishes these concepts and places them within a progressive flood-risk assessment pathway.

Flood susceptibility refers to the relative tendency of a location to experience flooding under specified environmental and human-induced conditions. Its principal question is: where are conditions conducive to flooding? Common predictors include elevation, slope, flow accumulation, drainage density, distance from rivers, rainfall, soil properties, lithology, land use/land cover, and topographic wetness. A susceptibility class usually represents relative spatial propensity and should not be interpreted as a time-bound probability unless the model explicitly estimates the likelihood of occurrence over a defined period (Alfa et al., 2018; Njoku et al., 2018; Chukwuma et al., 2021).

Flood hazard describes both the likelihood of a flood event and its physical characteristics, which, depending on the decision context, include inundation extent, depth, velocity, duration, recurrence, probability, and return period. A Sentinel-1-derived inundation layer shows where water was observed during a particular event; it is empirical evidence of event-specific flooding, but it does not automatically provide water depth, speed, duration, or recurrence. Susceptibility modelling, by contrast, provides prospective spatial prediction based on conditioning factors and historical evidence — the two forms of information are complementary, not interchangeable.

Exposure denotes people, buildings, roads, farms, utilities, schools, hospitals, commercial facilities, and other assets located inside a hazard footprint. Vulnerability denotes the propensity of those exposed elements to suffer harm, and may include physical, social, economic, institutional, and environmental dimensions — housing quality, poverty, age structure, disability, mobility, access to emergency routes, health-care access, insurance, social networks, and institutional response capacity can all influence outcomes. Two communities exposed to the same water depth can therefore experience very different losses and recovery trajectories (Wali et al., 2021; Amama et al., 2023; Gambo et al., 2024).

Flood risk is the potential for adverse consequences arising from the interaction of hazard, exposure, and vulnerability. The familiar expression, Flood Risk = Hazard × Exposure × Vulnerability, is conceptual rather than a universal calculation: it makes clear that susceptibility is a precursor and analytical input, not a complete risk measure. A robust assessment should proceed from flood-process diagnosis to hazard characterisation, susceptibility prediction, exposure assessment, vulnerability profiling, and consequence estimation, as summarised in Figure 1.

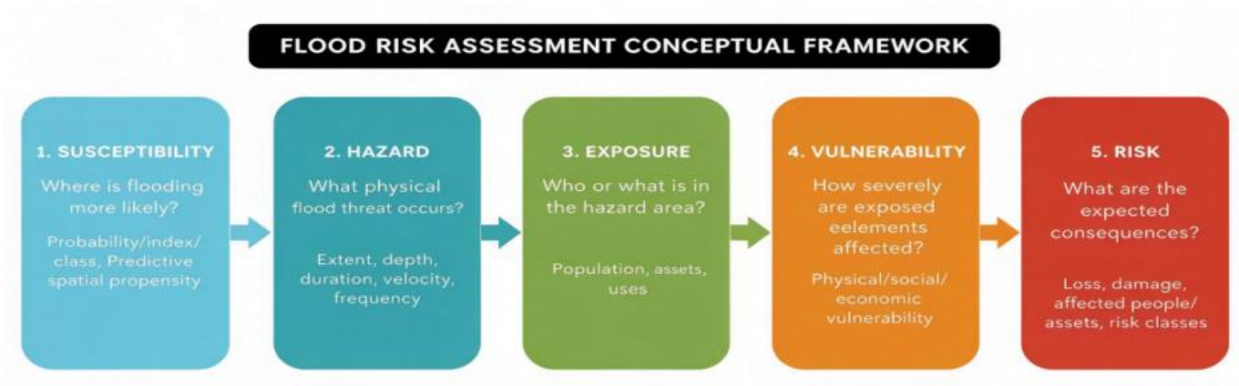

Figure 1. Conceptual progression from flood susceptibility to flood risk

Reviewed side by side, the Nigerian literature shows broad agreement on this conceptual sequence in principle, but considerable disagreement in practice over where a given study should be positioned within it. A majority of the studies reviewed here stop at the susceptibility-prediction stage, reporting maps labelled as "flood risk" or "flood vulnerability" that are, on closer inspection, purely susceptibility products derived from static physical predictors. A smaller but growing number of studies explicitly separate hazard characterisation from susceptibility prediction, and fewer still extend the analysis to exposure and vulnerability. This uneven adoption of the susceptibility-hazard-risk distinction is itself an important finding of the present review, because it indicates that the conceptual vocabulary of flood research in Nigeria has advanced faster than the corresponding analytical practice.

Evolution of Nigerian Flood Modelling

The development of Nigerian flood research can be organised into five overlapping methodological generations (Table 1). They are complementary pathways rather than a strict chronological ladder: a transparent MCDA model may be appropriate in a data-scarce catchment, while event mapping or hydrodynamic modelling may be indispensable in an operational risk setting.

Table 1. Overlapping methodological generations of flood modelling in Nigeria

Generation	Dominant approach	Central question	Main limitation
1	GIS-MCDA: AHP, weighted overlay, fuzzy approaches	Where are locations relatively prone to flooding?	Subjective weights and simplified interactions
2	Statistical and ML models: LR, ANN, RF, SVM, XGBoost	Can predictors estimate flood propensity?	Often remains restricted to susceptibility.
3	Event-based remote sensing: Sentinel-1 SAR and optical flood masks	Where did inundation occur during an event?	Usually maps 2-D extent only
4	Integrated Earth observation, environmental data and ML	How can event observations support prospective prediction?	Exposure, vulnerability, and independent validation remain uneven.
5	Explainable, uncertainty-aware GeoAI and dynamic scenarios	How can risk be predicted, explained and updated?	Emerging; needs stronger physical and field grounding.

GIS-MCDA and Expert-Led Mapping

GIS-MCDA has been a dominant approach because it can integrate DEM derivatives, rainfall, drainage, land cover, and local expertise within one transparent spatial workflow. AHP, weighted linear combination, and fuzzy overlay permit analysts to state which criteria are used and how each contributes to the composite map. This transparency is particularly useful in data-poor settings where flood inventories, gauges, or detailed hydraulic information are limited (Komolafe et al., 2020; Ajibade et al., 2021).

Its limitations are also well established. Weight allocation may depend heavily on expert judgement; interactions among terrain, rainfall, drainage, and urban development are frequently nonlinear; and results can vary substantially with chosen criteria, thresholds, raster resolution, and class breaks. Comparative work shows that MCDA, data mining, and fuzzy methods should be seen as different modelling philosophies rather than methods that can be compared only by a single accuracy score (Idrees et al., 2022; Tella et al., 2022).

Applications of GIS-MCDA across Nigerian cities and catchments illustrate both its reach and its variability. Studies in Ibadan (Ajibade et al., 2021; Tella & Balogun, 2020), the Ofu River catchment (Alfa et al., 2018), Ikom in Cross River State (Njoku et al., 2018), and Ilorin (Idrees et al., 2022) all apply broadly similar overlay logic to rainfall, elevation, drainage, and land-cover layers, yet arrive at susceptibility maps whose class boundaries and spatial patterns are not directly comparable because weighting schemes, factor sets, and classification thresholds differ from study to study. This lack of a common benchmark makes it difficult to say, with confidence, whether one Nigerian city is more flood-susceptible than another, even where both have been separately mapped using GIS-MCDA.

Machine Learning and Hybrid Approaches

Machine Learning has expanded because flood generation reflects complex interactions among topography, rainfall, drainage networks, soils, land use, and anthropogenic modification. ANN, random forest, support vector machines, and gradient-boosting methods can capture nonlinear relationships that expert-weighted overlays may not adequately represent. National and subnational studies demonstrate their usefulness for susceptibility prediction, including the nationwide application of GIS and ML by Ighile et al. (2022) and recent model comparisons and applications in Nigerian states (Okoli et al., 2026; Tique et al., 2026).

However, a high ROC-AUC, overall accuracy, or F1 score is not proof that a model estimates flood risk. In many applications, the target remains a flood/no-flood inventory or a susceptibility label. The appropriate question is therefore not whether ML should replace GIS-MCDA, but how expert knowledge, physical hydrology, satellite observations, and data-driven learning can be combined. Hybrid approaches can preserve transparency and local knowledge while improving representation of complex predictor interactions (Nkeki et al., 2023; Abubakar et al., 2025).

There is also broad agreement across the ML studies reviewed that ensemble tree-based methods (random forest, XGBoost) tend to outperform single classifiers such as logistic regression on Nigerian susceptibility data sets, echoing a wider international pattern. Where studies disagree is on which conditioning factors matter most: some rank elevation and slope as the dominant predictors, while others identify distance to drainage or rainfall intensity as more influential, and a smaller number find land use/land cover to dominate in rapidly urbanising catchments. This inconsistency likely reflects genuine differences in local flood-generating processes as much as it reflects methodological choices, and it reinforces the review's broader argument that predictor importance should be interpreted in light of process understanding rather than treated as a universal ranking transferable between catchments.

Remote Sensing and Observed Hazard

Remote sensing is the key bridge between prospective susceptibility prediction and observed flood hazard. Optical imagery can delineate water under clear skies, but severe floods in tropical West Africa often occur during periods of persistent cloud cover. Sentinel-1 SAR addresses this constraint by providing all-weather, day-and-night observations. Nigerian studies have used SAR to map flood extent and to examine event behaviour across diverse settings, including Borno State and the Niger Delta (Eteh et al., 2024; Okoduwa et al., 2024).

Event footprints can provide more credible flood inventories for model calibration than opportunistic point records alone. Yet remote-sensing flood masks should not be over-interpreted: they commonly omit depth, velocity, duration, and recession rate, all of which affect structural damage, crop loss, evacuation difficulty, and public safety. The research priority is therefore to combine satellite observations with gauge records, DEMs, hydraulic models, and field observations where available (Ibrahim & Balzter, 2024; Rahman et al., 2026).

The growing availability of free, regularly revisited Sentinel-1 and Sentinel-2 imagery, alongside cloud-based processing platforms, has lowered the technical and financial barriers that previously restricted flood-extent mapping in Nigeria to a small number of well-resourced research groups. This democratisation of access is visible in the geographic spread of the remote-sensing studies reviewed here, which now cover locations as varied as Borno State in the semi-arid north-east and the Niger Delta in the humid south, and as varied in land use as agricultural paddy fields and dense urban settlements (Eteh et al., 2024; Ibrahim & Balzter, 2024;

Okoduwa et al., 2024). What has not kept pace with this geographic spread, however, is a shared protocol for converting SAR backscatter into a validated flood mask, so that thresholding decisions, speckle-filtering choices, and validation procedures continue to vary from study to study in ways that complicate direct comparison of reported flood extents.

METHODOLOGY

This study uses a structured critical-synthesis approach rather than a purely descriptive narrative review. It concentrates on studies published between 2016 and 2026, a period associated with wider access to Sentinel-1 and Sentinel-2 imagery, open-access digital elevation models (DEMs), cloud-based geospatial processing, ML algorithms, ensemble modelling, and explainable AI. Earlier work was considered where it offered essential conceptual or methodological foundations.

Literature identification focused on combinations of Nigeria with flood susceptibility, flood hazard, flood risk, flood exposure, flood vulnerability, GIS, remote sensing, Sentinel-1, SAR, machine learning, deep learning, ensemble modelling, explainable AI, GeoAI, flood depth, and compound flooding. Included studies placed Nigeria at the centre of the analysis and contributed substantive evidence on flood mapping, prediction, hazard characterisation, exposure, vulnerability, or risk.

The selected literature was compared across eight dimensions: conceptual focus; flood-conditioning and hazard variables; contribution of remote sensing; modelling technique; validation strategy; integration of exposure and vulnerability; treatment of uncertainty and explainability; and relevance to decision-making. The aim was not to rank algorithms solely by performance statistics, but to assess whether each approach represents the relevant dimensions of a flood-risk problem. A full PRISMA-style screening flow is not provided because the underlying source compilation did not include a reproducible database export and complete screening log.

This structured critical-synthesis approach has clear limitations that should be stated openly. Because screening was not conducted through a single reproducible database query, the review cannot claim to be exhaustive in the manner of a formal systematic review, and the possibility that relevant studies were omitted cannot be entirely excluded. The approach is nonetheless well suited to the review's stated aim, which is conceptual and comparative rather than bibliometric: the eight-dimension comparison framework allows heterogeneous studies, spanning GIS-MCDA, statistical models, machine learning, and remote sensing, to be evaluated on a common set of criteria regardless of their specific technical vocabulary.

RESULTS

Characterising Hazard Severity

Binary inundation masks provide important evidence of where flooding occurred, but they are insufficient for estimating severity or consequences. Water depth, velocity, duration, recurrence, and flood recession determine whether an event causes shallow disruption, severe building damage, crop destruction, prolonged isolation, or loss of life. Studies that combine SAR extent with elevation-derived depth estimates, land-use exposure, and susceptibility modelling illustrate the direction needed for more comprehensive assessment: Rahman et al. (2026), for example, linked multiple dimensions in Kogi State and reported substantial local variation in estimated flood depth along the Niger–Benue confluence.

For riverine systems, hydrodynamic modelling can represent water-surface elevation, velocity, and duration more directly when terrain, flow, and boundary-condition data exist. For urban pluvial flooding, drainage capacity, imperviousness, rainfall intensity, and local depressions are critical. For coastal settings, tide, storm surge, and backwater effects may be essential. Hazard characterisation must therefore be process-specific rather than a uniform application of generic terrain variables.

Across the studies reviewed, agreement is strongest on the diagnosis that Nigerian flood hazard is multi-mechanism rather than uniform, but weakest on how to operationalise this diagnosis. Few of the reviewed studies report inundation depth or duration alongside extent, and fewer still attempt to translate remotely sensed extent into a depth or severity surface using auxiliary elevation or hydraulic information. Where such translation is attempted, as in Rahman et al. (2026), the results reveal considerable within-basin variability in flood depth that a binary or purely categorical susceptibility map would conceal entirely, underscoring the practical cost of treating extent as a proxy for severity.

Exposure and Vulnerability

Exposure assessment should move beyond simple population overlays. A planning-relevant inventory should identify residential structures, informal settlements, road and bridge networks, schools, hospitals, markets, industrial facilities, electricity and water assets, cropland, and ecological resources within defined hazard footprints. Intersecting buildings or population with an event footprint or return-period flood extent produces a more defensible estimate of potential impact than intersecting them with an uncalibrated susceptibility category (Chinedu et al., 2024; Umar et al., 2026).

Vulnerability adds social realism to spatial risk analysis. Nigerian studies have begun to examine social vulnerability, resilience, and multidimensional poverty, but coverage remains uneven because detailed household, building, and service data are difficult to obtain. Future work should integrate census data, targeted household surveys, building typology, accessibility analysis, and community knowledge, explicitly connecting vulnerability to exposure and hazard severity so that differential likely consequences can be understood (Chukwuma et al., 2021; Amama et al., 2023; Gambo et al., 2024).

The reviewed exposure and vulnerability studies agree that population and asset counts alone under-represent likely impact, but they diverge in how they attempt to correct for this. Some, such as Gambo et al. (2024), link flood risk explicitly to multidimensional poverty indicators; others, such as Amama et al. (2023), foreground resilience and social vulnerability indices derived from census-type variables. Very few combine both a physically grounded hazard layer and a socially grounded vulnerability layer within the same analysis, which means that, at present, Nigerian flood-risk studies tend to be either hazard-rich and vulnerability-poor, or vulnerability-rich and hazard-poor, rather than genuinely integrated across both dimensions.

Compound Flooding and Dynamic Risk

Flood types in Nigeria include pluvial, fluvial, coastal, flash, dam-release, and compound flooding. In Lagos and the Niger Delta, heavy rainfall may occur alongside river discharge, tidal effects, storm surge, drainage blockage, and wetland modification. These interactions mean that elevation and rainfall alone cannot represent the full flood process; process diagnosis must precede predictor selection and model training (Bello et al., 2024; Eteh et al., 2024).

Risk is also dynamic. Static susceptibility maps often assume that historical land cover and rainfall conditions remain representative, yet cities expand, wetlands are modified, populations grow, and extreme rainfall can change. Forward-looking assessment should couple historical flood evidence with climate scenarios, urban-growth models, population projections, and planned drainage or flood-defence investments — Lagos studies on land-use change demonstrate why future exposure can diverge materially from present-day conditions (Koko et al., 2021; Aniramu et al., 2026).

Taken together, the results presented above show a literature that agrees strongly on the qualitative description of Nigerian flood processes — that they are multi-mechanism, spatially variable, and increasingly shaped by urban growth — but that has not yet converged on a shared quantitative approach for translating this description into decision-ready hazard, exposure, and vulnerability products. This gap between conceptual consensus and analytical practice motivates the discussion that follows.

DISCUSSION OF FINDINGS

Validation is central to the credibility of spatial flood models. Randomly dividing raster pixels into training and testing sets can produce inflated performance because neighbouring pixels share similar terrain and environmental properties. This spatial autocorrelation causes data leakage: the test sample may be very similar to the training sample even where the model has not demonstrated genuine transferability. Reported high accuracy within one watershed should therefore not be assumed to demonstrate performance in another basin or during another event.

Four complementary validation practices should become routine: spatial-block cross-validation to separate nearby observations; temporal holdout testing using later events; independent validation with unseen satellite-derived flood footprints or field evidence; and cross-basin transferability testing across physiographically distinct environments. These approaches provide a more realistic measure of operational skill.

Uncertainty also requires explicit communication. DEM vertical error, flood-inventory completeness, spatial resolution, predictor selection, model parameters, algorithm choice, and future climate scenarios all contribute to uncertainty. Ensembles, sensitivity analysis, confidence intervals, and spatial disagreement maps can show where predictions are robust and where field surveys or local hydraulic modelling are most needed. Model consensus should not be treated as certainty, but as one indicator that must be interpreted alongside data quality and physical plausibility.

Comparing validation practice across the reviewed studies reveals a further disagreement: a majority report a single random train-test split and a single accuracy statistic, treating this as sufficient evidence of model performance, while a smaller minority explicitly discuss spatial autocorrelation or apply any form of spatial or temporal holdout. This is not a minor technical detail but a substantive threat to the credibility of comparative claims in the literature: two studies reporting similar accuracy figures may in fact differ considerably in true predictive skill if one has, and the other has not, guarded against data leakage.

Explainable AI can improve transparency. SHAP values and related feature-attribution methods can show how a fitted algorithm uses predictors and can help reveal implausible or unstable dependencies, although explanation is not causation: a variable ranked as important in a model is not automatically the physical trigger of flooding. Interpretability must be evaluated against hydrological process knowledge and observed conditions (Gilbert & Shi, 2026; Tique et al., 2026).

For disaster managers and planners, useful outputs must answer more than "where is flood-prone?" They should identify expected inundation extent and severity; exposed populations and assets; vulnerable groups; likely consequences; confidence or uncertainty; and priorities under alternative climate, land-use, and infrastructure scenarios. This is the shift from algorithmic benchmarking to decision-relevant flood intelligence.

It is worth noting explicitly where the reviewed literature agrees and where it does not on this point. There is near-universal agreement, at the level of stated motivation, that flood research should serve disaster-risk reduction and planning; disagreement emerges once studies move from motivation to method, with the great majority defaulting to susceptibility mapping as a tractable proxy for the broader risk question they set out to answer. This review does not regard that default as a failure of individual studies so much as a structural feature of a still-maturing field, one that a shared reporting framework, of the kind proposed below, could help to correct over time.

An integrated Nigerian flood-risk framework, summarised in Table 2, should treat susceptibility as one component in an operational chain. Individual studies need not implement every stage, but they should indicate clearly which dimensions are covered, which are excluded, and how those omissions constrain interpretation.

Table 2. Integrated framework for future Nigerian flood-risk assessment

Stage	Core function	Representative methods/data	Planning output
1. Process diagnosis	Identify dominant mechanisms	Rainfall, gauges, terrain, drainage, tides, dam operation	Appropriate modelling design
2. Hazard characterisation	Quantify flood dynamics	Sentinel-1, optical imagery, DEM, gauges, hydraulic models	Extent, depth, velocity, duration and recurrence
3. Susceptibility prediction	Estimate spatial propensity	GIS-MCDA, RF/XGBoost, hydro-geomorphic factors	Calibrated propensity or probability maps
4. Exposure assessment	Locate people and assets	Buildings, roads, WorldPop, land use, facilities	Exposed populations and asset inventories
5. Vulnerability profiling	Assess differential sensitivity and capacity	Surveys, census, poverty, building typology, services	Social, physical and economic vulnerability maps
6. Consequence estimation	Estimate likely impacts	Depth–damage functions, crop-loss and disruption models	Loss and impact estimates
7. Reliability analysis	Explain predictions and quantify uncertainty	Spatial CV, ensembles, SHAP, sensitivity analysis	Confidence and uncertainty surfaces
8. Dynamic scenarios	Project future risk	Climate projections, urban growth, infrastructure plans	Adaptation trajectories and priorities
9. Decision support	Translate analysis into intervention	Risk zoning, cost–benefit, early warning, evacuation planning	Targeted investment and risk-informed plans

The framework is particularly applicable to Port Harcourt and the Niger Delta, where low elevation, wetlands, dense and expanding development, degraded drainage, upstream flows, and tidal influences can interact. A defensible assessment in such areas requires more than static terrain suitability: it should connect observed inundation, hydrodynamic conditions, drainage performance, asset exposure, social vulnerability, and future environmental change. Its most important contribution is conceptual transparency — it prevents a susceptibility map from being overclaimed as risk, while showing researchers how a susceptibility result can be productively incorporated into a larger evidence chain, so that a subsequent project can extend a prior susceptibility study with event observation, exposure mapping, vulnerability surveys, hydraulic modelling, or scenario analysis.

CONCLUSION

Flood research in Nigeria has progressed from expert-weighted GIS overlays to multi-sensor satellite observation, machine-learning models, exposure assessment, and emerging explainable GeoAI. Sentinel-1 SAR has improved event-scale mapping in cloud-prone tropical conditions, while data-driven methods have expanded the capacity to represent nonlinear interactions among flood-conditioning variables. These developments are significant, but they do not eliminate the need for conceptual and physical rigour. Flood susceptibility identifies relative spatial propensity; it does not independently quantify flood risk. A more complete assessment must characterise physical hazard severity, identify exposed people and assets, represent vulnerability, estimate likely consequences, and communicate uncertainty. The principal gaps in the Nigerian literature therefore concern depth, duration, and velocity; comprehensive asset inventories; social vulnerability; compound-process representation; independent spatial and temporal validation; uncertainty mapping; and forward-looking climate and urbanisation scenarios. The scientific contribution of this review lies in making that distinction explicit and in showing, through a systematic comparison of the Nigerian literature across eight evaluative dimensions, exactly where current practice falls short of a complete risk assessment. Its practical relevance lies in providing disaster-management agencies, planners, and researchers with a shared vocabulary and checklist against which any new flood study — whether GIS-MCDA, machine-learning, or remote-sensing based — can be positioned, so that its outputs are neither underused nor overclaimed.

RECOMMENDATION

Future studies should diagnose the dominant flood mechanism before selecting predictors; use satellite observations to support hazard inventories; integrate hydrodynamic information where feasible; apply spatially independent validation; map uncertainty; and translate results into land-use controls, drainage priorities, early-warning thresholds, and equitable adaptation investments. GIS-MCDA and Machine Learning should be treated as complementary methods. By connecting physical process understanding, Earth observation, transparent modelling, and social-risk analysis, Nigerian flood research can produce actionable risk intelligence rather than increasingly sophisticated susceptibility maps alone.

At an institutional level, journals, funders, and research supervisors reviewing Nigerian flood studies could usefully require authors to state explicitly which of the nine stages summarised in Table 2 their study addresses, and which it does not. Such a reporting convention would cost little to implement, would not require any single study to attempt the full chain from process diagnosis to decision support, and would nonetheless substantially improve the comparability and cumulative value of the literature, by making explicit the scope and limits of each contribution rather than leaving readers to infer them.

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