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(Research Article)

Geospatial machine learning for flood risk assessment in contrasting physiographic environments

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Abstract

One of the biggest hydrological hazards in Sub-Saharan Africa is flooding, which is exacerbated by increasing rainfall, inadequate drainage systems, and growing urbanization. In Nigeria, fragmented datasets and inadequate methodological integration continue to limit the ability to map flood susceptibility in a spatially detailed manner. This work presents a hybrid framework that creates interpretable and highly accurate flood susceptibility models for two physiographically distinct regions: Ile-Ife (inland uplands) and Ilaje (coastal lowlands) by combining the Analytic Hierarchy Process (AHP) with the Random Forest (RF) classifier. For Ilaje and Ile-Ife, a total of 43,825 and 8,632 spatial sample points were produced. In order to create a composite Flood Susceptibility Index (FSI), four flood-related predictors elevation, slope, rainfall, and distance to river were normalized and weighted using AHP. To train RF models for each region, the FSI was reclassified into three risk categories. F1-scores, precision, recall, and confusion matrices were used to assess the model's performance. According to the results, Ilaje and Ile-Ife had classification accuracy rates of 98% and 97%, respectively. In both areas, rainfall and river proximity were the most important predictors, whereas the complexity of the terrain affected the patterns of susceptibility. The AHP-RF framework proved to be highly transparent and dependable, providing a scalable flood risk zoning tool, especially in settings with limited data. This work promotes interpretable geospatial modeling for disaster risk reduction by combining machine learning and expert judgment. The results provide a replicable model for climate adaptation in flood-prone areas of Sub-Saharan Africa and support the incorporation of physiographically informed flood planning into policy frameworks.

Keywords: Flood Susceptibility Mapping; Machine Learning; Analytic Hierarchy Process (AHP); Random Forest Classifier; Geospatial Modeling; Flood Susceptibility Index (FSI)

1. Introduction

With serious socioeconomic, environmental, and infrastructure repercussions, flooding is a ubiquitous hazard on a global scale [1, 2, 3]. Its frequency and intensity have increased over the past 20 years, especially in the Global South, as a result of land-use change, urban sprawl, deforestation, and intensifying rainfall linked to climate variability [4, 5]. Both inland and coastal communities in Nigeria have frequently suffered catastrophic floods [6,7], but there are still few efficient early-warning and spatial risk zoning systems in place [8]. This has made the creation of flexible, scalable, and interpretable data-driven methods for assessing flood susceptibility necessary.

Even though conventional hydrological and hydraulic models are well-established, they are less useful in areas with limited data because they frequently call for large amounts of field data and computational resources [9, 10]. In response, there has been an increase in the use of machine learning (ML) and remote sensing techniques for geospatial modeling. Because of their ability to handle high-dimensional, nonlinear data, machine learning classifiers like Random

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Forest (RF), Support Vector Machine (SVM), and XGBoost have been widely used for flood susceptibility mapping [11, 12, 13]. With the added advantage of interpretability through variable importance scores, RF has shown itself to be particularly robust among these [14, 15].

But ML models by themselves frequently don't reveal how decisions are made; this is known as the "black-box" problem. As a result, researchers are increasingly using hybrid approaches that integrate machine learning (ML) with expert-informed decision frameworks such as the Analytic Hierarchy Process (AHP) [16, 17]. When combined with geospatial tools, AHP has been successfully used in flood modeling, allowing for the systematic assignment of weights to input variables based on domain knowledge [18]. Notwithstanding these developments, the majority of flood susceptibility studies conducted in Nigeria have been limited to specific geographic areas and have relied solely on machine learning or deterministic modeling [19, 20, 21]. Limited research has been done on integrated AHP–ML models in various physiographic regions [22]. Few studies, specifically, have used a consistent methodological framework to compare flood drivers and modeling behavior in inland and coastal environments [23, 22, 24].

By applying a hybrid AHP–Random Forest approach in two physiographically distinct areas of southwestern Nigeria Ile-Ife, a topographically diverse inland environment, and Ilaje, a low-lying coastal floodplain this study fills that gap [25, 26]. Based on theoretical and empirical evidence of flood risk drivers, four geospatial predictors were chosen: elevation, slope, rainfall, and distance to river. The study enhances regional flood modeling and advances scalable and interpretable risk zoning for environments with limited data by examining these variables across various terrains.

The study uses the Analytic Hierarchy Process (AHP) to determine expert-informed weights for important environmental factors that affect flood susceptibility in order to accomplish these goals. These weights are then incorporated into a hybrid modeling framework that combines Random Forest classification with AHP, enabling both predictive robustness and interpretability. Confusion matrices, precision, recall, and feature importance rankings are used to evaluate the model's performance. In order to find spatial differences in flood drivers and susceptibility patterns, the study also compares the flood susceptibility of two physiographically different regions: inland Ile-Ife and coastal Ilaje. The study offers a new and transferable framework for flood risk modeling in settings with both spatial diversity and data constraints by fusing expert judgment with data-driven machine learning in a cross-regional setting.

2. Materials and Methods

In order to model flood susceptibility across two physiographically distinct regions in southwest Nigeria, this study uses a hybrid methodological framework that combines supervised machine learning with expert-based multi-criteria analysis. The workflow consists of five main steps: (1) defining the study areas; (2) obtaining and preprocessing environmental variables; (3) utilizing the Analytic Hierarchy Process (AHP) to determine variable weights; (4) calculating a Flood Susceptibility Index (FSI); and (5) classifying the data using the Random Forest (RF) algorithm.

2.1. Study Areas

The two chosen study areas, Ile-Ife in Osun State and Ilaje in Ondo State, reflect different physiographic conditions. Low elevation, a lot of rainfall, estuarine water bodies, and little drainage relief make Ilaje a coastal area that is particularly vulnerable to tidal and fluvial flooding [26]. Ile-Ife, on the other hand, is an inland area characterized by complicated topography, including drainage basins, rolling hills, and more fluctuating hydrological conditions [25]. The sensitivity and generalizability of flood susceptibility modeling frameworks under various hydrological and geomorphological conditions can be assessed thanks to this regional contrast. The figure 1 depicted the study areas.

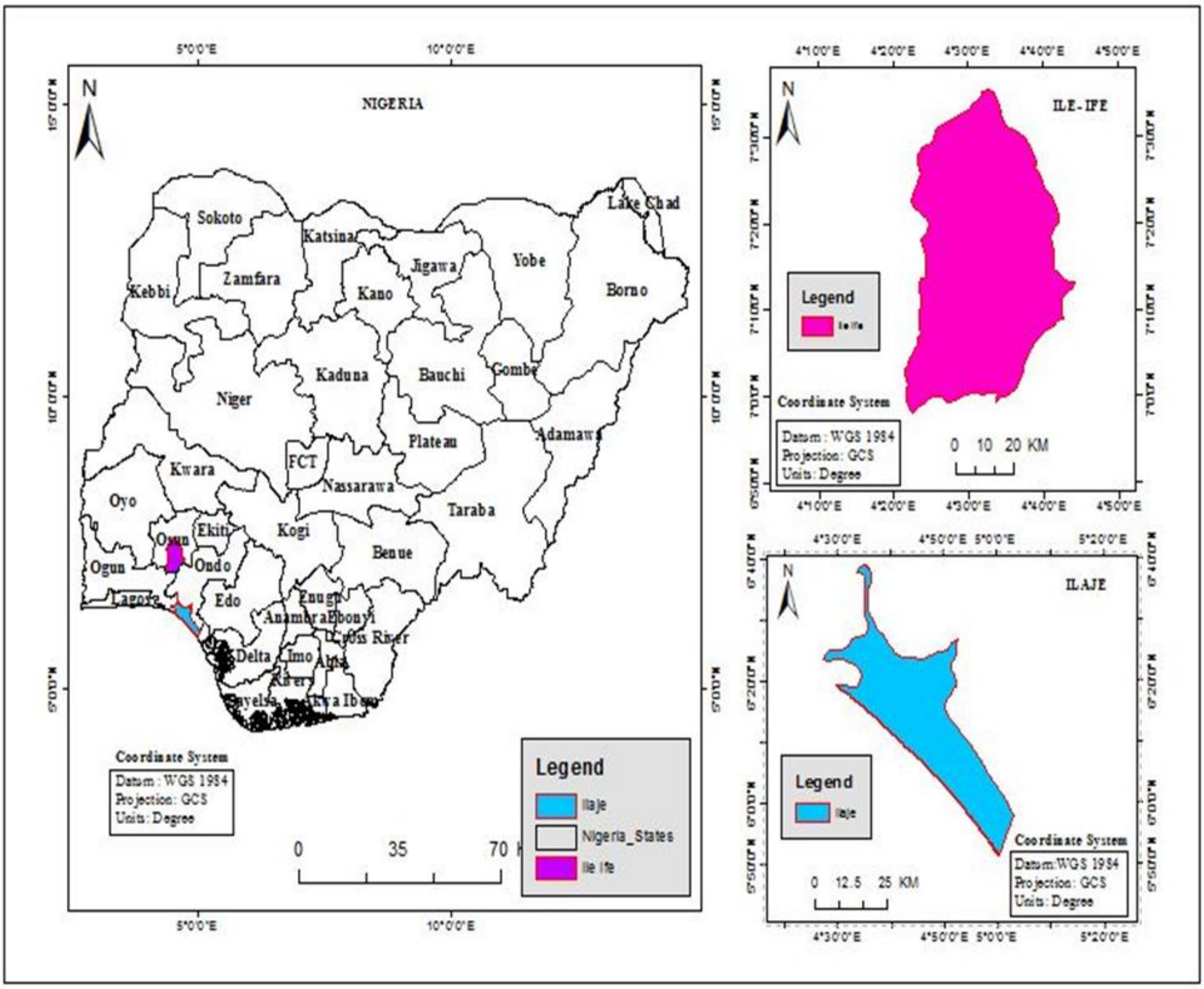

Figure 1 The study area maps

2.2. Data Acquisition and Preprocessing

Spatial sampling points were created over each study region using Google Earth Engine (GEE). Ilaje received 43,825 points in total, while Ile-Ife received 8,632 points. The area's greater lowland extent and spatial homogeneity, which necessitated denser sampling to capture subtle variability, are reflected in Ilaje's higher point count. On the other hand, fewer but more topographically informative samples were needed due to the more complicated terrain of Ile-Ife. Four important flood-related environmental variables were obtained at each location: (i) elevation, taken from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (30 m resolution); (ii) slope, taken from the elevation layer using the GEE terrain function; (iii) mean annual rainfall, taken from the CHIRPS v2 dataset (1981–2023); and (iv) distance to the closest river, taken from the JRC Global Surface Water dataset. To guarantee spatial consistency, all layers were projected to WGS 84 (EPSG:4326). Min–max scaling was used to normalize the four variables to a [0, 1] scale. Elevation, slope, and river distance variables that were negatively associated with flood susceptibility were inversely normalized, meaning that higher normalized values consistently represented a higher potential for flood risk.

2.3. AHP-Based Weight Derivation

Each variable was given a relative importance weight using the Analytic Hierarchy Process (AHP). Expert judgment and pertinent literature were used to build a pairwise comparison matrix [27, 28, 29]. To validate the matrix, the Saaty Consistency Ratio (CR) was computed; a CR < 0.10 indicates acceptable consistency. Elevation (0.30), slope (0.20), rainfall (0.30), and distance to river (0.20) were the final weights assigned. At each spatial point, a Flood Susceptibility Index (FSI_AHP) was calculated using these weights as a weighted linear combination of the normalized variables:

$$FSI_{AHP}=0.30\cdot E_{inv}+0.20\cdot S_{inv}+0.30\cdot R+0.20\cdot D_{inv}$$

where E_{inv}, S_{inv}, and D_{inv} represent the inverse-normalized values of elevation, slope, and distance to river, respectively, and R denotes the normalized rainfall.

2.4. Classification and Model Training

The quantile-based thresholds were used to reclassify the continuous FSI_AHP values into three distinct classes: Class 0 (No Flood), Class 1 (Moderate Flood Risk), and Class 2 (High Flood Risk) in order to facilitate supervised classification. In addition to improving model generalization, this classification scheme guarantees statistical balance across classes [30, 31, 32]. A Random Forest Classifier (RFC) was independently trained using the labeled datasets for each region. 20% of the data was used for testing and validation, and the remaining 80% was used for model training. The RF algorithm was selected because it provides internal feature importance rankings, is robust against overfitting, and can handle non-linear feature interactions. Standard metrics, such as confusion matrices, precision, recall, and F1-scores, were calculated for each class in order to assess the model's performance. In order to evaluate each environmental variable's contribution to the classification process, feature importance scores were also extracted. Interpretability and predictive reliability in a variety of physiographic contexts are made possible by this dual approach, which combines AHP and ML.

3. Results and Discussion

The results of the flood susceptibility modeling procedure for Ilaje and Ile-Ife are shown and explained in this section. The Random Forest (RF) models' classification performance, feature importance interpretation, confusion matrix analysis, and comparative regional insights are all included. Where appropriate, figures and tables are cited to bolster important conclusions.

3.1. Classification Performance for Flood Susceptibility

Three common evaluation metrics precision, recall, and F1-score were computed for every class in order to evaluate the model's classification performance in addition to overall accuracy. A more detailed picture of the model's predictive behavior is offered by these metrics:

In order to evaluate the model's ability to prevent false positives, precision measures the percentage of accurate positive predictions among all positive predictions. It is computed as:

$$\text{Precision} = \text{True Positives} / (\text{True Positives} + \text{False Positives})$$

Recall measures the model’s ability to identify all actual positive instances, reflecting its effectiveness in minimizing false negatives. It's calculated as:

$$\text{Precision} = \text{True Positives} / (\text{True Positives} + \text{False Positives})$$

F1-score represents the harmonic mean of precision and recall, providing a balanced evaluation where both false positives and false negatives are important. Calculated as:

$$F1 = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

80% of the labeled data was used to train the Random Forest classifier, and the remaining 20% was used for testing. The model's overall classification accuracy was 97% for Ile-Ife and 98% for Ilaje. The precision, recall, and F1-scores for every class in both regions are shown in Tables 1 and 2.

Table 1 Classification Metrics for Ile-Ife

Class	Label	Precision	Recall	F1-Score	Support
0	No Flood	0.99	0.98	0.99	555
1	Moderate Risk	0.95	0.97	0.96	551
2	High Risk	0.98	0.96	0.97	567
Accuracy		--	--	0.97	1673

Macro Avg		0.97	0.97	0.97	1673
Weighted Avg		0.97	0.97	0.97	1673

Model Accuracy: 0.97

Table 2 Classification Metrics for Ilaje

Class	Label	Precision	Recall	F1-Score	Support
0	No Flood	0.98	0.98	0.98	2782
1	Moderate Risk	0.97	0.97	0.97	2848
2	High Risk	0.98	0.99	0.99	3017
Accuracy		--	--	0.98	8647
Macro Avg		0.98	0.98	0.98	8647
Weighted Avg		0.98	0.98	0.98	8647

Model Accuracy: 0.98

The model performed especially well in identifying high-risk zones in both regions. The slightly lower recall in Class 2 (High Risk) in Ile-Ife suggests a small number of false negatives, likely due to complex terrain-induced transitions.

3.2. Confusion Matrix Interpretation

The confusion matrices in Figures 2a and 2b show the predicted vs. actual class distribution.

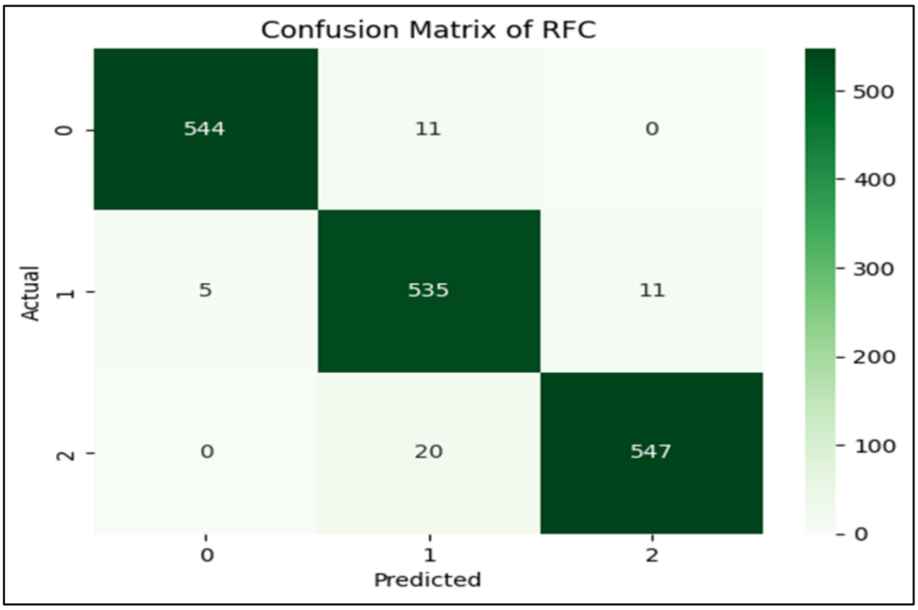

Figure 2a Confusion Matrix for Ile-Ife

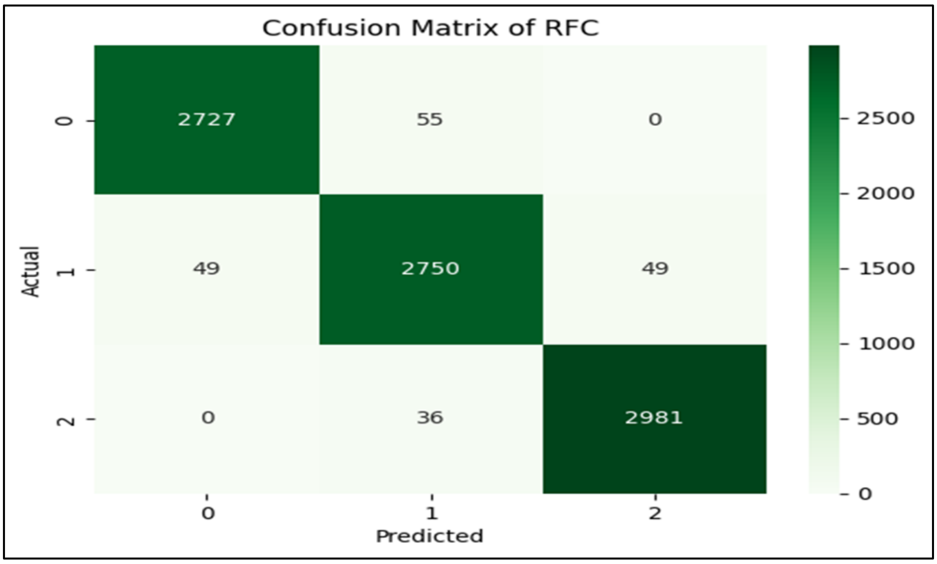

Figure 2b Confusion Matrix for Ilaje

In Ile-Ife, the model correctly predicted:

- 544 out of 555 instances of Class 0 (No Flood)
- 535 out of 551 instances of Class 1 (Moderate Risk)
- 547 out of 567 instances of Class 2 (High Risk)

In Ilaje, the RF model correctly classified:

- 2,727 out of 2,782 instances of Class 0
- 2,750 out of 2,848 instances of Class 1
- 2,981 out of 3,017 instances of Class 2

Strong diagonal dominance is confirmed by these matrices, suggesting high class-specific accuracy and little confusion, especially between Class 1 and Class 2.

3.3. Analysis of Feature Importance

Internal feature importance scores, which measure each variable's contribution to classification decisions, are provided by Random Forest. The feature importance plots for Ilaje and Ile-Ife are shown in Figures 3a and 3b, respectively.

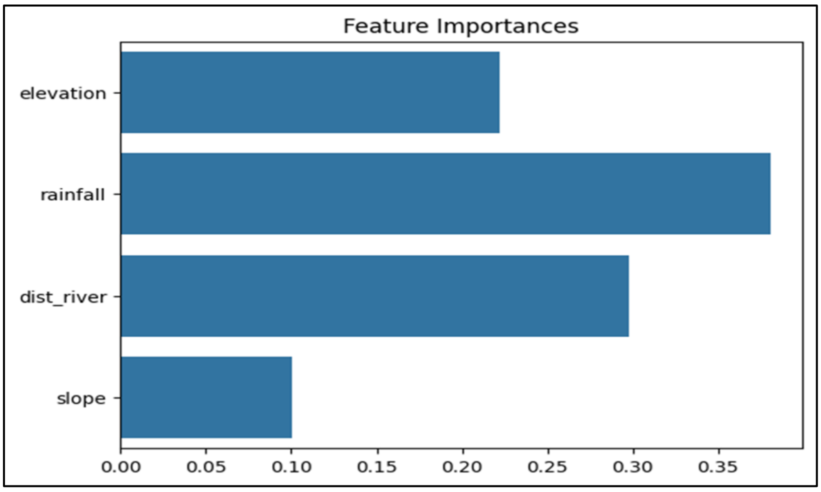

Figure 3a Feature Importance (Ile-Ife)

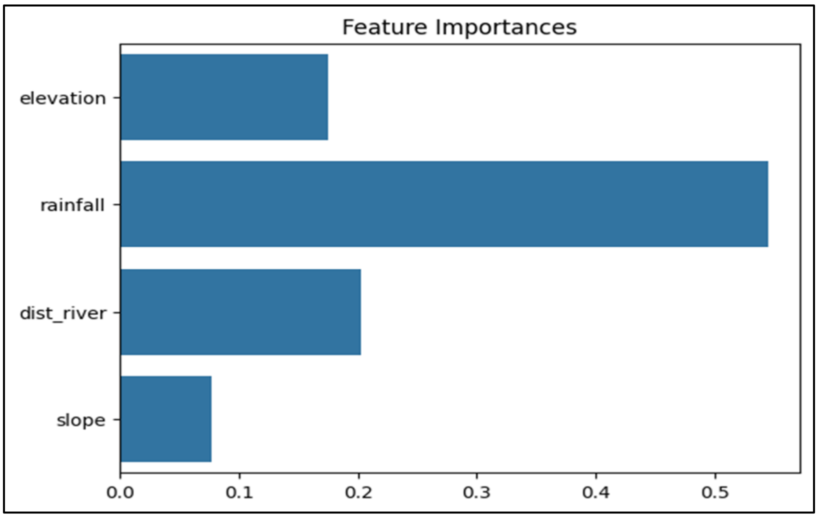

Figure 3b Feature Importance (Ilaje)

Rainfall and river proximity were found to be the most significant factors in both Ile-Ife and Ilaje, underscoring the importance of hydrological inputs and river proximity in determining flood susceptibility in both inland and coastal terrains.

3.4. Regional Interpretation in Comparison

The usefulness of using a consistent hybrid modeling framework across disparate physiographic environments is illustrated by the comparative results between Ilaje and Ile-Ife. Although the two regions' primary flood drivers were rainfall and river proximity, there were notable differences in the spatial expression of flood risk. Ilaje's extensive hydrological networks and uniform elevation made it more spatially continuous in terms of flood susceptibility. Ile-Ife's vulnerability, on the other hand, was more dispersed and influenced by slope variability and topographic complexity. These results demonstrate the significance of context-specific planning for flood risk mitigation and validate the framework's sensitivity to local hydrology and terrain.

4. Conclusion

The Analytic Hierarchy Process (AHP) and the Random Forest (RF) machine learning algorithm are combined in this study to create a novel hybrid framework for flood susceptibility modeling that produces high-accuracy, interpretable flood risk maps. The study provides one of the first cross-regional, ML-enhanced flood assessments in the nation by using this approach in two physiographically distinct regions: Ile-Ife (an inland upland terrain) and Ilaje (a low-lying coastal environment) in southwest Nigeria. By filling two enduring gaps in the geospatial flood modeling literature the limited investigation of physiographic heterogeneity in flood risk mapping and the black-box nature of machine learning models this comparative design advances the field.

Despite having distinct spatial expressions of risk, the results show that rainfall and river distance are the main predictors of flood susceptibility in both regions. Because of its flat terrain and closeness to estuarine and coastal channels, Ilaje's vulnerability is spatially continuous, but Ile-Ife shows a more fragmented risk pattern that is influenced by intricate slope dynamics and elevation profiles. Notwithstanding these variations, the suggested AHP–RF framework produced strong classification results, with 98% and 97% accuracy rates in Ilaje and Ile-Ife, respectively. The model's excellent performance in differentiating between low, moderate, and high flood risk zones was further supported by evaluation metrics such as precision, recall, and F1-score.

The hybrid model makes important conceptual and practical contributions in addition to its technical performance. Methodologically, it enables both interpretability and data-driven classification by fusing the flexibility of RF with the transparency of AHP. From a conceptual standpoint, it shows how a consistent modeling framework can be used with great spatial sensitivity in a variety of physiographic zones. Because of its scalability, the model can be used to adapt to other flood-prone and data-poor Sub-Saharan African regions. Additionally, the operational viability of the framework for planners and local authorities is improved by the utilization of publicly available geospatial datasets and open-source tools such as Google Earth Engine.

This work has equally significant policy implications. The AHP–RF framework's proven scalability and dependability provide urban and regional planners with a useful tool for incorporating flood susceptibility into infrastructure development, land-use zoning, and disaster preparedness plans. Second, evidence-based decision-making and stakeholder engagement are facilitated by the model's interpretability, which is demonstrated by both AHP weights and RF feature importance. Third, the necessity for focused catchment management techniques, such as afforestation, floodplain restoration, and real-time hydrological monitoring, is highlighted by the discovery that rainfall and river proximity are the two most important variables.

Crucially, the findings require policy responses that take terrain into account. Wetland conservation, hydrological connectivity, and the development of drainage infrastructure should be given top priority in policy initiatives in flat coastal regions like Ilaje. Slope stabilization, zoning enforcement on susceptible hillsides, and stormwater control system investment should be prioritized in upland urban areas such as Ile-Ife. These unique approaches can support larger climate adaptation initiatives while enhancing local flood resilience.

In the end, this research closes the gap between innovative methodology and useful policy assistance. It adds a robust, interpretable, and reproducible modeling approach to the expanding field of geospatial disaster risk science. The model could be improved in future work by adding dynamic environmental variables, experimenting with different ensemble learning algorithms, and comparing results with participatory GIS or historical flood inventories. Frameworks like this, which are based on both data and domain knowledge, are essential for promoting equitable and sustainable flood risk governance in vulnerable areas as climate change exacerbates hydrological variability.

5. Limitations of the study

By combining the Analytic Hierarchy Process (AHP) and Random Forest (RF), this study presents a strong and understandable framework for flood susceptibility modeling; however, in order to put the results in perspective and direct future developments, some limitations must be noted. Elevation, slope, long-term mean rainfall, and distance to rivers are the main static environmental variables used in the modeling approach, which are obtained from globally distributed and remotely sensed datasets. Even though these factors are commonly acknowledged as key factors that influence flood vulnerability, the model's ability to respond to short-term flood drivers like intense rainfall, seasonal variations in land cover, or abrupt hydrological changes is constrained by the lack of temporal variability. This lessens its usefulness for early warning or real-time flood forecasting applications.

Furthermore, rather than using historical flood occurrence records, the classification labels used for supervised learning were derived from a reclassified Flood Susceptibility Index (FSI). Despite being interpretable and methodologically sound, this approach may introduce latent biases because it lacks empirical ground-truth validation. Therefore, an incomplete representation of actual flood dynamics may limit the model's performance in areas with localized or undocumented flooding events. Although it is based on the spatial extent and terrain structure, the disparity in sampling density between Ilaje and Ile-Ife may also introduce minor discrepancies in comparative performance. Although methodological reasoning supported this design choice, it might have an impact on the level of detail in the spatial patterns recorded in each area.

Furthermore, the study was restricted to four main variables, leaving out potentially significant elements like soil type, drainage density, infrastructure proximity, and land use/cover. The model’s capacity to represent anthropogenic and compound flood risks may be improved by adding such variables, especially in quickly urbanizing environments where hydrological processes are heavily mediated by human activity.

Lastly, although statistically balanced, the conversion of continuous FSI values into categorical flood risk classes using quantile-based thresholds may mask transitional gradients in susceptibility. In areas where risk boundaries are not clearly defined, this could result in overgeneralization. When combined, these drawbacks emphasize how crucial it is to make additional improvements, especially by incorporating ground-truth flood inventories, dynamic datasets, and a wider range of predictor variables. The model's operational reliability will be increased, and its applicability to adaptive flood resilience planning, participatory risk mapping, and early warning systems will be expanded.

Compliance with ethical standards

Disclosure of conflict of interest

According to the authors, there were no business or financial relationships that would have raised concerns about a potential conflict of interest during the study.

Declarations of Ethics and Transparency

Author Contributions: The authors acknowledge that they played a major role in the study's design, execution, and reporting.

Adebisi Joseph Ademusire contributed to the conceptualization of the study, provided critical review of the methodology, and participated in the analysis and visualization of results, including charts and maps.

John Adeyemi Eyinade led the methodological design, including data collection, preprocessing, and model development. He prepared the initial manuscript draft, coordinated the integration of all analytical components, and was responsible for substantive manuscript editing and intellectual oversight.

The final draft of the manuscript was examined and approved by both authors, who also pledged to take responsibility for every part of the work, guaranteeing its integrity and accuracy.

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