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Integrating Machine Learning and Multi-Criteria Decision Analysis for Flood Susceptibility Mapping in the Hadejia–Jama'are River Basin

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Abstract

Flooding remains a recurrent environmental hazard in semi-arid northern Nigeria, particularly within the Hadejia–Jama'are River Basin, where the interaction of topographic, hydrological, and anthropogenic factors intensifies vulnerability. This study developed an integrated geospatial modelling framework combining machine learning techniques with Multi-Criteria Decision Analysis (MCDA) to produce accurate and spatially explicit flood susceptibility maps. A hybrid approach integrating the Analytical Hierarchy Process (AHP) with Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF) models was applied using ten conditioning factors, including elevation, slope, rainfall, drainage density, Topographic Wetness Index, land use/land cover, soil texture, flow accumulation, and river proximity, standardized to 30 m resolution. Multicollinearity diagnostics (VIF < 5; TOL > 0.2) ensured model reliability, while performance was evaluated using ROC–AUC metrics. Results revealed that low-lying northern zones (316–435 m), areas with high drainage density (27.2–34.2 km/km²), and regions receiving 1180–1440 mm rainfall exhibited the highest flood susceptibility. The AHP model classified 83.7% of the basin as moderate risk, whereas SVM showed more spatial differentiation with 29.2% moderate, 27.3% high, and 11.5% very high susceptibility (6,323.11 km²). ANN and RF models also indicated dominance of moderate susceptibility (76.1% and 73.3%), with high-risk areas reaching 18.5% and 22.7%, respectively. AHP achieved the highest predictive accuracy (AUC = 0.91), followed by SVM (0.83), RF (0.81), and ANN (0.79), demonstrating that while AHP ensures robustness, machine learning models provide better spatial discrimination of flood-prone zones.

Keywords: Flood susceptibility mapping; Machine learning; Analytical Hierarchy Process (AHP); Hadejia–Jama'are River Basin; Geographic Information Systems (GIS)

INTRODUCTION

Flooding remains one of the most recurrent and destructive natural hazards globally, with disproportionate impacts in semi-arid and riverine environments where rapid hydrological responses and limited infrastructure exacerbate vulnerability (Nabinejad and Schüttrumpf, 2023). In Nigeria, the Hadejia–Jama'are River Basin (HJRB) is particularly prone to seasonal flooding driven by intense rainfall, upstream inflows, low-lying floodplains, and anthropogenic alterations such as dam operations and land-use change (Iliyasu, 2017). These recurrent flood events have significant implications for agriculture, livelihoods, infrastructure, and ecosystem stability, especially within the Hadejia–Nguru wetlands. As climate variability intensifies rainfall extremes and population pressures expand into flood-

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prone areas, the need for accurate and spatially explicit flood susceptibility assessments has become increasingly urgent (Bello et al., 2024).

Flood susceptibility mapping provides a critical decision-support tool for identifying areas at risk and guiding mitigation strategies, land-use planning, and disaster preparedness (Rezvani et al., 2023). Traditional approaches, including hydrological and statistical models, have offered valuable insights but are often constrained by data limitations, assumptions of linearity, and challenges in capturing complex interactions among environmental factors (Kumar et al., 2023). In recent years, machine learning (ML) techniques have gained prominence due to their ability to model nonlinear relationships, handle large geospatial datasets, and improve predictive accuracy (Siddique, 2024). Algorithms such as Random Forest, Support Vector Machine, and Boosted Regression Trees have demonstrated strong performance in flood susceptibility modelling by learning from historical flood occurrences and multiple conditioning factors (Choubin et al., 2019).

Previous studies in the Hadejia–Jama'are River Basin (HJRB) have employed diverse methodological approaches to understand flood dynamics, vulnerability, and impacts. Early work by Kimmage and Adams (1992) and Thompson (1995) used hydrological and field-based assessments to examine floodplain dynamics, revealing that flood extent, timing, and duration are critical for sustaining wetland agriculture and groundwater recharge, but are increasingly altered by river basin development and dam regulation. Similarly, Thomas (1996) and Thomas and Adams (1997) analyzed ecological and spatial-temporal changes using environmental monitoring and basin-scale analysis, finding that dam construction significantly modifies natural flooding regimes and wetland ecosystems. From a hydro-climatic perspective, Odunuga et al. (2011) applied hydro-climatic data analysis to demonstrate variability in river flow and floodplain inundation linked to climate fluctuations and land-use change, while Ibrahim et al. (2016) conducted flood frequency analysis using statistical distribution models on long-term discharge data, identifying increasing trends in extreme flood events. More recent studies have incorporated geospatial and remote sensing techniques; Yahaya et al. (2010) applied GIS-based multi-criteria analysis (MCA) to map flood-vulnerable areas, highlighting topography, drainage, and land use as key determinants, whereas Odewole et al. (2020) utilized Earth observation data for flood damage assessment, showing significant land cover loss and spatial variability in flood impacts during the 2018 event. In addition, Babati et al. (2022) employed statistical and probabilistic models to predict flood occurrence and magnitude, reporting that upstream hydrological controls and rainfall variability strongly influence flood behavior in the basin. Despite the substantial body of research on flood dynamics in the Hadejia–Jama'are River Basin, a clear gap remains in the development of integrated, data-driven, and decision-support-oriented flood susceptibility models. Consequently, there is limited exploration of hybrid methodologies that combine the predictive strength of machine learning with the interpretability and structured decision-making of MCDA. This gap is particularly critical in the HJRB, where complex interactions among hydro-climatic variability, land-use dynamics, and anthropogenic interventions require more robust, accurate, and context-sensitive modelling approaches for effective flood risk assessment and management.

The objective of this study was to develop an integrated geospatial framework that combines machine learning algorithms and multi-criteria decision analysis (MCDA) to produce accurate and reliable flood susceptibility maps for the Hadejia–Jama'are River Basin. The significance of this work lies in its potential to enhance flood risk assessment and support informed decision-making for land-use planning, disaster risk reduction, and climate resilience in a highly vulnerable river basin. The novelty lies specifically in the systematic integration and comparative evaluation of Multiple Machine Learning (ML) models (SVM, ANN, RF) with an MCDA-based AHP framework within a single geospatial modelling environment. Unlike many previous studies that either apply these methods independently or combine them without rigorous validation, this study not only integrates them but also quantitatively compares their predictive performance using ROC–AUC metrics, thereby providing empirical insight into their relative strengths under semi-arid conditions. Furthermore, this study incorporates multicollinearity testing, standardized spatial datasets, and consistent validation procedures, ensuring methodological robustness. In terms of contribution, this research provides: (1) a replicable hybrid modelling framework for flood susceptibility mapping; (2) improved spatial characterization of flood-prone zones, particularly along river corridors where ML models demonstrated higher sensitivity; and (3) context-specific evidence showing that expert-driven approaches like AHP can achieve competitive or superior performance when supported by high-quality data and domain knowledge. Importantly, this study advances the discourse by demonstrating that ML and MCDA approaches are complementary rather than competing, providing practical guidance for policymakers on selecting appropriate methods based on data availability, expertise, and application context. The findings are particularly relevant to a wide audience, including researchers in geospatial science and hydrology, urban and regional planners, environmental managers, policymakers, and disaster management agencies seeking effective tools for flood risk mitigation.

MATERIALS AND METHODS

The Study Area

The Hadejia–Jama'are River Basin (HJRB), located between 10^0N–13^0N and 7^0E–12^0E in northern Nigeria, spans parts of Kano, Jigawa, Yobe, Bauchi, Plateau, Kaduna, and Katsina states and forms a critical part of the Komadugu-Yobe drainage system feeding into Lake Chad (Odewole et al., 2020). Elevations range from 316 m in the northern lowlands to 1761 m in the southern highlands, shaping runoff and flood dynamics. The semi-arid climate exhibits extreme temperatures (12–40^0C) and highly seasonal rainfall, increasing from 200 to 600 mm (Jajere et al., 2023). Soils vary from sandy loam to clay-rich types, with low-permeability clays in southern areas exacerbating runoff, while vegetation transitions from Sahel to Sudan Savanna, dominated by drought-tolerant grasses, shrubs, and scattered trees. The basin's dendritic drainage network, major rivers, floodplains, and human activities such as agriculture and settlements along rivers enhance susceptibility to seasonal flooding. The interplay of topography, rainfall, soil, vegetation, and land use creates spatially variable flood risks, highlighting the importance of geospatial and hydrological analyses for effective flood management and land-use planning.

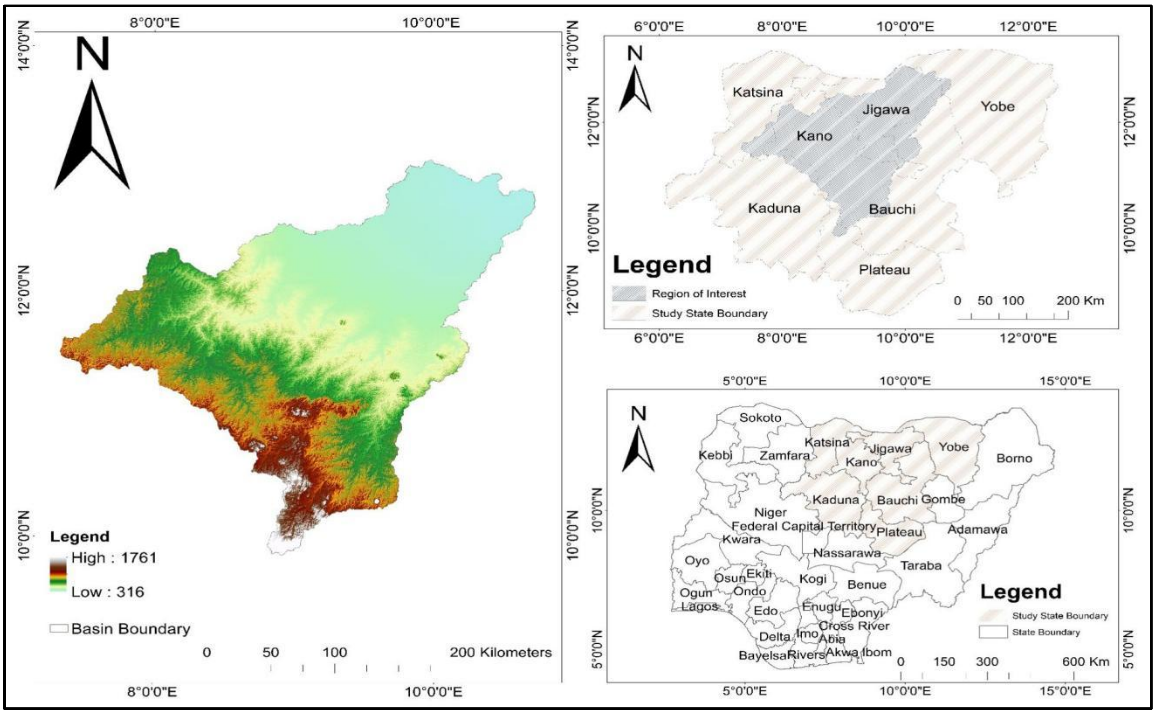

Figure 1: Study Area Map

METHODOLOGY

Data Collection and Processing

Flood susceptibility modelling requires the integration of diverse topographic, hydrological, and environmental datasets. For the Hadejia–Jama'are River Basin (HJRB), data were sourced from remote sensing platforms and historical records. A 30 m resolution Digital Elevation Model (DEM) from ALOS PALSAR was used to derive topographic indices (Giacon and da Silva, 2025). Rainfall data were obtained from the CHIRPS dataset spanning 1994–2024 to capture long-term precipitation trends (Rahbeh et al., 2026). Land Use and Land Cover (LULC) information was derived from Sentinel-2 imagery using the ESA WorldCover product, while soil data were sourced from the Harmonized World Soil Database (HWSD). All datasets were standardized to a 30 m spatial resolution and projected to UTM Zone 32N to ensure consistency in the modelling process.

Table 1: Data Type and Sources

Layer	Data Type	Source	Spatial Resolution
Elevation	Raster (DEM)	Shuttle Radar Topography Mission (SRTM) via ALOS PALSAR	12.5 m (ALOS PALSAR)
Slope	Raster	Derived from DEM (ALOS PALSAR)	12.5 m
Drainage Density	Raster	Derived from DEM and River Network data	12.5 m
Topographic Wetness Index (TWI)	Raster	Derived from DEM (ALOS PALSAR)	12.5 m
Land Use Land Cover (LULC)	Raster	Sentinel-2 (ESA Copernicus)	10 m (Sentinel-2)
Soil Texture	Vector	Harmonized World Soil Database (HWSD) by FAO	1 km (HWSD)
River Proximity (Distance to River)	Raster	Derived from River Network (extracted from DEM, Land Use Land Cover and OpenStreetMap)	12.5 m
Flow Accumulation	Raster	Derived from DEM (ALOS PALSAR)	12.5 m

Rainfall	Point Data	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and Nigerian Meteorological Agency (NiMet)

Geospatial Layer Derivation and Factor Selection: Flood conditioning factors were derived using GIS techniques from processed datasets. Topographic variables (elevation, slope, aspect) were extracted from the DEM, while hydrological indices such as the Topographic Wetness Index (TWI) were computed to represent runoff and water accumulation potential (Khan et al., 2026). Environmental variables, including distance to rivers and drainage density, were generated using Euclidean distance and line density functions, which influence runoff direction and flood distribution. To ensure model reliability, multicollinearity analysis was conducted using Variance Inflation Factor (VIF) and Tolerance (TOL), retaining only variables with VIF < 5 and TOL > 0.2 to avoid redundancy and improve predictive accuracy (Long et al., 2025; Swain et al., 2020).

Flood Susceptibility Modelling: A hybrid approach integrating Multi-Criteria Decision Analysis (MCDA) and Machine Learning (ML) was employed. The Analytical Hierarchy Process (AHP) was used to assign weights to conditioning factors through pairwise comparison, ensuring consistency (Abubakar et al., 2022). Three ML models Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF) were implemented. SVM with an RBF kernel captured non-linear relationships, ANN modeled complex patterns through iterative learning, while RF, an ensemble of decision trees, enhanced prediction accuracy and minimized overfitting.

Support Vector Machine (SVM): SVM is a statistical learning-based method used for classification and regression, particularly effective for small, non-linear, and high-dimensional datasets (Khan et al., 2023). It operates by constructing an optimal hyperplane that maximizes the margin between data points, ensuring strong generalization. Key parameters include the kernel function, which captures data similarity, and the regularization parameter, which controls model complexity.

Accuracy Assessment and Mapping: Model performance (AHP, SVM, ANN, RF) was evaluated using ROC–AUC, alongside sensitivity, specificity, and Kappa coefficient (Maeng et al., 2006). Final flood susceptibility maps were generated in GIS and classified into five categories (Very Low to Very High) using the Natural Breaks method.

Flood Susceptibility Indicators: Key indicators included elevation (316–1760 m), soil texture, TWI (−9.2 to 15.8), drainage density (4.87–34.2 km/km^2), flow accumulation, slope, rainfall (77.5–1440 mm), river proximity, and LULC. Low elevation, clay soils, high TWI, dense drainage, and built-up areas were associated with higher flood risk, consistent with findings in similar semi-arid basins.

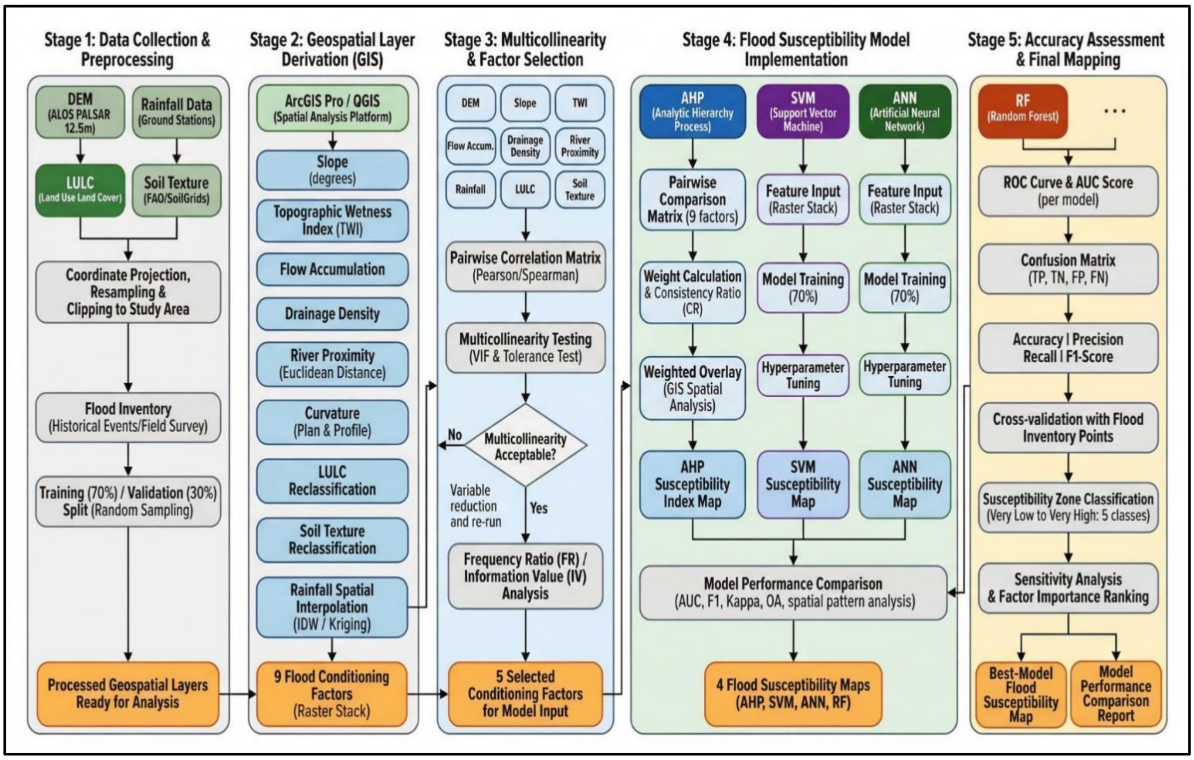

Figure 2: Methodology Flowchart

RESULTS AND DISCUSSION

The elevation pattern in Figure 3(a) shows a clear gradient, with low-lying areas (316–435 m) dominating the northern zones and higher elevations (>725 m) concentrated in the south, indicating that runoff is generated in upland areas and accumulates in downstream plains, increasing flood risk. This finding aligns with studies that identify low-elevation floodplains as primary zones of inundation due to water convergence (Paira and Drago, 2007; Jay et al., 2016). Similarly, the flow accumulation map (Figure 3b) highlights major drainage pathways where runoff concentrates, with high accumulation zones corresponding to river channels and depressions, consistent with findings that areas of high flow convergence are more prone to flooding during intense rainfall (Osterkamp and Friedman, 2000). The LULC distribution (Figure 3c) indicates dominance of farmland and shrubland, with built-up areas contributing to increased runoff due to reduced infiltration, while wetlands provide temporary storage; this agrees with Mahmoud and Gan (2018), who noted that urban and agricultural expansion intensifies flood susceptibility. Furthermore, the TWI map (Figure 3d) shows that moderate to high values dominate the basin, indicating widespread soil moisture and saturation potential, particularly in low-lying areas. This is consistent with findings by Kelleher and McPhillips, (2020), who emphasized that high TWI zones correspond to areas of increased runoff generation and flood likelihood.

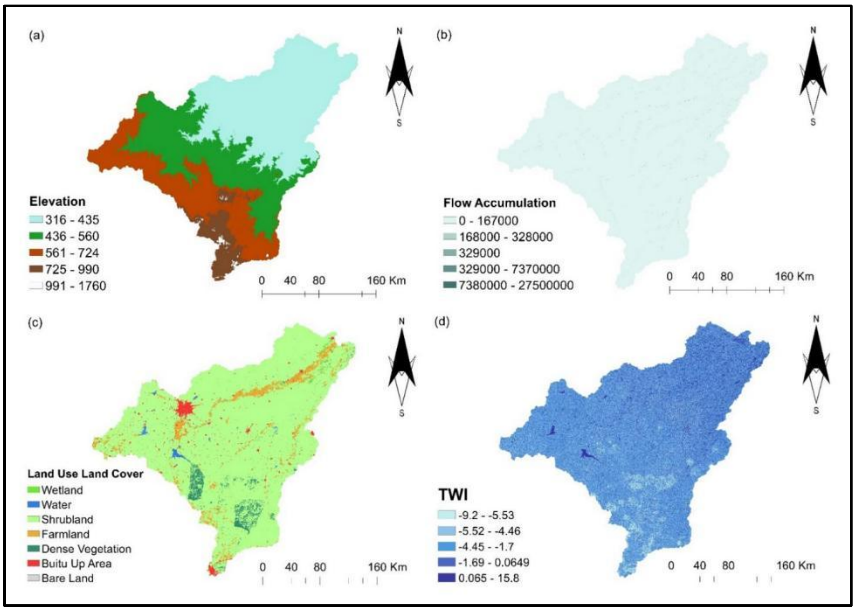

Figure 3: Geospatial Features of Generating Flood Susceptibility Map a) Elevation b) Flow Accumulation c) Land Use Land Cover, d) Topographic Wetness Index (TWI)

The rainfall distribution in Figure 3(e) shows a south–north gradient, with higher precipitation (1180–1440 mm) in the southern basin and lower values (77.5–624 mm) in the north, indicating that southern zones are more prone to intense runoff generation and flooding. This pattern is consistent with studies that link high rainfall intensity to increased flood susceptibility, especially in tropical and semi-arid basins (Abubakar et al., 2025). The drainage density map (Figure 3f) reveals that northeastern areas with high values (27.2–34.2 km/km²) are more vulnerable to rapid runoff concentration and flash floods, aligning with Abubakar et al. (2025), who emphasized that dense drainage networks accelerate flow convergence and flood peaks. Soil distribution (Figure 3g) shows dominance of sandy loam with patches of clay-rich soils, which under prolonged rainfall can reduce infiltration and enhance surface runoff; this agrees with Marapara et al. (2021), who identified low-permeability soils as key contributors to flood generation. Furthermore, slope analysis (Figure 3h) indicates that gentle slopes (0–2.5°) dominate the basin, promoting water accumulation and prolonged inundation, while steeper slopes facilitate runoff but may increase downstream flood risk. This finding supports Zhang et al. (2023), who noted that flat terrains are more susceptible to flooding due to poor drainage.

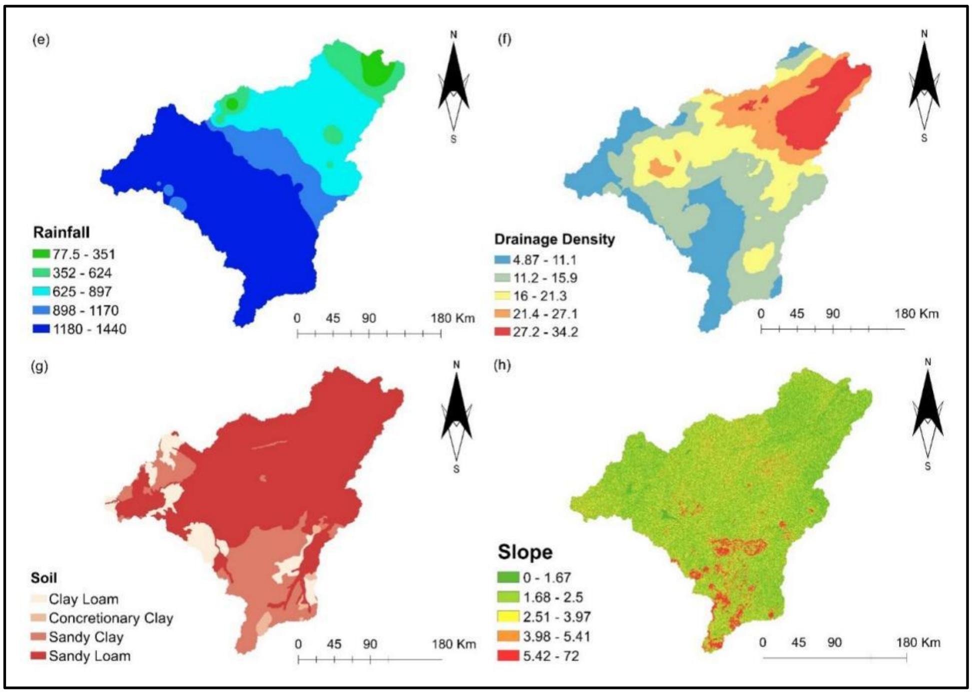

Figure 3: Continue. e) Rainfall f) Drainage Density g) Soil Texture, h) Slope

Figure 3(i) highlights the spatial relationship between water bodies and settlements using buffer zones, revealing that many communities are concentrated within 400–800 m of river channels, particularly in the central and northeastern basin. This close proximity increases flood vulnerability due to exposure to river overflow, bank erosion, and rapid inundation during peak flows. Similar findings have been reported in floodplain studies, where settlements near rivers are consistently identified as high-risk zones due to direct hydraulic connectivity (Yang et al., 2022). The clustering of settlements along river corridors reflects dependence on water resources for agriculture and livelihoods, a pattern widely observed in developing regions despite associated risks. In contrast, settlements located beyond 1000 m show relatively lower exposure to riverine flooding, although they may still be affected by pluvial or upstream-driven flooding processes. This spatial variation aligns with studies indicating that flood risk decreases with increasing distance from river channels but remains influenced by other factors such as rainfall intensity and drainage conditions (O'Neill et al., 2016).

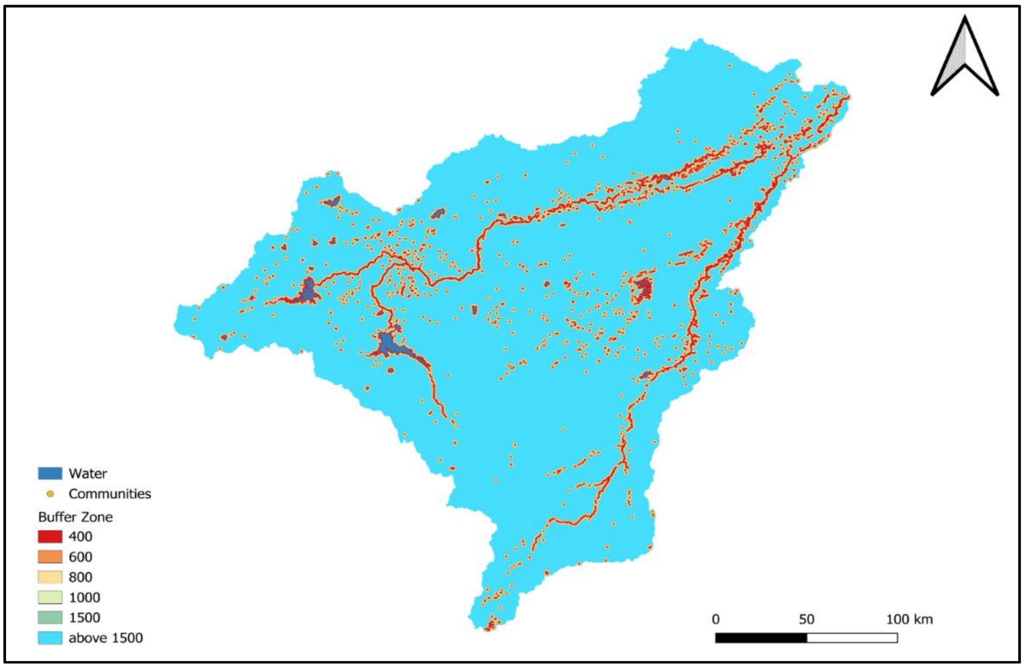

Figure 3(i): Continue. Spatial distribution of water bodies and community settlements in the Hadejia–Jama'are River Basin showing proximity-based buffer zones (400 m, 600 m, 800 m, 1000 m, 1500 m, and >1500 m) used to assess settlement exposure to riverine flood risk

Flood Susceptibility Maps

Figure 4 compares flood susceptibility outputs from AHP, SVM, ANN, and RF models, revealing clear methodological differences. The AHP model produces a largely uniform pattern dominated by moderate susceptibility (≈45,699.89 km²), with limited high-risk delineation and negligible very high zones (0.03 km²), reflecting its reliance on expert-driven weighting and tendency to generalize spatial variability. This aligns with studies noting that AHP often smooths flood patterns and underrepresents localized extremes (Abubakar et al., 2025). In contrast, machine learning models exhibit greater spatial detail. The SVM model identifies extensive high (15,045.22 km²) and very high (6,323.11 km²) risk zones, particularly along the river corridors, demonstrating strong capability in capturing nonlinear relationships, consistent with findings by Samanta et al. (2016). The ANN model shows improved differentiation but with dominance of moderate zones (41,566.42 km²), reflecting its strength in pattern recognition but some generalization. Meanwhile, the RF model provides a more balanced distribution, with clear moderate (40,014 km²) and high-risk (12,384.01 km²) zones, supporting its robustness and resistance to overfitting (Khosravi et al., 2018; Pham et al., 2021).

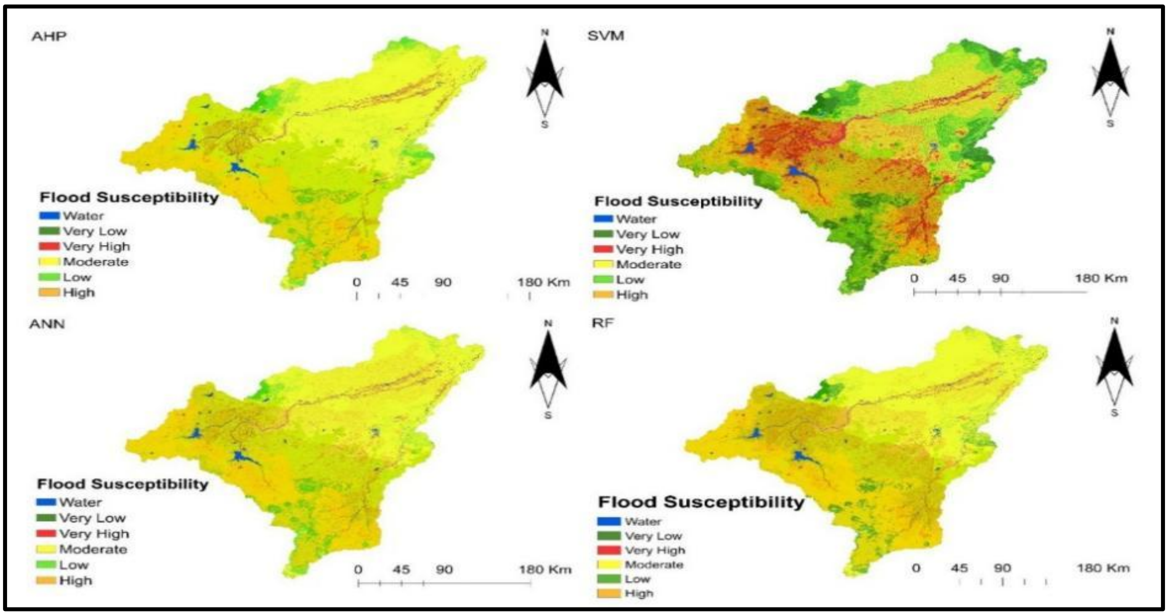

Figure 4: Flood Susceptibility Maps a) AHP b) SVM c) ANN and d) RF

Figure 5 highlights notable differences in flood susceptibility classification across the four models. The AHP model is strongly dominated by the moderate class (83.7%), with minimal representation of low (8.0%) and high (8.3%) categories and almost no very high-risk areas, indicating a generalized pattern typical of expert-based weighting approaches (Abubakar et al., 2025; Rahmati et al., 2016). Similarly, the ANN model shows a high concentration in the moderate class (76.1%) but with improved representation of high-risk zones (18.5%), reflecting its ability to capture nonlinear relationships, though still prone to output smoothing. In contrast, the SVM model presents the most balanced distribution (29.2% moderate, 27.3% high, 21.9% low, 11.5% very high, 10.0% very low), demonstrating strong discriminatory power and consistency with studies that highlight its effectiveness in handling complex environmental data. The RF model shows a moderate dominance (73.3%) with notable high-risk areas (22.7%) but minimal extremes, suggesting a more conservative yet stable classification. This aligns with literature identifying RF as robust and reliable, effectively balancing bias and variance in flood susceptibility modelling (Ren et al., 2024).

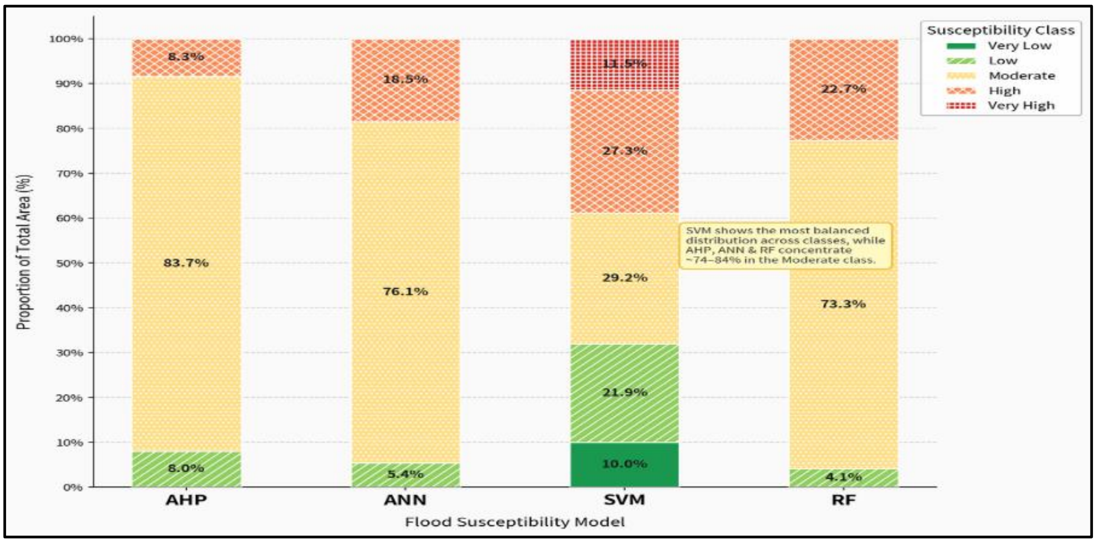

Figure 5: Distribution of Flood Risk Locations from AHP, ANN, SVM and RF

Model Performance and Validation

The predictive performance of the four flood susceptibility models (AHP, SVM, RF, ANN) was evaluated using ROC curves and AUC values (Figure 6), where higher AUC indicates better discrimination between flood-prone and non-flood-prone areas (Rahmati et al., 2016). The AHP model achieved the highest AUC (0.91), reflecting excellent predictive capability despite its knowledge-driven approach, likely due to accurate weighting of flood conditioning factors; similar findings have been reported where expert judgment aligns well with environmental conditions (Abubakar, 2025). However, many studies often report lower MCDA accuracy compared to machine learning, emphasizing the importance of input quality and weight assignment (Vojtek et al., 2021). Among the ML models, SVM performed best (AUC = 0.83), followed by RF (0.81) and ANN (0.79), indicating good predictive accuracy. SVM's superior performance aligns with literature highlighting its strength in handling nonlinear, high-dimensional data for environmental modelling (Camps-Valls et al., 2004). RF demonstrated robustness due to its ensemble structure, consistent with reports of RF effectively managing multicollinearity and preventing overfitting, though its slightly lower AUC may reflect parameter sensitivity or data distribution. ANN, while still acceptable, showed the lowest AUC, corroborating previous studies that its performance depends heavily on network configuration, training data size, and parameter tuning, and may underperform if not properly optimized (Abdolrasol et al., 2021).

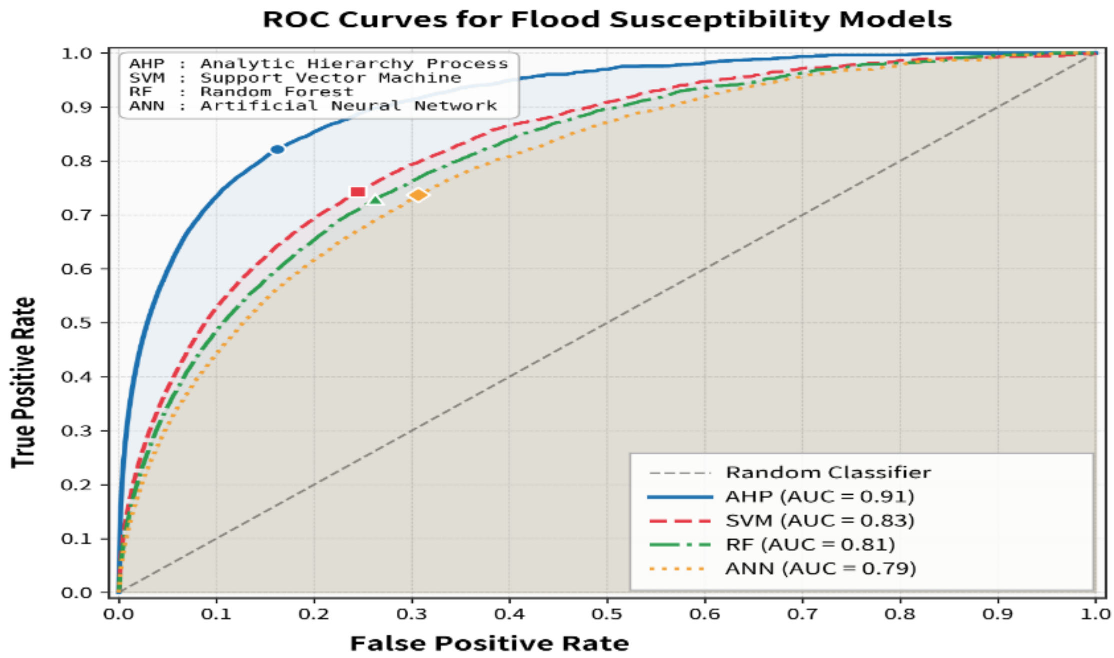

Figure 6: ROC and AUC Analysis for Flood Susceptibility Models (AHP, SVM, RF and ANN)

Correlation Analysis of Flood Causative Factors

Understanding correlations among flood causative factors is essential for model reliability. The heat map (Figure 7) shows strong negative correlation between Elevation and Drainage Density (r = -0.768), moderate negative between Rainfall and Drainage Density (r = -0.648), and moderate positive between Rainfall and Elevation (r = 0.586), reflecting orographic effects and Sahelian hydrology. Flow Accumulation–TWI (r = 0.488) and Slope–TWI (r = -0.356) highlight terrain-driven moisture retention, while Soil Texture–Elevation (r = 0.475) indicates coarser soils at higher altitudes. In MCDA models like AHP, high correlations (e.g., Elevation–Drainage Density) risk double-counting, potentially biasing results, whereas ML models (SVM, ANN, RF) benefit from feature scaling and screening to improve stability and interpretability. RF can generally handle correlated predictors, though variable importance should note dependencies among Elevation, Drainage Density, and Rainfall. Comparable studies in Jiangxi and the Lower Niger Basin report similar patterns, validating the generalizability of these relationships. Categorical variables such as Land Use/Land Cover and Soil Texture should be treated appropriately to avoid misleading correlations. Notably, AHP outperformed ML models in AUC for this dataset, suggesting that expert-driven weighting can sometimes surpass purely data-driven approaches, depending on local conditions and data quality. These results underscore the value of addressing multicollinearity, careful feature engineering, and potentially integrating MCDA with ML in hybrid frameworks to leverage both expert knowledge and algorithmic strengths for robust flood susceptibility mapping.

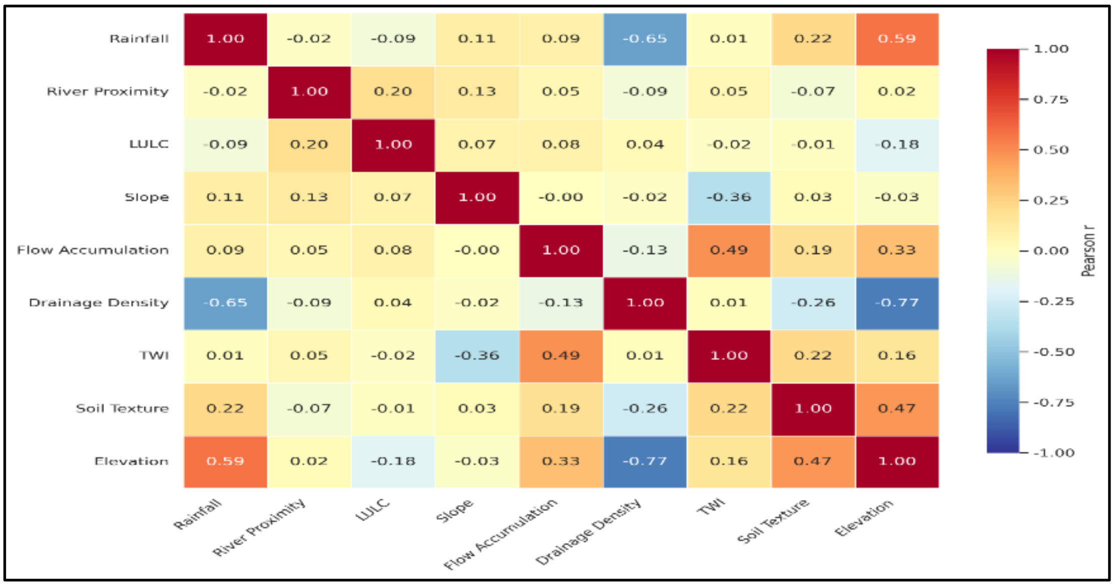

Figure 7: Correlation Matrix of Flood Causative Factors

CONCLUSION

This study addressed the persistent challenge of accurately identifying flood-prone areas in the Hadejia–Jama'are River Basin, where the interaction of topographic, hydrological, climatic, and anthropogenic factors increases vulnerability to recurrent flooding. The findings reveal that flood susceptibility is largely concentrated in low-elevation northern zones, areas characterized by high drainage density, moderate-to-high Topographic Wetness Index values, and regions experiencing relatively higher rainfall intensity, highlighting the dominant role of terrain and hydrological processes in shaping flood dynamics. The results further show clear differences in model outputs, with the Analytical Hierarchy Process (AHP) producing more generalized susceptibility patterns but achieving the highest predictive accuracy, while machine learning models particularly Support Vector Machine (SVM) and Random Forest (RF) provided improved spatial discrimination and more detailed identification of high-risk zones, especially along river channels and floodplains. These findings highlight the importance of balancing predictive accuracy with spatial detail in flood susceptibility assessments. A key takeaway from this study is that no single modelling approach is universally superior; rather, the effectiveness of each method depends on the characteristics of the study area and the quality of available data. This study therefore contributes valuable insights for flood risk management by providing spatially explicit information that can support land-use planning and disaster mitigation efforts. It also emphasizes the need for future research to integrate real-time hydrological data and refine modelling approaches to enhance prediction accuracy and strengthen resilience in flood-prone regions.

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