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RESEARCH ARTICLE

Applications of Satellite Remote Sensing for Flood Risk and Disaster Management in Abuja, Nigeria

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Abstract
Flooding remains a major environmental challenge in Abuja, Nigeria, driven by rapid urbanisation, land-use changes, inadequate drainage infrastructure, and climate variability. This study employed satellite remote sensing and Geographic Information System (GIS) techniques to assess flood risk within the Federal Capital Territory using Sentinel-1 SAR imagery, ESRI Sentinel-2 land-use/land-cover data, SRTM Digital Elevation Model data, rainfall records, and drainage information. Flood susceptibility was evaluated through a Multi-Criteria Decision-Making (MCDM) framework incorporating land use/land cover, drainage density, elevation, rainfall, slope, and river proximity factors. The land-cover classification achieved an overall accuracy of 90% with a Kappa coefficient of 0.86. Rangeland and cropland constituted the dominant land-cover classes, accounting for 41.85% and 33.69% of the study area, respectively. The flood susceptibility model classified approximately 9% of Abuja as very high risk, 17% as high risk, 39% as moderate risk, 19% as low risk, and 16% as very low risk. High-risk zones were concentrated within AMAC, Bwari, Gwagwalada, Kwali, and Abaji due to low elevations, dense drainage networks, proximity to rivers, and increasing urban development. The findings demonstrate the effectiveness of integrating remote sensing and GIS technologies for flood risk assessment and provide valuable evidence for disaster management, urban planning, and climate adaptation strategies in rapidly growing African cities.

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1. INTRODUCTION

Flooding is among the most devastating environmental hazards affecting communities worldwide. It is responsible for significant loss of life, destruction of infrastructure, displacement of populations, and disruption of economic activities (Cao *et al*., 2022; Devitt *et al*., 2023). Rapid urbanisation, climate change, deforestation, and poor land-use planning have further intensified flood risks, particularly in developing countries where infrastructure development often lags population growth (Prashar *et al*., 2023).

Nigeria has experienced recurrent flood disasters over the past two decades, affecting major urban centres such as Lagos, Ibadan, Makurdi, and Abuja. These flood events have resulted in extensive socio-economic losses, destruction of property, disruption of transportation networks, and displacement of affected communities (Nkeki *et al*., 2022; Idowu & Zhou, 2021). Abuja, the Federal Capital Territory of Nigeria, has witnessed increasing flood occurrences due to rapid population growth, land-use changes, urban expansion, and encroachment on natural drainage systems. The conversion of natural vegetation and permeable surfaces into built-up environments has significantly increased surface runoff and reduced infiltration, thereby increasing flood susceptibility within the city (Adeola *et al*., 2025; Aniramu *et al*., 2026).

Satellite remote sensing provides a powerful tool for monitoring environmental changes and assessing disaster risks. Modern satellite platforms such as Sentinel-1, Sentinel-2, and Landsat provide high-resolution imagery that enables the detection of flood extent, land-use changes, and terrain characteristics. When combined with Geographic Information Systems (GIS), these datasets can be used to develop detailed flood risk maps and support disaster management strategies (Teng *et al*., 2017; Schumann & Moller, 2015). Despite the availability of these technologies, flood management in Abuja remains largely reactive. Disaster responses often focus on post-event relief rather than proactive risk assessment and mitigation. There is therefore a need to integrate satellite remote sensing and GIS into urban planning and disaster management systems to improve flood preparedness and resilience.

2. MATERIALS AND METHODS

2.1 The Study Area

The study was conducted in Abuja, the Federal Capital Territory (FCT) of Nigeria. Abuja lies between latitudes 8°25′N and 9°20′N and longitudes 6°45′E and 7°39′E. The territory covers approximately 8,000 km² and comprises six Area Councils, namely Abuja Municipal Area Council (AMAC), Bwari, Gwagwalada, Kuje, Abaji, and Kwali. Abuja experiences a tropical wet-and-dry climate characterised by a rainy season extending from April to October and a dry season from November to March. The city has experienced rapid urban expansion over the last two decades, resulting in increasing pressure on drainage infrastructure and natural floodplains. The location and administrative boundaries of the study area are shown in Figure 1.

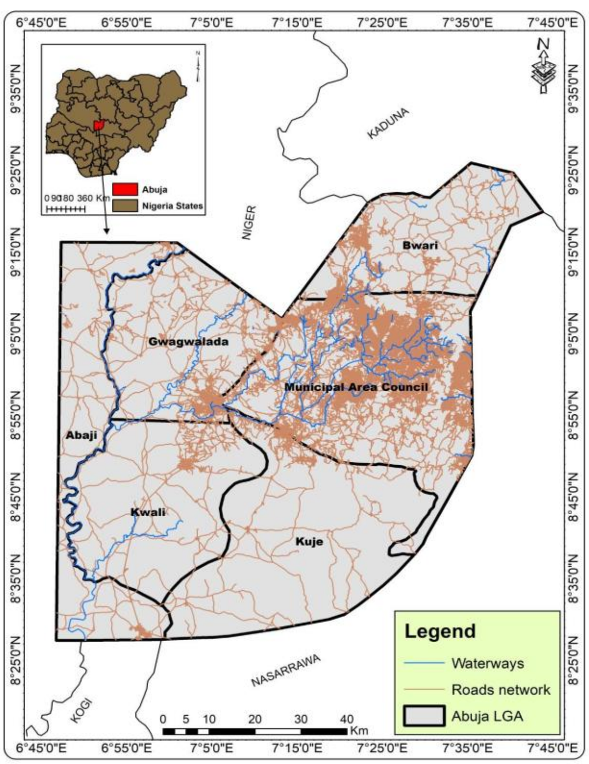

Figure 1. Map showing the study area

2.2 Data Sources and Description

This study adopts a geospatial analytical approach using satellite remote sensing and GIS techniques to assess flood risk in Abuja. The research methodology involves the acquisition, processing, and analysis of multi-source satellite datasets to identify flood-prone areas and develop flood risk maps. The study area covers Abuja within the Federal Capital Territory. Abuja lies between latitude 8°25'N and 9°20'N and longitude 6°45'E and 7°39'E. The city experiences a tropical wet-and-dry climate with annual rainfall occurring mainly between April and October.

The datasets used in this research include Sentinel-1 SAR imagery for flood detection, Sentinel-2 and Landsat imagery for land-use classification, and SRTM Digital Elevation Model data for terrain analysis. Additional datasets, such as rainfall records and drainage network data are incorporated to improve flood risk modeling. Table 1 presents the datasets used in this study, including their sources, spatial resolution, acquisition dates, and applications within the flood risk modelling framework.

Table 1. Study datasets

S/N	Dataset	Source	Spatial Resolution	Acquisition Date	Purpose
1.	Sentinel-1 SAR	Copernicus/ESA	10m	April 2026	Flood detection
2.	ESRI Sentinel-2 LULC	ESRI Land Cover Database	10m	April 2026	Land use/land cover analysis
3.	SRTM DEM	USGS	30m	April 2026	Elevation and slope analysis
4.	Rainfall Data	Meteorological Records	Variable	April 2026	Rainfall interpolation
5.	Road Network	OpenStreetMap	Vector	April 2026	Road proximity analysis
6.	River Network	Hydrological Dataset	Vector	April 2026	River proximity analysis

Satellite images are preprocessed to remove noise and atmospheric effects. Flood extent is detected using change detection techniques applied to Sentinel-1 SAR imagery. Land-use classification is performed using supervised classification methods to identify urban areas, vegetation, water bodies, and bare land.

Rainfall was incorporated as one of the flood-conditioning factors in the flood susceptibility assessment. Rainfall data were processed within the ArcGIS environment and converted into a continuous spatial surface using interpolation techniques. To facilitate integration with other flood-conditioning parameters during the weighted overlay analysis, the rainfall layer was standardised and normalised to a common scale. Consequently, the values presented in the rainfall map do not represent direct rainfall measurements in millimetres; rather, they represent relative rainfall intensity indices derived from the processed rainfall surface. The resulting rainfall index values ranged from 2.36 to 2.91, where higher values indicate areas with relatively greater rainfall influence and, therefore, a higher potential contribution to flood occurrence within the study area.

The weighted overlay approach has been widely applied in flood susceptibility mapping because it enables the integration of multiple flood-conditioning factors within a GIS environment (Chaulagain *et al*., 2023; Shuaibu *et al*., 2022). Terrain analysis is conducted using DEM data to derive elevation, slope, and flow accumulation maps. These environmental variables are integrated with land-use data using GIS spatial overlay techniques.

Flood susceptibility is evaluated using multi-criteria analysis in which each environmental factor is assigned a weight based on its contribution to flood risk. The weighted layers are combined to generate flood risk maps categorizing areas into high, moderate, and low flood susceptibility zones. The flood risk analysis for the study area was carried out using Geographic Information System (GIS) and remote sensing techniques within the ArcMap 10.7 environment. Several flood-conditioning parameters, including land use/land cover, drainage density, rainfall, slope, elevation, road proximity, and river proximity, were selected based on their influence on flood occurrence. These variables were processed, standardized, and integrated to produce the final flood risk map.

2.2.1 ESRI Sentinel-2 Dataset Characteristics

The Land Use/Land Cover (LULC) dataset used in this study was obtained from the ESRI Sentinel-2 Land Cover database, which provides global 10m spatial resolution land cover data derived from Sentinel-2 satellite imagery. The satellite imagery used for the analysis was acquired in April 2026. The dataset has a spatial resolution of 10m × 10m pixel size and was projected using the WGS 1984 UTM Zone 32N coordinate reference system, which is suitable for spatial analysis within the study area.

The ESRI Land Cover dataset was developed using a deep learning classification approach based on the U-Net Convolutional Neural Network (CNN) architecture implemented within the ArcGIS deep learning framework. The deep learning algorithm integrates spectral, spatial, and temporal characteristics of Sentinel-2 imagery to classify land cover into multiple thematic classes, including water bodies, trees, cropland, built-up areas, bare ground, and rangeland.

The LULC dataset was imported into ArcGIS 10.7 and clipped to the boundary of the Federal Capital Territory, Abuja. The classified raster data were subsequently reclassified according to their flood susceptibility contribution, where built-up areas and impermeable surfaces were assigned higher flood risk weights due to increased runoff generation, while vegetation-covered areas were assigned lower flood susceptibility ranks because of their higher infiltration capacity and runoff reduction potential.

The elevation and slope maps were derived from the Digital Elevation Model (DEM) using spatial analyst tools in ArcMap 10.7. Slope was generated from the DEM using the slope analysis function, while elevation values were extracted directly from the DEM dataset. Areas with low elevation and gentle slopes were ranked higher in flood susceptibility because they encourage water accumulation and poor drainage, whereas higher elevations and steep slopes were assigned lower flood risk rankings. The drainage density map was produced by first extracting the drainage network from the DEM and hydrological analysis tools. The Line Density tool in Spatial Analyst was then used to calculate the concentration of drainage channels within the study area. Areas with high drainage density were ranked higher due to their tendency to accumulate and convey runoff rapidly during rainfall events.

The rainfall map was developed using annual rainfall data obtained for the study area. The rainfall values were spatially interpolated using interpolation techniques to create a continuous rainfall surface. Areas with higher rainfall intensity were assigned higher flood risk rankings because increased rainfall contributes significantly to runoff generation and flood occurrence. Road and river proximity maps were generated using the Euclidean Distance tool in ArcMap 10.7. Distance maps were created to determine the spatial relationship between roads, rivers, and surrounding areas. Areas closer to rivers were assigned higher flood susceptibility rankings due to the increased likelihood of river overflow and inundation. Similarly, areas close to roads were considered more vulnerable because road networks can alter natural drainage patterns and increase surface runoff.

After generating all thematic layers, the datasets were reclassified into common suitability classes using the Reclassify tool in Spatial Analyst. Each variable was assigned ranks based on its relative contribution to flood occurrence. Weights were then assigned to the parameters according to their level of influence on flood risk. Finally, the Weighted Sum overlay analysis tool was applied to integrate all the weighted variables and generate the final flood risk map. The resulting flood risk map was classified into five categories: very low, low, moderate, high, and very high flood risk zones. This integrated GIS-based approach provided an effective means of identifying flood-prone areas within the study area for planning and disaster management purposes.

2.3 Land Use/Land Cover Data Processing

The Land Use/Land Cover (LULC) map was generated using ESRI Sentinel-2 satellite imagery obtained from the ESRI Land Cover database. The satellite data was processed and classified into different land cover categories such as water bodies, vegetation/trees, cropland, built-up areas, bare ground, and rangeland. The classified LULC map was then converted into raster format and reclassified according to the level of flood susceptibility associated with each land cover type. Built-up areas and waterlogged surfaces were assigned higher flood risk ranks due to their low infiltration capacity, while vegetation-covered areas were assigned lower flood risk ranks because they enhance infiltration and reduce runoff.

2.4 Accuracy Assessment of LULC Classification

The accuracy assessment of the Land Use/Land Cover (LULC) classification was conducted using the Confusion Matrix (Error Matrix) method within the ArcGIS 10.7 environment. The assessment involved comparing the classified LULC map with reference or ground truth sample points to evaluate the reliability and classification performance of the generated land cover map.

2.5 Accuracy Assessment Procedure

Random validation points were generated using the Create Accuracy Assessment Points tool in ArcGIS and subsequently updated using the Update Accuracy Assessment Points tool to assign reference land cover classes based on visual interpretation and available reference data. The classified raster values were then compared against the reference values using the Compute Confusion Matrix tool available in ArcGIS Spatial Analyst.

2.6 Preparation of Flood Conditioning Factors

The preparation of flood-conditioning factors constitutes a critical stage in flood susceptibility modelling because it enables the integration of multiple environmental and anthropogenic variables that influence flood occurrence. Flooding is a complex phenomenon controlled by the interaction of topography, hydrology, climate, land use patterns, and human activities. Consequently, the selection and preparation of appropriate conditioning factors are essential for producing reliable flood risk maps.

In this study, seven major flood-conditioning factors were considered: land use/land cover, drainage density, elevation, rainfall, slope, river proximity, and road proximity. These factors were selected based on their established influence on flood generation and their widespread application in previous GIS-based flood susceptibility studies (Shuaibu *et al*., 2022; Chaulagain *et al*., 2023; Ahmad *et al*., 2025). Each dataset was processed within the ArcGIS 10.7 environment and converted into raster format to ensure compatibility with the weighted overlay analysis.

To facilitate multi-criteria integration, all variables were standardised to a common suitability scale ranging from 1 to 5, where 1 represented very low flood susceptibility and 5 represented very high flood susceptibility. The reclassification criteria were established using hydrological principles, expert knowledge, and evidence from existing literature. Parameters that enhance runoff generation, reduce infiltration, or increase water accumulation were assigned higher susceptibility scores, whereas factors that promote infiltration and efficient drainage received lower scores. The resulting thematic layers formed the basis for the development of the final flood susceptibility model. The scoring criteria for flood-conditioning factors are presented in Table 2.

Table 2. Internal Feature Scoring Criteria for Flood-Conditioning Factors

Factor	Class Range	Score	Flood Susceptibility Interpretation
Elevation (m)	>700	1	Very Low
	600–700	2	Low
	500–600	3	Moderate
	400–500	4	High
	<400	5	Very High
Slope (°)	>15	1	Very Low
	10–15	2	Low
	5–10	3	Moderate
	2–5	4	High

Factor	Class Range	Score	Flood Susceptibility Interpretation
	<2	5	Very High
Drainage Density	Very Low	1	Very Low
	Low	2	Low
	Moderate	3	Moderate
	High	4	High
	Very High	5	Very High
Rainfall Index	2.36–2.50	1	Very Low
	2.50–2.60	2	Low
	2.60–2.70	3	Moderate
	2.70–2.80	4	High
	2.80–2.91	5	Very High
River Proximity (m)	>5000	1	Very Low
	3000–5000	2	Low
	2000–3000	3	Moderate
	1000–2000	4	High
	<1000	5	Very High
Road Proximity (m)	>3000	1	Very Low
	2000–3000	2	Low
	1000–2000	3	Moderate
	500–1000	4	High
	<500	5	Very High
Land Use/Land Cover	Waterbody	5	Very High
	Built-up Areas	5	Very High
	Cropland	4	High
	Bareground	3	Moderate
	Rangeland	2	Low
	Trees/Forest	1	Very Low

2.6.1 Land Use/Land Cover Factor

Land use and land cover (LULC) represent one of the most significant determinants of flood susceptibility because they directly influence infiltration capacity, evapotranspiration, surface roughness, and runoff generation. Changes in land cover, particularly urbanisation and deforestation, modify natural hydrological processes and often increase flood occurrence in rapidly developing environments.

The LULC map used in this study was derived from the ESRI Sentinel-2 Land Cover dataset with a spatial resolution of 10m. The dataset was generated using a deep learning classification approach based on the U-Net Convolutional Neural Network (CNN) architecture within the ArcGIS deep learning framework. The imagery employed for the analysis was acquired in April 2026 and projected using the WGS 1984 UTM Zone 32N coordinate reference system.

The classified land cover categories included water bodies, trees, cropland, built-up areas, bare ground, and rangeland. Each class was assigned a flood susceptibility score according to its hydrological characteristics. Built-up areas received the highest susceptibility rankings because impervious surfaces such as roads, rooftops, and pavements reduce infiltration and increase runoff accumulation. Croplands and bare surfaces were assigned moderate to high susceptibility values due to soil disturbance and reduced vegetation cover. Conversely, forests and dense vegetation were assigned lower susceptibility rankings because vegetation intercepts rainfall, enhances infiltration, stabilises soil structure, and slows runoff velocity.

The importance of LULC in flood modelling has been widely reported in previous studies. Idowu and Zhou (2021) demonstrated that rapid urbanisation significantly increased flood hazards in Lagos State, while Adeola *et al*. (2025) found that land cover changes and vegetation loss substantially intensified flood risks in Ibadan. These findings underscore the critical role of LULC analysis in understanding flood dynamics and informing sustainable urban planning.

2.6.2 Drainage Density Factor

Drainage density refers to the total length of streams and drainage channels per unit area and serves as an important indicator of runoff concentration and hydrological response. It reflects the efficiency with which water is collected and conveyed through a watershed and therefore plays a significant role in flood occurrence. The drainage density map for Abuja was generated from hydrological analysis of the Digital Elevation Model (DEM) using ArcGIS Spatial Analyst tools. Flow direction and flow accumulation algorithms were first applied to delineate drainage networks, after which the Line Density tool was employed to compute drainage density values across the study area.

Areas characterised by high drainage density were assigned higher flood susceptibility rankings because dense channel networks facilitate rapid runoff concentration and increase the likelihood of flooding during intense rainfall events. In contrast, regions with lower drainage density generally promote infiltration and slower surface runoff movement, thereby reducing flood vulnerability.

High drainage density often indicates highly dissected landscapes with limited infiltration opportunities, particularly where anthropogenic modifications have altered natural hydrological systems. Previous studies have consistently identified drainage density as a dominant flood-conditioning factor. Shuaibu *et al*. (2022) reported that areas with dense drainage networks within the Hadejia River Basin exhibited significantly higher flood risks, while Raufu *et al*. (2023) reached similar conclusions in their flood vulnerability assessment of Akure South. The incorporation of drainage density into flood susceptibility modelling therefore provides important information regarding water concentration processes and supports more accurate identification of flood-prone zones.

2.6.3 Elevation Factor

Elevation constitutes one of the most fundamental determinants of flood susceptibility because it governs the movement, accumulation, and storage of surface water. Low-lying areas generally exhibit greater flood vulnerability since runoff naturally converges towards depressions and plains, whereas elevated regions facilitate rapid drainage and reduce water retention. The elevation map used in this study was derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model with a spatial resolution of 30m. The DEM was processed using ArcGIS 10.7 to extract elevation values and generate terrain representations across the Federal Capital Territory.

Elevation values within the study area ranged from approximately 52m to 937m above sea level. Areas characterised by lower elevations were assigned higher flood susceptibility scores due to their increased tendency to accumulate runoff and experience prolonged inundation. Conversely, higher elevation zones received lower susceptibility rankings because they generally possess better drainage characteristics and reduced flood exposure. The relationship between elevation and flooding has been extensively documented in hydrological literature. Low-lying urban environments frequently experience recurrent flooding because water from surrounding higher terrains naturally drains into these areas. Studies by Chaulagain *et al*. (2023) and Ahmad *et al*. (2025) similarly identified elevation as one of the most influential parameters controlling flood susceptibility within urban catchments. Consequently, elevation analysis provides critical insights into flood-prone locations and supports evidence-based disaster management planning.

2.6.4 Rainfall Factor

Rainfall represents the principal climatic driver of flooding because it determines the volume of water available for runoff generation, river discharge, and surface water accumulation. Intense or prolonged precipitation events frequently exceed the infiltration capacity of soils and the carrying capacity of drainage systems, thereby resulting in flood occurrence. Rainfall data for this study were obtained from meteorological records and processed within the ArcGIS environment. To generate a continuous rainfall surface covering the entire study area, the Inverse Distance Weighting (IDW) interpolation technique was employed. The IDW method assumes that geographically proximate observations exhibit greater similarity than distant observations and has been widely applied in environmental and hydrological studies.

The interpolation process utilised a power parameter of two and a variable search radius to produce a smooth rainfall distribution surface. The resulting raster layer was subsequently standardised and normalised to facilitate integration with other flood-conditioning variables within the weighted overlay framework. Consequently, the rainfall values presented in the flood susceptibility analysis represent relative rainfall intensity indices rather than direct rainfall measurements in millimetres.

Areas exhibiting higher rainfall intensity indices were assigned greater flood susceptibility scores because increased precipitation contributes directly to runoff generation and water accumulation. The importance of rainfall as a flood determinant has been consistently emphasised in previous studies. Idowu and Zhou (2021) reported that rainfall distribution significantly influenced flood patterns in Lagos, while Shuaibu *et al*. (2022) identified rainfall as one of the dominant variables controlling flood occurrence in northern Nigeria. The integration of rainfall data therefore enhances the climatic realism and predictive capability of flood susceptibility models.

2.6.5 Slope Factor

Slope determines the velocity and direction of surface runoff and consequently exerts a strong influence on flood susceptibility. Areas characterised by gentle slopes generally experience greater flood risks because water moves slowly and accumulates more readily, whereas steep slopes facilitate rapid drainage and reduce water stagnation. The slope map was generated from the SRTM Digital Elevation Model using the Slope function within ArcGIS Spatial Analyst. The resulting values ranged from 0° to 56°, reflecting substantial topographic variation across the study area.

Low slope classes were assigned higher flood susceptibility rankings because flat terrains encourage runoff accumulation and reduce drainage efficiency. Conversely, steep slopes received lower flood susceptibility scores owing to enhanced runoff velocity and limited water retention. Although steep terrains may be susceptible to erosion and landslides, their vulnerability to prolonged flooding is generally lower.

Hydrological studies have consistently identified slope as a critical parameter in flood modelling. Chaulagain *et al*. (2023) demonstrated that gentle slopes significantly increased flood susceptibility in Kathmandu, while Adelodun *et al*. (2021) reported similar findings for Ibadan, Nigeria. The incorporation of slope analysis into flood susceptibility assessments therefore provides valuable information regarding terrain-controlled runoff dynamics.

2.6.6 River Proximity Factor

Distance to rivers is a crucial determinant of flood susceptibility because areas located near river channels are inherently more exposed to river overflow, channel spills, and floodplain inundation during heavy rainfall events. The likelihood of flooding generally decreases with increasing distance from major watercourses. The river proximity map was generated using the Euclidean Distance tool within the ArcGIS Spatial Analyst environment. This method calculates the shortest straight-line distance between each raster cell and the nearest river channel, thereby producing a continuous representation of river influence across the study area. Areas situated close to rivers were assigned higher flood susceptibility scores because they are more likely to experience inundation during periods of high discharge and extreme rainfall. Conversely, locations farther from river systems received lower susceptibility rankings owing to their reduced exposure to riverine flooding.

The significance of river proximity in flood modelling has been widely documented. Ouma and Tateishi (2014) emphasised the importance of river networks in urban flood risk assessments. In Abuja, settlements located near major waterways and natural drainage corridors are particularly vulnerable to flooding due to increasing urban expansion and encroachment upon floodplains. The incorporation of river proximity into the flood susceptibility model therefore enables more accurate identification of areas exposed to riverine flooding and supports effective land-use planning and disaster risk reduction initiatives.

2.7 Classification Performance

The confusion matrix produced statistical measures including Overall Accuracy, Producer's Accuracy, User's Accuracy, and the Kappa Coefficient. A total of 200 validation sample points were used for the assessment. The overall classification accuracy obtained for the LULC map was 90%, while the Kappa Coefficient was 0.86, indicating a strong agreement between the classified data and reference samples. According to standard remote sensing classification assessment criteria, classification accuracy values above 85% are considered highly reliable for environmental and geospatial analysis. In summary, Table 3 shows the confusion matrix, which indicates that rangeland constitutes the dominant land cover class, accounting for 41.85% of the total study area, followed by cropland (33.69%). Together, these two classes cover over 75% of Abuja's land area, reflecting the semi-rural and agricultural characteristics of large portions of the FCT.

Table 3. Confusion Matrix and Classification Accuracy Assessment for LULC Mapping

Class Value	Waterbody	Trees	Crops	Built-up Areas	Bareground	Rangeland	Total	User Accuracy
Waterbody	1	0	0	0	0	0	1	1.00
Trees	0	22	0	0	0	0	22	1.00
Crops	0	1	67	0	2	0	70	0.96
Built-up Areas	0	0	0	23	0	0	23	1.00
Bareground	0	0	0	0	0	0	0	0.00
Rangeland	0	4	9	0	4	67	84	0.80
Total	1	27	76	23	6	67	200	
Producer Accuracy	1.00	0.81	0.88	1.00	0.00	1.00		
Kappa Coefficient								0.86

Built-up areas account for approximately 11.60% of the study area and are primarily concentrated within the Abuja Municipal Area Council and surrounding urban districts. Although built-up areas occupy a smaller proportion of the total land area, they contribute disproportionately to flood generation due to increased surface sealing, reduced infiltration, and higher runoff coefficients. Vegetation-covered areas comprising trees and forests account for 12.30% of the study area and serve an important role in reducing flood susceptibility through interception, evapotranspiration, and soil stabilization processes. The Bareground class was represented by a very small spatial extent (0.03% of the study area), resulting in insufficient validation samples during the random accuracy assessment process. Consequently, no independent producer or user accuracy statistics could be reliably estimated for this class.

2.8 Flood Susceptibility Modelling

2.8.1 Weighting Procedure and Rationale for Factor Selection

The flood susceptibility model was developed using a Multi-Criteria Decision Analysis (MCDA) framework implemented through the Weighted Overlay tool in ArcGIS 10.7. The selection and weighting of flood-conditioning factors were guided by previous studies on flood risk assessment in Nigeria and other developing regions (Shuaibu *et al*., 2022; Chaulagain *et al*., 2023; Ahmad *et al*., 2025). The factors considered in this study include rainfall, elevation, drainage density, slope, land use/land cover, river proximity, and road proximity. These variables were selected because of their established influence on surface runoff generation, water accumulation, drainage efficiency, and anthropogenic modification of natural hydrological processes. Assigned weights for the flood conditioning factors of the study are shown in Table 4, and Table 5 shows the flood susceptibility classification criteria.

Weights were assigned based on expert judgement and literature-supported importance rankings. Rainfall received the highest weight because it is the principal driver of flood occurrence, while elevation and drainage density were assigned substantial weights due to their influence on runoff concentration and water accumulation. Land use/land cover and proximity factors were assigned comparatively lower weights because their effects are largely indirect and spatially dependent.

Table 4. Assigned Weights for Flood-Conditioning Factors

S/N	Factor	Weight (%)	Rationale
1.	Rainfall	25	Primary driver of runoff generation and flood occurrence
2.	Elevation	20	Controls water accumulation and flow direction
3.	Drainage Density	20	Influences the concentration and movement of surface water
4.	Slope	15	Determines runoff velocity and infiltration potential
5.	Land Use/Land Cover	10	Affects permeability and surface sealing
6.	River Proximity	5	Indicates susceptibility to riverine flooding
7.	Road Proximity	5	Reflects anthropogenic modifications to drainage systems
	Total	**100**	

Although the Analytical Hierarchy Process (AHP) is widely employed in flood susceptibility studies, the present study adopted an expert judgement approach informed by published literature and local environmental characteristics due to data availability constraints and the exploratory nature of the assessment.

Table 5. Flood Susceptibility Classification Criteria

FSI Range	Risk Category	Interpretation
1.00–1.80	Very Low	Minimal flood potential
1.81–2.60	Low	Limited flood susceptibility
2.61–3.40	Moderate	Moderate flood exposure
3.41–4.20	High	Significant flood susceptibility
4.21–5.00	Very High	Extreme flood vulnerability

2.8.2 Rainfall Interpolation Procedure

Rainfall data obtained from meteorological records were transformed into a continuous spatial surface using the Inverse Distance Weighting (IDW) interpolation technique in ArcGIS 10.7. The IDW method was selected because of its computational efficiency, simplicity, and widespread application in environmental and hydrological studies where measurement stations are spatially distributed. The technique assumes that observations located closer to one another exhibit greater similarity than those farther apart.

The interpolation process employed a power parameter of 2 and a variable search radius to generate a smooth rainfall surface covering the entire study area. The resulting raster was subsequently clipped to the Abuja boundary and resampled to maintain consistency with the spatial resolution of other flood-conditioning factors used in the analysis.

2.8.3 Flood Susceptibility Modelling Criteria

Each flood-conditioning factor was standardised and reclassified into a common suitability scale ranging from 1 to 5, where 1 represents very low flood susceptibility, and 5 represents very high flood susceptibility. The reclassification criteria were established based on hydrological principles, local environmental conditions, and previous flood susceptibility studies.

Lower elevations, gentle slopes, higher rainfall intensity, greater drainage density, shorter distances to rivers, and built-up land uses were assigned higher susceptibility scores due to their greater contribution to flood generation and water accumulation. Conversely, higher elevations, steeper slopes, dense vegetation cover, and areas located farther from river channels received lower susceptibility rankings.

2.8.4 Mathematical Framework for Flood Susceptibility Modelling

The flood susceptibility assessment employed a Weighted Linear Combination (WLC) approach within a Multi-Criteria Decision-Making (MCDM) framework. The methodology integrates multiple flood-conditioning factors by assigning each parameter a standardised susceptibility score and a corresponding relative importance weight. The final Flood Susceptibility Index (FSI) was obtained through the aggregation of all weighted factors. In Table 6, we present the Mathematical Representation of the Multi-Criteria Flood Susceptibility Model

Weight Normalization

The normalised weight assigned to each flood-conditioning factor was computed as in equation 1:

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \qquad \text{(Equation 1)}$$

Where:

W_i = normalised weight of the i^{th} factor;

w_i = original assigned importance value;

n = Total number of conditioning factors.

Since the total assigned weights equal 100, the normalised weights sum to unity as shown in equation 2:

$$\sum_{i=1}^{n} w_i = 1 \qquad \text{(Equation 2)}$$

The final flood susceptibility index (FSI) was computed using the weighted linear combination approach presented in equation 3:

$$FSI = \sum_{i=1}^{n} W_i X_i = 0.25R + 0.20E + 0.20D + 0.15S + 0.10L + 0.05P_r + 0.05P_d \qquad \text{(Equation 3)}$$

Where:

R = Rainfall score;

E = Elevation Score;

D = Drainage density score

S = Slope score;

L = Land use/land cover score;

P_r = River proximity score;

P_d = Road proximity score.

Higher FSI values indicate greater flood susceptibility.

Table 6: Mathematical Representation of the Multi-Criteria Flood Susceptibility Model

S/N	Factor	Symbol	Standardised Score Range	Normalised Weight	Weighted Contribution
1.	Rainfall	R	1–5	0.25	$0.25R$
2.	Elevation	E	1–5	0.20	$0.20E$
3.	Drainage Density	D	1–5	0.20	$0.20D$

S/N	Factor	Symbol	Standardised Score Range	Normalised Weight	Weighted Contribution
4.	Slope	S	1–5	0.15	$0.15S$
5.	Land Use/Land Cover	L	1–5	0.10	$0.10L$
6.	River Proximity	P_r	1–5	0.05	$0.05P_r$
7.	Road Proximity	P_d	1–5	0.05	$0.05P_d$
	Total			**1.00**	

where W_i represents the weight assigned to the i^{th} factor and X_i denotes the corresponding standardised factor score. The resulting flood susceptibility values were subsequently classified into five categories: very low, low, moderate, high, and very high flood risk.

2.9 Validation of the Flood Susceptibility Map

The reliability of the generated flood susceptibility map was evaluated through qualitative validation using historical flood occurrence records, field observations, and consistency with previously reported flood-prone locations within the Federal Capital Territory. Areas identified as highly susceptible in the model corresponded closely with locations that have experienced recurrent flooding, particularly within the Abuja Municipal Area Council, Bwari, Kuje, Abaji, and Gwagwalada.

In addition, the validity of the underlying land use/land cover dataset was assessed using a confusion matrix approach. The classification achieved an overall accuracy of 90% and a Kappa coefficient of 0.86, indicating strong agreement between the classified data and reference samples. The high classification accuracy provides confidence in the reliability of the spatial inputs used in the flood susceptibility analysis.

Future studies may employ quantitative validation approaches such as Receiver Operating Characteristic (ROC) analysis, Area Under the Curve (AUC) statistics, and independent flood inventory datasets to further assess the predictive performance of the flood susceptibility model.

2.10 Limitations and Future Quantitative Validation Approaches

Although the present study adopted established GIS and Multi-Criteria Decision-Making (MCDM) techniques for flood susceptibility assessment, explicit statistical validation metrics such as Receiver Operating Characteristic (ROC) curves, Area Under the Curve (AUC) statistics, prediction-rate curves, and success-rate analyses were not implemented due to the absence of a comprehensive georeferenced flood inventory dataset for Abuja. Consequently, the validation strategy relied primarily on qualitative comparisons with historical flood occurrences, previous scientific investigations, and expert interpretation of environmental conditions. While this approach provides reasonable confidence in the generated susceptibility patterns, it does not offer the predictive performance measures commonly reported in data-driven flood susceptibility models.

Future studies should therefore develop comprehensive flood inventory databases using historical disaster records, field surveys, community-based observations, and remotely sensed flood extent products derived from Sentinel-1 SAR imagery. Such datasets would facilitate the application of quantitative validation techniques, including ROC/AUC analysis, confusion matrices for susceptibility classes, and machine-learning-based model evaluation frameworks. The incorporation of these methods would substantially improve model reproducibility, predictive assessment, and the scientific robustness of flood risk analyses within Abuja and other rapidly urbanising African cities.

2.11 Parameter Standardization

The flood-conditioning factors considered in this study were derived from heterogeneous datasets with different units of measurement, scales, and spatial characteristics. To enable their integration within the weighted overlay framework, all parameters were standardised and transformed into a common ordinal suitability scale ranging from 1 to 5, where 1 represents very low flood susceptibility, and 5 represents very high flood susceptibility.

The standardisation process involved raster reclassification using hydrological principles, expert knowledge, and established practices reported in previous flood susceptibility studies. Parameters that increase flood occurrence, such as high rainfall intensity, dense drainage networks, low elevations, gentle slopes, proximity to rivers, and extensive built-up areas, were assigned higher suitability scores. Conversely, areas characterised by higher elevations, steeper slopes, dense vegetation cover, and greater distances from river channels received lower susceptibility rankings. This standardisation procedure ensured comparability among all flood-conditioning variables and facilitated their subsequent integration using the weighted linear combination approach.

3. RESULTS AND ANALYSIS

This section presents the spatial distribution and influence of flood-conditioning factors and discusses their contribution to flood susceptibility across Abuja using GIS-based weighted overlay analysis. Areas located along river channels and low-lying terrains show higher flood risk compared to elevated regions. Flood extent mapping using Sentinel-1 SAR imagery indicates that several districts in Abuja experience seasonal flooding during periods of intense rainfall. The flood maps show that floodwaters tend to accumulate in areas with poor drainage infrastructure and high levels of urban development.

The flood susceptibility analysis demonstrates that elevation, slope, land-use patterns, and drainage density significantly influence flood risk. Low-lying areas with gentle slopes and high concentrations of impervious surfaces are particularly vulnerable to flooding. GIS overlay analysis identifies specific communities within Abuja that fall within high flood risk zones. These areas include rapidly expanding urban districts where infrastructure development has not kept pace with population growth. The results highlight the importance of integrating satellite remote sensing data into urban planning processes. Flood risk maps can provide valuable information for land-use zoning, infrastructure planning, and disaster preparedness strategies.

This section presents the results and discussion of the flood risk analysis carried out using GIS and remote sensing techniques in ArcMap 10.7. Various flood-conditioning factors, including land use/land cover, drainage density, road proximity, river proximity, slope, rainfall, and elevation, were analyzed and integrated to generate the flood risk map of the study area. The thematic maps produced for each parameter revealed the spatial distribution and influence of the variables on flood occurrence. Weighted overlay analysis was employed to determine the contribution of each factor to flood susceptibility. The results provide a clearer understanding of areas that are highly vulnerable to flooding and serve as a basis for effective flood management and planning.

3.1 Land Use/Land Cover Analysis

Figure 2 presents the land use/land cover (LULC) map of Abuja derived from the ESRI Sentinel-2 land cover dataset. The map illustrates the spatial distribution of major land cover classes, including water bodies, trees, cropland, built-up areas, bare ground, and rangeland across the study area.

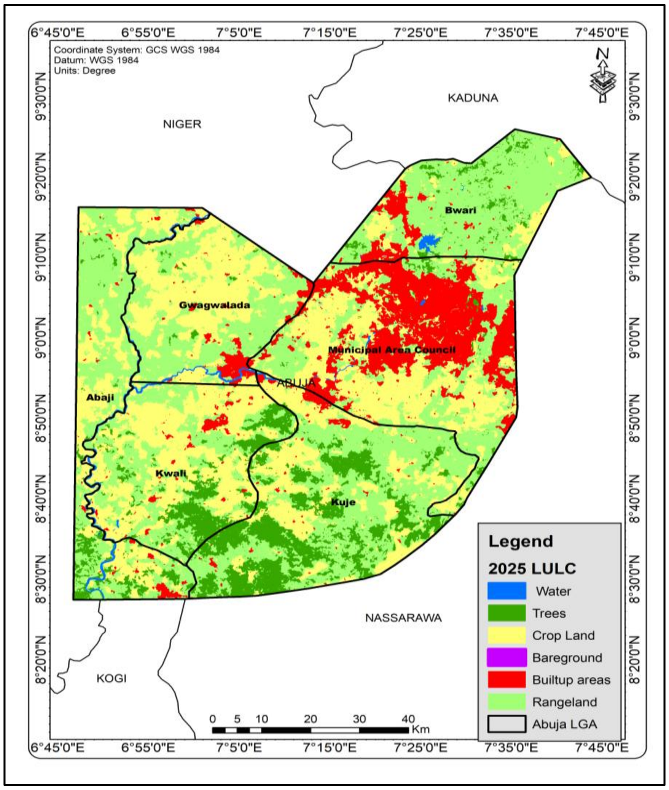

Figure 2. Land use/land cover map of Abuja

Table 7 shows the area statistics and percentage coverage of the different land use/land cover (LULC) classes, providing insight into the dominant landscape features influencing flood susceptibility within the study area.

Table 7. Land use land cover area and percentages

S/N	Land use land cover (LULC)	Area (sq km)	Percentage (%)
1.	Water body	40.58058	0.5360
2.	Trees	930.80139	12.2955
3.	Crop land	2550.25588	33.6880
4.	Built-up area	878.05155	11.5987
5.	Bare ground	2.266434	0.02999
6.	Range land	3168.26024	41.8516
7.	TOTAL	7570.216096	100

The analysis revealed that rangeland occupies the largest portion of the study area with 41.85%, followed by cropland (33.69%), trees/vegetation (12.30%), and built-up areas (11.60%), while water bodies and bare ground accounted for only 0.54% and 0.03%, respectively. The dominance of rangeland and cropland indicates that a significant part of the area is characterized by open and agricultural surfaces, which may increase surface runoff during heavy rainfall events, especially where vegetation cover is sparse. Similarly, the presence of built-up areas contributes to flood susceptibility due to the expansion of impervious surfaces that reduce infiltration and increase runoff accumulation.

The result further shows that areas covered by vegetation and trees are less vulnerable to flooding because vegetation enhances infiltration, intercepts rainfall, and reduces runoff velocity. In contrast, built-up and cultivated lands are more prone to flooding due to soil compaction and human activities that alter the natural drainage system. This finding agrees with the study conducted by Aniramu *et al*. (2026), which reported that increasing urbanization and land cover changes significantly increase flood risk in urban environments.

Similarly, Adeola *et al*. (2025) observed that the reduction in vegetation cover and rapid expansion of built-up areas contributed greatly to flood occurrences in Ibadan, Nigeria.

3.2 Drainage Density Analysis

Figure 3 presents the drainage density distribution within the study area, which represents the concentration and closeness of drainage channels within the study area and serves as an important parameter in flood risk analysis. Drainage density influences the movement, accumulation, and discharge of surface runoff during rainfall events. Areas with high drainage density are characterized by a large number of streams and channels within a given area, resulting in rapid runoff concentration and increased flood potential. Conversely, areas with low drainage density generally experience slower runoff movement and lower flood susceptibility due to better infiltration and reduced surface water accumulation.

The result shows that very high drainage density values (248-308) are concentrated mainly around parts of Abaji, Abuja Municipal Area Council, and some portions of Kuje, represented by the red color on the map. These areas are more vulnerable to flooding because the dense network of drainage channels can quickly collect and convey runoff, especially during intense rainfall events. Moderate drainage density zones are distributed across Gwagwalada and central parts of the study area, while low drainage density areas (0.787-62.2), shown in blue, dominate the northern and southeastern sections, indicating relatively lower flood susceptibility.

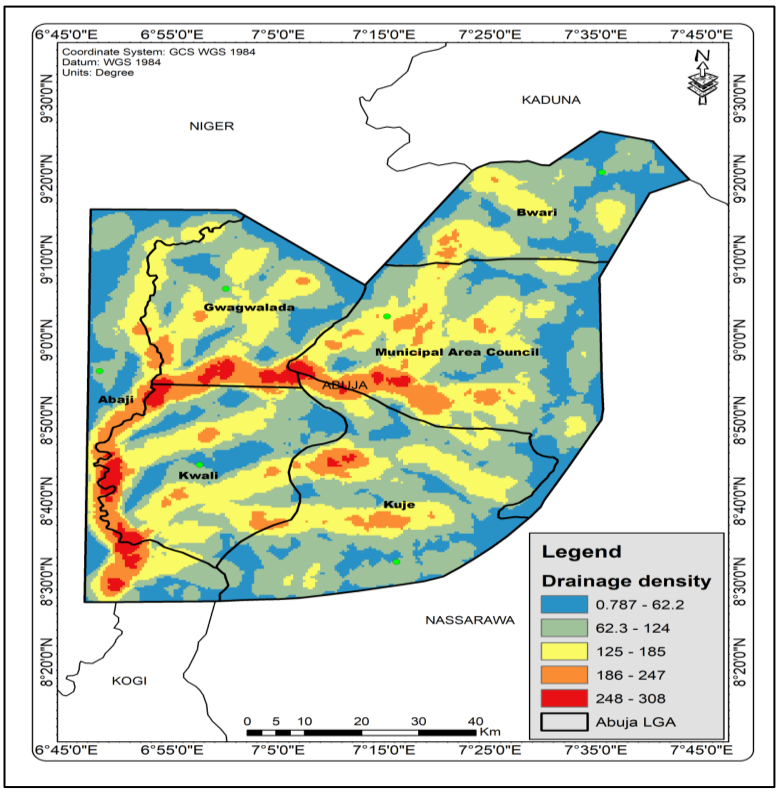

Figure 3. Drainage density map

This finding agrees with the study of Idowu and Zhou (2021), which reported that areas with high drainage density are more prone to flooding due to faster runoff concentration and reduced infiltration opportunities.

3.3 Elevation Analysis

Elevation is an important parameter in flood risk analysis because it influences the direction, accumulation, and movement of surface runoff within a landscape. Low-lying areas are generally more susceptible to flooding because water tends to accumulate in depressions and plains, while high-elevation areas usually experience lower flood risk due to faster runoff movement and better drainage conditions.

The elevation map of the study area is illustrated in Figure 4, showing values ranging from 52m to 937m above sea level. Areas with low elevation values (52-201 m), represented by the brown color, are mainly concentrated in Abaji, Kwali, and parts of Gwagwalada. These areas are more vulnerable to flooding because runoff water from higher terrains naturally flows and accumulates within the lowland regions. Moderate elevation zones are distributed across the Municipal Area Council and Kuje, while high elevation areas (605-937 m), shown in blue, are predominantly found in Bwari and some eastern parts of the study area, indicating relatively lower flood susceptibility.

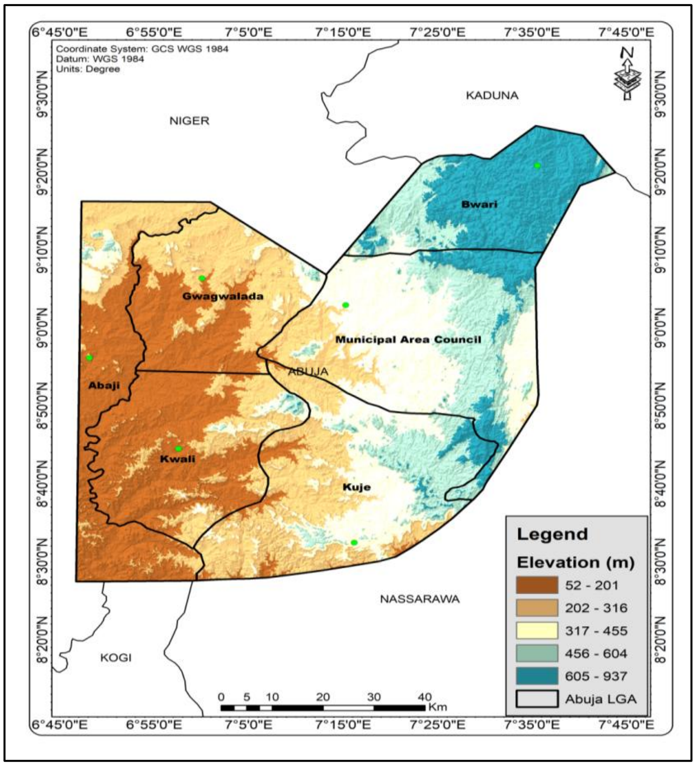

Figure 4. Elevation map

3.4 Rainfall Factor

Rainfall is one of the most important parameters in flood risk analysis because it directly influences the volume of surface runoff generated within a watershed. Areas receiving high annual rainfall are generally more susceptible to flooding due to increased water accumulation, runoff generation, and possible overflow of rivers and drainage channels. Conversely, areas with lower rainfall amounts usually experience reduced flood intensity and lower runoff concentration.

The annual rainfall map presented in Figure 5 illustrates the spatial distribution of rainfall influence across the study area. The rainfall layer was standardised and normalised during preprocessing to facilitate integration with other flood-conditioning factors within the weighted overlay analysis. Consequently, the values shown on the map (2.36–2.91) represent relative rainfall intensity indices rather than direct rainfall measurements in millimetres. Areas with higher rainfall index values (2.80–2.91), represented by the red colour, indicate locations with relatively greater rainfall influence and therefore a higher contribution to flood susceptibility.

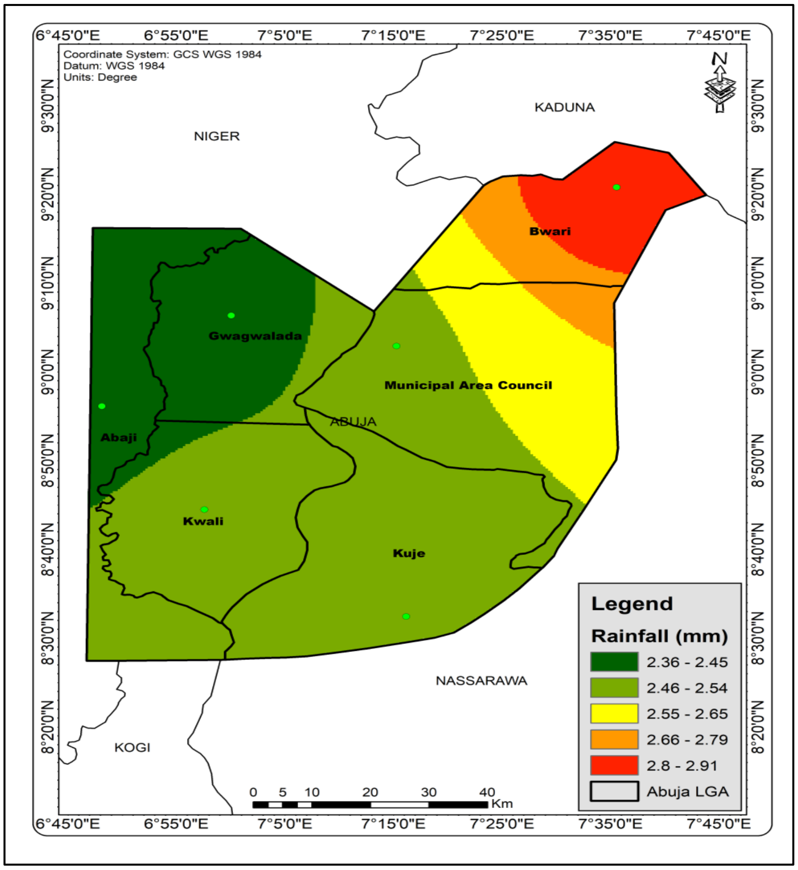

Figure 5. Annual rainfall distribution map

3.5 Slope Analysis

Slope is an important parameter in flood risk analysis because it controls the speed and direction of surface runoff within a landscape. Areas with gentle or low slopes tend to experience higher flood susceptibility because water flows slowly and accumulates easily, whereas steep slope areas encourage rapid runoff movement, thereby reducing water accumulation and flood occurrence.

The slope map of the study area was derived from the Digital Elevation Model with slope values ranging from 0° to 56°. Low slope areas (0-2.8°), represented by dark green, dominate most parts of the study area, including Abaji, Gwagwalada, Municipal Area Council, and Kuje. These areas are more vulnerable to flooding because the relatively flat terrain promotes water stagnation and runoff accumulation during heavy rainfall events. Moderate slope zones are scattered across the study area, while steep slope areas (20-56°), shown in red, occur mainly around the southeastern and northeastern parts of the study area. These steep regions are less susceptible to flooding due to faster runoff movement, although they may be prone to erosion. Figure 6 illustrates the slope distribution within Abuja derived from the Digital Elevation Model and highlights areas of varying runoff potential.

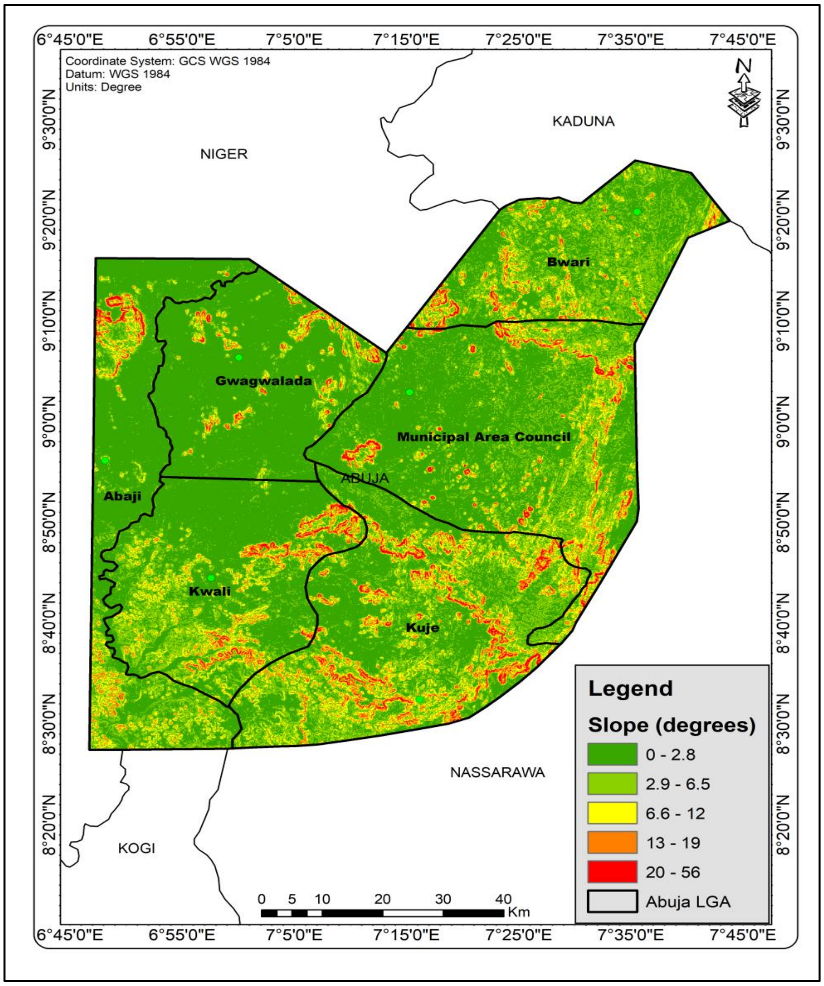

Figure 6. Slope Map

3.6 River and Road Proximity Analysis

Distance to the river is an important parameter in flood risk analysis because areas located closer to rivers are generally more vulnerable to flooding due to river overflow, channel spills, and surface water accumulation during heavy rainfall events. Conversely, areas farther away from rivers usually experience lower flood susceptibility because the influence of river overflow decreases with increasing distance.

In this study, the River Euclidean Distance map was generated using the Euclidean Distance tool in the Spatial Analyst extension of ArcGIS 10.7. The tool was used to calculate the straight-line distance of every location within the study area from the nearest river channel. The resulting distance values were then classified into different flood susceptibility zones. Areas closer to rivers, represented by lower distance values (0-8,210 m), were assigned higher flood risk rankings because they are more likely to experience inundation during peak runoff periods. Areas farther from rivers, represented by higher distance values (32,900-41,100 m), were assigned lower flood risk rankings due to reduced exposure to river flooding. Figure 7 illustrates river proximity zones within Abuja. The map shows that areas around the Municipal Area Council, Gwagwalada, Abaji, and parts of Bwari are relatively close to river channels and therefore more susceptible to flooding. In contrast, southern parts of Kuje and other distant areas exhibit lower vulnerability due to their greater distance from major waterways.

Figure 8 presents road proximity classes used in the flood risk model. The map shows that most parts of the Municipal Area Council, Bwari, Gwagwalada, and Abaji are located close to road networks and are therefore more vulnerable to flooding. Conversely, some parts of Kuje and peripheral areas farther away from major roads exhibit relatively lower flood susceptibility.

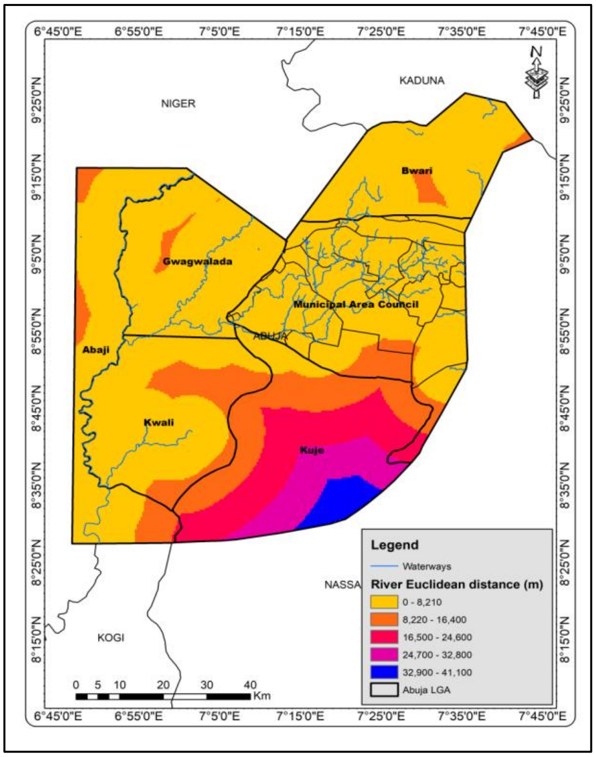

Figure 7. River proximity map

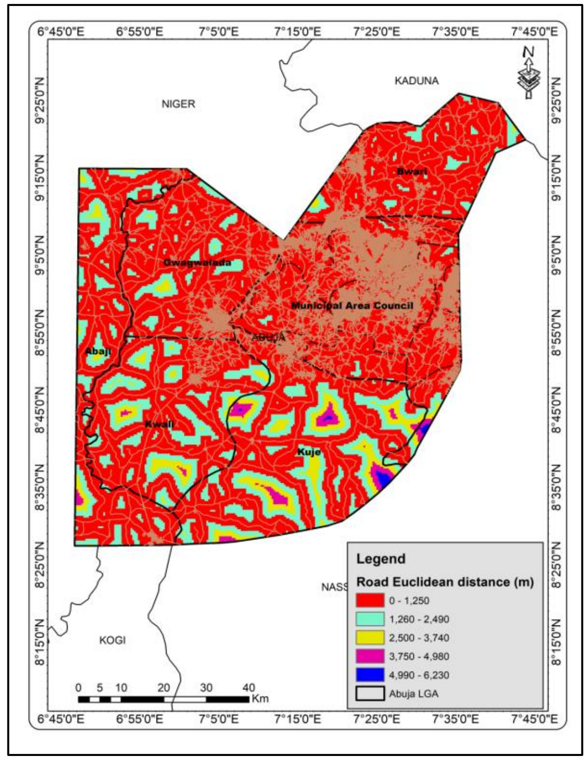

Figure 8. Road proximity map

Road distance is an important parameter in flood risk analysis because road networks influence natural drainage patterns, surface runoff movement, and water accumulation. Areas located close to roads are often more susceptible to flooding due to the presence of impervious surfaces such as asphalt and concrete, which reduce infiltration and increase runoff generation during heavy rainfall events. In addition, poorly designed drainage systems along roads can contribute to waterlogging and localized flooding.

In this study, the Road Euclidean Distance map was generated using the Euclidean Distance tool in the Spatial Analyst extension of ArcGIS 10.7. The tool calculated the straight-line distance from roads to surrounding areas within the study area. The resulting distance values were classified into different flood susceptibility zones. Areas closer to roads, represented by lower distance values (0-1,250 m), were assigned higher flood risk rankings because they are more exposed to runoff accumulation and drainage obstruction. Areas farther from roads, represented by higher distance values (4,990-6,230 m), were assigned lower flood risk rankings due to reduced anthropogenic influence on surface runoff processes.

3.8 Flood Susceptibility Analysis

Figure 9 shows the final flood susceptibility map generated from the weighted overlay analysis. The map represents the spatial distribution of flood susceptibility within the study area based on the integration of various flood-conditioning factors, including land use/land cover, drainage density, rainfall, slope, elevation, road proximity, and river proximity using GIS-based analysis. The map classified the study area into five flood risk zones: very low, low, moderate, high, and very high flood risk.

The result shows that areas classified as very high flood risk (red color) are mainly concentrated around the Municipal Area Council, parts of Bwari, Abaji, Kwali, and some sections of Gwagwalada. These areas are highly vulnerable to flooding due to the combined influence of high drainage density, low slope, proximity to rivers, built-up surfaces, and increased runoff accumulation. High flood risk zones (purple color) are also distributed around central and northern parts of the study area, indicating areas with significant flood susceptibility.

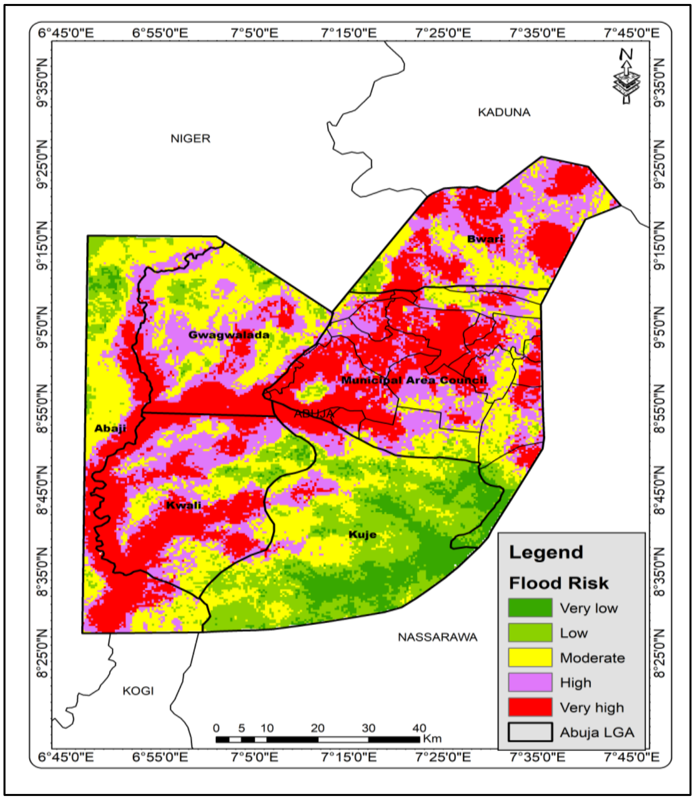

Figure 9. Flood risk map of Abuja

Moderate flood risk areas (yellow color) are widely spread across the study area and represent transition zones between highly vulnerable and less vulnerable areas. Low and very low flood risk zones (light green and dark green) are mainly concentrated in Kuje and the southern portions of the study area, where higher elevation, better drainage conditions, and relatively lower rainfall reduce flood vulnerability.

The findings agree with studies by Idowu and Zhou (2021), which reported that flood occurrence is strongly influenced by topography, rainfall intensity, drainage characteristics, land use patterns, and proximity to water bodies. Therefore, the flood risk map provides useful information for flood disaster management, urban planning, and sustainable development within the study area.

3.9 Comparison with Previous Flood Studies

The findings of this study are consistent with previous flood susceptibility assessments conducted across Nigeria and other rapidly urbanising African cities. The identification of the Abuja Municipal Area Council (AMAC), Bwari, Kuje, Abaji, and Gwagwalada as highly vulnerable flood zones corroborates the findings of Akande *et al*. (2023), who reported that residential areas such as Lokogoma, Galadimawa, Lugbe, Kubwa, and Gwagwalada experience increasing flood vulnerability due to rapid urban growth, inadequate drainage infrastructure, and encroachment on natural waterways.

The present study further demonstrates that rainfall, elevation, drainage density, and land use/land cover constitute the most influential flood-conditioning factors within Abuja. Similar conclusions were reached by recent flood-risk studies in the Abuja Municipal Area Council, where integrated AHP, GIS, and remote sensing approaches identified low elevation, proximity to river networks, and increasing built-up surfaces as the principal determinants of urban flood susceptibility. The observed influence of urban expansion and impervious surfaces agrees with studies conducted in Lagos State. Salami and Okoh (2022) employed geospatial techniques to demonstrate that wetland conversion, dense urban development, and inadequate drainage systems significantly increased flood vulnerability in low-lying districts of Lagos. Likewise, Adelekan (2013) and subsequent studies have shown that rapid urbanisation, land reclamation activities, and poor drainage maintenance are major drivers of recurrent flooding in the Lagos metropolis.

Comparable patterns have been documented in Ibadan. Adelodun *et al*. (2021) applied both Analytical Hierarchy Process (AHP) and Fuzzy AHP within a GIS framework and found that rainfall intensity, drainage density, slope, and land-use changes were the dominant factors controlling flood occurrence in the city. Their findings align closely with the present study, particularly regarding the importance of topography and anthropogenic land transformations in shaping flood risk.

Similarly, Raufu *et al*. (2023) demonstrated that flood vulnerability in Akure South is primarily influenced by rainfall patterns, elevation, soil characteristics, land use, and drainage conditions. Using remote sensing and GIS techniques, the authors reported that built-up areas and low-lying terrain exhibited significantly higher flood susceptibility, reinforcing the results obtained in Abuja.

Beyond Nigeria, the findings correspond with studies from other African cities. Msabi and Makonyo (2021) reported that flood susceptibility in Dodoma, Tanzania, is strongly controlled by topographic factors, rainfall distribution, and land-use dynamics, while Ouma and Tateishi (2014) demonstrated that integrated AHP-GIS approaches effectively capture urban flood vulnerability patterns in rapidly growing cities. These studies collectively suggest that the interaction between climatic drivers, terrain characteristics, and anthropogenic modifications represents a common mechanism underlying flood risk across African urban environments.

The consistency of findings across Abuja, Lagos, Ibadan, Akure, and other African cities underscores the importance of integrating remote sensing and GIS technologies into urban planning and disaster risk management frameworks. The present study therefore contributes to the growing body of evidence that geospatial approaches provide effective, scalable, and cost-efficient tools for identifying flood-prone areas, supporting climate adaptation policies, and enhancing urban resilience in developing countries.

3.10 Socioeconomic Implications of Flood Risk in Abuja

The spatial distribution of flood susceptibility identified in this study has significant socioeconomic implications for residents and economic activities within the Federal Capital Territory. High-risk areas, particularly within AMAC, Bwari, Kuje, Abaji, and Gwagwalada, contain rapidly expanding residential communities, transportation corridors, agricultural lands, educational institutions, and commercial establishments. Flood events within these locations therefore have the potential to disrupt livelihoods, damage infrastructure, and impose substantial economic costs on households and government institutions.

Urban flooding frequently destroys roads, bridges, drainage facilities, and public utilities, thereby affecting mobility, access to markets, and service delivery. In rapidly urbanising environments, transportation disruptions caused by flooding can reduce economic productivity and hinder emergency response operations. Similar patterns have been observed in large metropolitan areas where road interruptions constitute one of the most significant consequences of urban flooding.

Flood disasters also disproportionately affect vulnerable populations, including low-income households residing in poorly planned settlements and flood-prone environments. Such communities often possess limited adaptive capacity, inadequate insurance coverage, and restricted access to disaster recovery resources. The resulting impacts include displacement, loss of property, food insecurity, health risks associated with contaminated floodwaters, and long-term psychological stress.

From an agricultural perspective, recurrent flooding within peri-urban areas such as Abaji and Kwali may threaten crop production, reduce household incomes, and undermine local food security. Conversely, the increasing conversion of agricultural and vegetated lands into built-up areas reduces natural infiltration capacity and further intensifies runoff generation, creating a feedback mechanism that increases flood vulnerability over time.

The findings therefore underscore the importance of integrating flood risk assessments into urban development planning, infrastructure investment decisions, land-use regulation, and climate adaptation policies. The adoption of satellite-based monitoring systems and GIS-driven decision-support tools can help government agencies identify vulnerable communities, prioritise mitigation measures, and enhance resilience to future flood events.

4. CONCLUSION AND RECOMMENDATIONS

This study demonstrates the potential of satellite remote sensing and GIS technologies for flood risk assessment and disaster management in Abuja. The integration of multi-source satellite datasets enables the identification of flood-prone areas and provides spatial information that can support disaster preparedness and urban planning. The results show that environmental factors such as elevation, slope, and drainage density play a critical role in determining flood vulnerability. Urban expansion and land-use changes also contribute significantly to flood risk. To improve flood management in Abuja, government agencies should integrate satellite remote sensing into disaster monitoring systems. Urban planners should incorporate flood risk maps into land-use planning and infrastructure development strategies.

The reliability of the LULC classification was further validated through accuracy assessment using the confusion matrix method. The classification achieved an overall accuracy of 90% and a Kappa Coefficient of 0.86, indicating a high level of agreement between the classified land cover data and the reference samples. The high accuracy values demonstrate that the ESRI Sentinel-2 10m land cover dataset and deep learning classification approach provided reliable thematic information for flood risk analysis within the study area. The strong classification performance therefore enhances the credibility of the generated flood susceptibility maps and spatial analysis results. Future research should explore the use of machine learning and real-time satellite monitoring systems to improve flood prediction and early warning systems. Additionally, higher-resolution satellite imagery and socio-economic data should be incorporated to enhance flood risk modeling.

Furthermore, subsequent research should prioritise the establishment of a georeferenced flood inventory database for the Federal Capital Territory through the integration of historical disaster records, satellite-derived flood extent products, field verification campaigns, and community-based reporting systems. The availability of such datasets would enable the application of robust statistical validation procedures, including Receiver Operating Characteristic (ROC) analysis, Area Under the Curve (AUC) calculations, prediction-rate assessments, and machine-learning performance metrics. The adoption of quantitative validation frameworks would improve the predictive capability, reproducibility, and scientific reliability of flood susceptibility models and support evidence-based disaster management and urban planning initiatives within Nigeria.

REFERENCE

Adelodun, B., Ajibade, F. O., Ighalo, J. O., Ogunshola, A. M., & Oba, S. N. (2021). *Flood-prone area mapping using GIS-based analytical hierarchy frameworks for Ibadan City, Nigeria*. *Environmental Challenges, 5*, 100346. https://doi.org/10.1002/mcda.1759

Adeola, O., Aniramu, O., Adenegan, O., & Orimoogunje, O. (2025). Land use change, planning instruments, and sustainable strategies for urban flood risk management in Ibadan, Nigeria. *Discover Environment, 3*(1), 284. https://doi.org/10.1007/s44274-025-00478-2

Ahmad, S., Peng, X., Ashraf, A., Yin, D., Chen, Z., Ahmed, R., Israr, M., & Jia, H. (2025). Building resilient urban drainage systems by integrated flood risk index for evidence-based planning. *Journal of Environmental Management, 374*, 124130. https://doi.org/10.1016/j.jenvman.2025.124130

Akande, A. O., Obi-George, L. C., Ahmed, S., Nwokorie, A. J., & Makun, C. Y. (2023). Flood vulnerability and adaptation practices of residential areas in Abuja, Nigeria. *Khulna University Studies, 20*(1), 111–129. https://doi.org/10.53808/KUS.2023.20.01.2225-se

Aniramu, O., Iyanda, O., & Orimoogunje, O. (2026). Remote sensing and GIS-based modelling of land use dynamics and urban flood risk in Lagos megacity for future flood mitigation. *Scientific Reports*. https://doi.org/10.1038/s41598-026-38544-1

Cao, W., Zhou, Y., Güneralp, B., Li, X., Zhao, K., & Zhang, H. (2022). Increasing global urban exposure to flooding: An analysis of long-term annual dynamics. *Science of the Total Environment, 817*, 153012. https://doi.org/10.1016/j.scitotenv.2022.153012

Chaulagain, D., Rimal, P. R., Ngando, S. N., Nsafon, B. E. K., Suh, D., & Huh, J. S. (2023). Flood susceptibility mapping of Kathmandu metropolitan city using GIS-based multi-criteria decision analysis. *Ecological Indicators, 154*, 110653. https://doi.org/10.1016/j.ecolind.2023.110653

Devitt, L., Neal, J., Coxon, G., Savage, J., & Wagener, T. (2023). Flood hazard potential reveals global floodplain settlement patterns. *Nature Communications, 14*, 2801. https://doi.org/10.1038/s41467-023-38498-9

Idowu, D., & Zhou, W. (2021). Land use and land cover change assessment in the context of flood hazard in Lagos State, Nigeria. *Water, 13*(8), 1105. https://doi.org/10.3390/w13081105

Msabi, M. M., & Makonyo, M. (2021). Flood susceptibility mapping using GIS and multi-criteria decision analysis: A case of Dodoma Region, Central Tanzania. *Remote Sensing Applications: Society and Environment, 21*, 100445. https://doi.org/10.1016/j.rsase.2020.100445

Nkeki, F. N., Bello, E. I., & Agbaje, I. G. (2022). Flood risk mapping and urban infrastructural susceptibility assessment using a GIS and analytic hierarchical raster fusion approach in the Ona River Basin, Nigeria. *International Journal of Disaster Risk Reduction, 77*, 103097. https://doi.org/10.1016/j.ijdrr.2022.103097

Ouma, Y. O., & Tateishi, R. (2014). Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: Methodological overview and case study assessment. *Water, 6*(6), 1515–1545. https://doi.org/10.3390/w6061515

Prashar, N., Lakra, H. S., Kaur, H., & Shaw, R. (2024). Urban flood resilience: Mapping knowledge, trends and structure through bibliometric analysis. *Environment, Development and Sustainability, 26*(4), 8235–8265. https://doi.org/10.1007/s10668-023-03177-0

Raufu, I. O., Mukaila, I., Olaniyan, K., & Awodele, Z. (2023). Application of remote sensing and geographical information system (GIS) in flood vulnerability mapping: A scenario of Akure South, Nigeria. *International Journal of Environment and Geoinformatics, 10*(1), 90–99. https://doi.org/10.30897/ijegeo.1073697

Salami, M. A., & Okoh, I. (2022). Flood vulnerability mapping using geospatial techniques: Case study of Lagos State, Nigeria. *Asian Journal of Applied Science and Technology, 6*(4), 81–88. https://doi.org/10.38177/ajast.2022.6408

Schumann, G. J. P., & Moller, D. K. (2015). Microwave remote sensing of flood inundation. *Physics and Chemistry of the Earth, Parts A/B/C, 83–84*, 84–95. https://doi.org/10.1016/j.pce.2015.05.002

Shuaibu, A., Hounkpè, J., Bossa, Y. A., & Kalin, R. M. (2022). Flood risk assessment and mapping in the Hadejia River Basin, Nigeria, using hydro-geomorphic approach and multi-criterion decision-making method. *Water, 14*(22), 3709. https://doi.org/10.3390/w14223709

Teng, J., Jakeman, A. J., Vaze, J., Croke, B. F. W., Dutta, D., & Kim, S. (2017). Flood inundation modelling: A review of methods, recent advances and uncertainty analysis. *Environmental Modelling & Software, 90*, 201–216. https://doi.org/10.1016/j.envsoft.2017.01.006