

# IMPROVING FLOOD HAZARDS ASSESSMENT WITH GEOSPATIAL AND GEOPHYSICAL INTEGRATION: A CASE STUDY OF LOKOJA, NIGERIA

<sup>1</sup>Mogaji, K. A., <sup>2</sup>Komolafe, A. A., <sup>1</sup>Akinlalu, A. A., <sup>2</sup>Adeyemi, A. B., <sup>1</sup>Adeniyi, O. T., and <sup>3</sup>Dada, B. M.



[DOI10.51459/jostir.2026.2.1.0210](https://doi.org/10.51459/jostir.2026.2.1.0210)

<sup>1</sup>Department of Applied Geophysics, Federal University of Technology, Akure, Nigeria.

<sup>2</sup>Department of Remote sensing Geoscience information system, Federal University of Technology, Akure, Nigeria.

<sup>3</sup>Department of Meteorology and Climate Science, Federal University of Technology, Akure, Nigeria.

**Correspondence**  
kamogaji@futa.edu.ng

## History

Received:

Accepted:

Published:



<https://www.futa.edu.ng>

**JOSTIR**  
JOURNAL OF SCIENCE, TECHNOLOGY  
AND INNOVATION RESEARCH

<https://jostir.futa.edu.ng>

## ABSTRACT

The major issue experienced in Lokoja, the meeting point of the Benue and Niger rivers, is flooding. The high rains and the terrain which is low raise lives, properties, and livelihoods to constant destruction. This paper used combined geospatial and geophysical methods to map flood prone regions in the Sub-Niger River Basin. Aeromagnetic data were used with remote sensing and GIS techniques to assess both surface and subsurface factors that caused flooding. Seven parameters including the elevation, slope, the drainage density, the distance to rivers, the lineament density, the land use/land cover, and the annual precipitation were standardized and weighted with the aid of the Analytical Hierarchy Process and overlaid in GIS. Findings suggest that the basin area located in high to very high flood-prone areas is 36.85 percent (2,087.22 km<sup>2</sup>) especially in the areas of Ganaja, Sarkin-Noma, Kabawa, and Gadumo. The factors that contribute greatly to susceptibility are low elevation, low topography, high density of drainage, closeness to rivers, thick lineaments, and elevated rainfall. The agricultural lands (60.22) and built-up areas (4.27) have high exposure. Model validation using flood inventory data and ROC analysis yielded an accuracy of 0.78 and AUC of 0.81, confirming strong predictive reliability. The resulting map supports improved floodplain zoning, land-use planning, and disaster preparedness, demonstrating the value of integrating geospatial and geophysical data for flood risk assessment.

**Keywords:** Flood Susceptibility Mapping; Geophysical data; Analytical Hierarchy Process (AHP); Sub-Niger River Basin (Lokoja); Remote Sensing and GIS

## 1. | Introduction

Flooding is one of the most prevalent and most damaging natural disasters worldwide. According to the World Meteorological Organization, about 1.81 billion people, or about 23 % of the world's population, are at present exposed to a '1-in-100-year' flood catastrophe. Out of these, about 89 % are from low- and middle-income countries. In Africa, for example, recent findings have indicated that extremely heavy rainfall from 2024 hit 27 countries in the tropical

region, where about 11 million people were affected and 4 million were displaced. The humanitarian and economic impact of flood disasters continues to rise. According to the International Federation of Red Cross and Red Crescent Societies (IFRC), in the year 2024, catastrophic floods impacted the lives of 50 million people worldwide. The above statistics demonstrate the scale of flood hazards that is a planetary problem. Flooding is responsible for 40% of disaster incidence, and millions of people are

affected by floods every year (Gupta *et al.*, 2021). In the Nigerian context, flood hazards have become a major problem. Based on the report by the National Emergency Management Agency (NEMA), in 2024, flooding occurred in 35 states, and 401 local government areas, affecting 5,264,097 people, with 1,237 lives lost, 1,243,638 people displaced, over 116,172 houses destroyed, and 1,439,296 hectares of farmland affected. The recent estimates have shown the rapid increase in flood effects in Nigeria in the mid-2020s. Moreover, floods have become more frequent and severe in Nigeria due to climate variability, rapid urbanization, land use change, and the absence of adequate infrastructure (Adelekan, 2016; Ologunorisa & Abawua, 2005). In 2012, close to two million individuals were displaced by the countrywide flood, and the economic damage was over US16 billion (Nkwunonwo *et al.*, 2016). The floods of 2018 and 2020 have also demonstrated lately how vulnerable the urban and rural territories of Nigeria are to floods, which have disrupted livelihoods and have led to increased poverty (Aderogba, 2012; Ishola *et al.*, 2021).

Lokoja is a city prone to floods in Nigeria and this can be explained by many people as the location of the city at confluence of the hugging rivers Niger and Benue. Consequently, it has been and will remain susceptible to seasonal flooding particularly during the time when water is released through these rivers and also when it rains (Merz *et al.*, 2021). In the past, the flooding of Lokoja has been an affliction and in recent years, the flooding has displaced thousands of families, as well as interrupted the economic relationship between the south and north of Nigeria, as was witnessed in the 2012, 2018, and 2020 floods (Ishaya *et al.*, 2014). Nevertheless, the literature regarding flood vulnerability of the region is minimal which considers both ground and surface data. In this regard therefore, additional studies are required on the same area due to the strategic positioning of the city.

However, in the recent past, Remote Sensing and

Geographic Information Systems have become critical instruments in flood hazard and susceptibility analysis as it gives a chance to observe all the factors that constitute flooding (Elkhrachy, 2015; Nguyen *et al.*, 2020). The effects of the flood-controlling factors on flooding, which include slope, rainfall, drainage density, and land use/cover have also been researched using Multi-Criteria Decision Analysis, especially the application of the Analytical Hierarchy Process. These strategies have been employed by a number of researchers to demonstrate the usefulness of these strategies. Indicatively, Komolafe *et al.*, (2015) applied GIS-based Multi-Criteria Decision Analysis in examining and quantifying flood risk in Southwestern Nigeria. The researchers could demonstrate the effect of rainfall and change in land use on flood hazard. In a different research, Komolafe *et al.*, (2020) noted that hydrological modeling and GIS should be enhanced to enhance flood forecasting in Nigerian basins. These have been used by other researchers to examine the existence of flooding in such locations as Lagos, Calabar, and Osun Basin hence demonstrating the usefulness of the strategies in reducing the risk of the occurrence of flood disasters (Ayeni *et al.*, 2025; Eze and Efiog, 2010).

But still there are numerous gaps in knowledge. Even though geospatial methodologies are being utilised in Nigeria, not many studies have realised the successful implementation of geophysical information such as lineament density and underground geological landmarks (Obiora & Ibuot, 2023) that have large effects to groundwater circulation and surface water circulation. These determinants are not considered in flood-prone models. Moreover, flood susceptibility models that have been developed in Lokoja and in consideration of the hydro-geomorphic location of the area, being at the intersection of the Niger and Benue rivers, have not been sufficiently successful in doing this (Adeyemi and Komolafe, 2025; Ishola *et al.*, 2021). This shows that there is need to have a more profound flood risk assessment in Lokoja. This paper integrates the strength of the Remote Sensing,

GIS, geophysical data and the analytical models to fill the gaps existing in earlier research on flood prone in Lokoja. These weaknesses include the absence of subsurface information assessment, absence of particular Lokoja flood vulnerability models, and absence of assessment of computational models. The approach will be providing a more accurate flood susceptibility model of the area.

### 1.1 | Study Area

The region under study is the Sub-Niger River Basin in Lokoja in Kogi State, Nigeria. Lokoja is at the confluence of the Niger and Benue rivers thus it is among the most vulnerable areas in the country of flooding. The study area (Figure 1) is geographically located between 7 deg40 N and 8 deg45 N and 5 deg55 E and 7deg0 E which is approximately 5,300 km<sup>2</sup>. The region has a low profile floodplain and an upland, with height ranging between 32 m close to the river and more than 600 m in the surrounding highlands. Lokoja is a tropical wet-and-dry climate

with the characteristics of Guinea savannah ecological zone. The rain is seasonal, and it takes place between the months of April and October with an average of 1,100 -1,300 mm annually (Olatunde & Sullaiman, 2025). The wet season is common with the occurrence of severe storms resulting into the discharging of rivers and rampant floods. Temperatures are between 26degC to 34degC in months and relative humidity may go as high as 80 percent during rainy season. The principal features of the basin hydrologically are the Niger and Benue rivers. Niger and Benue are also northwestern and northeastern tributaries respectively. They converge at Lokoja creating an extensive floodplain that overflows on an annual basis. It is a place that puts people at risk of floods because the effects of backwaters and large volumes of discharge coincide with intensified rains. There are also a number of tributaries that result in localised floods when it is raining heavily including the Meme, Okura and Omi rivers.

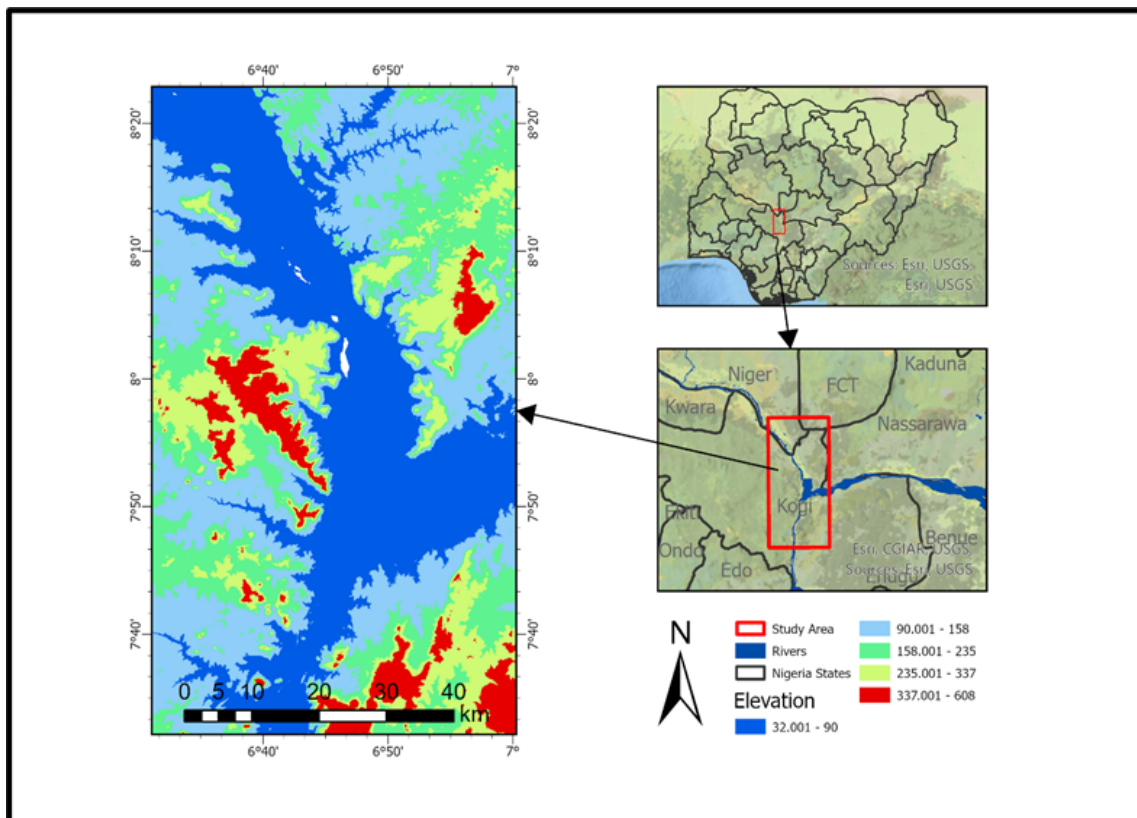


Figure 1 | Study area map

Geologically, the region is covered with Precambrian Basement complex rocks and this is predominantly comprised of granites, migmatites and gneisses, with the river valleys having younger sedimentary rocks. Significant structural characteristics such as fractures and lineaments were also determined in this work of aeromagnetic data. These constructions influence the ground water flow and surface hydrology, and they are significant in flood vulnerability determination. The land use and land cover of Lokoja are varied with the agricultural land predominant (arable farming and plantations), then the natural vegetation land, built-up areas, wetlands, and water bodies.

The high rate of population increase and urbanization in Lokoja has encroached the floodplains exposing people to the risk of floods. In 2016, the population of Lokoja metropolis was estimated to be more than 195,000 and has since then increased considerably mainly because of its strategic geographical position as a transport and administrative center. Lokoja is rated with the history of severe flood disasters. Thousands of people lost their homes, farmlands were flooded, and transport was interrupted because of major events in 2012, 2018, and 2022. It is also situated at a confluence of the two rivers hence serious rainfall occurring any where upstream in either the Niger or Benue basins will result in high local flood levels. This makes it a key field of research in the study of flood hazards and vulnerability in Nigeria.

## 2 | Methodology

**Table 1** | Data used with resolution and source

S/N	Data	Resolution	Source
1.	SRTM DEM Imagery	30 m	USGS Earth Explorer
2.	Landsat 9 Imagery	30 m	Google Earth Engine - USGS Earth Explorer
3.	Precipitation (Rainfall)		CHIRPS website
4.	Administrative Data (Vector)		Open Street Map

### 2.1 | Data Used and Sources

Various datasets were used to reach the objective of the research, such as the Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM), Landsat imagery, and rainfall data. According to Table 1, the SRTM DEM data, having a spatial resolution of 30 m, were downloaded in the USGS Earth Explorer site ([www.earthexplorer.usgs.gov](http://www.earthexplorer.usgs.gov)). The srtm dems data plays a critical role in hydrology and flood studies as it has the data at the elevation that can be used to calculate the terrestrial dynamics of slope, density of drainage, and accumulation of flows which directly affect the flood processes. The United States Geological Survey (USGS) Earth Explorer database was accessed on Google Earth Engine (GEE) to retrieve the Landsat satellite imagery (Landsat 9). The Landsat imagery has a 30m spatial resolution and was utilised for land use/land cover (LULC) classification of the research area. Rainfall data utilised for this investigation were collected from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Rainfall is the principal hydrological driver of flooding, and long-term average precipitation statistics are crucial in understanding spatial patterns of flood-prone locations. Administrative data comprising road network and settlement locations are downloaded from the Open Street Map (OSM) website.

### 2.2 | Software and Tools Used

The software and tools utilised to evaluate the gathered data and achieved the objectives of this

study include:

### 1. *ArcGIS Pro*

ArcGIS Pro which is developed by ESRI, was the primary software used for spatial data processing, analysis, and cartographic presentation in this study. It is commonly used for mapping, processing spatial data, and displaying data. The ArcGIS Pro 3.5 software was used in data management, spatial and terrain analysis (e.g., slope, drainage density, and buffer analysis), raster reclassification, weighted overlay, and map generation.

### 2. *Google Earth Engine*

Google Earth Engine (GEE), a cloud-based geospatial analysis platform developed by Google, was utilized for the processing of large-scale remote sensing data. It is a software application that allows users to “explore and examine satellite imagery of the world.” It is a planetary-scale analytical platform, which integrates a petabyte library of geographical information and satellite images. GEE platform was primarily applied in this study as the preprocessing of Landsat images and analysing geospatial data to map land use and land cover (LULC) using JavaScript programming. It was even used with the management of rainfall information. The access of various open-source data sets and processing of huge data sets were done using the GEE platform.

### 2.3 | **Data Preparation**

The data obtained in the course of this study was preprocessed to be compatible and fit in the future analysis. A data subset was clipped out to clip the obtained satellite images using the shapefile of the research area boundary (AOI). The geometry and form of research area was sustained to further process with the images.

**DEM Preprocessing:** The SRTM DEM was clipped to the research area boundary, and adjusted for sinks and depressions using the fill tool in ArcGIS Pro. Derived terrain parameters such as slope, drainage

density, and stream network were further created using the DEM.

**Landsat Preprocessing:** The Landsat imagery was corrected for atmospheric and radiometric variation. Using GEE, cloud and shadow masks were applied, and composite image was formed i.e. true colour composite or false colour composite. This help in identifying the features in the research area from another during the supervised classification analysis that was carried out in ArcGIS Pro to produce the LULC map.

**Rainfall Data Preprocessing:** CHIRPS rainfall data were downloaded, trimmed to the study area, and transformed to raster format for integration with other spatial parameters. Mean yearly rainfall values were derived for the flood susceptibility mapping.

### 2.4 | **Flood Influencing Factors**

Seven (7) flood influencing factors comprising elevation, slope, drainage density, distance from river, rainfall, lineament density, and land use and land cover (LULC) were selected based on literature assessment and their relevance to flood processes in the study area. The thematic maps of all selected elements were made using applicable tools in ArcGIS and Google Earth Engine. These parameters and their mapping process are individually discussed below.

**Elevation:** Elevation is a significant aspect in flood susceptibility mapping, often employed alongside other characteristics to identify places at risk of flooding (Nwanosike *et al.*, 2021). The topography between high and low grounds is central in assessing the risk of floods because it has the power to determine the way the surface water moves and also the intensity whereby it moves, whereby it dictates the susceptibility of people to instances of floods. Ground level sites are usually more likely to store the runoff and are susceptible to floods (Mudashiru *et al.*, 2022). The DEM provided values of elevation that were classified into zones of susceptibility.

**Slope:** The slope is another fixed and paramount property that has been emphasized in the flood susceptibility map in several studies. As an example, it has been stated that steep slopes increase drainage and flat slopes promote the build-up of water (Nguyen *et al.*, 2020). The DEM was used to obtain the slope. This may cause drainage system failures and result in flash flooding and may cause erosion, which causes the movement of soil particles, when it becomes increased. The slopes may raise the surface runoff in urban regions where the impervious surface is predominant, leading to flooding. In addition, the presence of water concentration of some channels as well as the dynamics of rivers also highlights the role of slope in flood vulnerability, and thus it is a critical issue that should be taken into account during flood mitigation.

**Drainage Density** Drainage density is a representation of the network of natural and artificial drainage features within a particular region. Areas that contain more rivers and streams are more prone to floods because of the high concentration of the runoffs. Areas of high drainage density would contain more rivers, streams, and drainage systems that would help in the effective circulation of water and minimize the chances of flooding by providing drainage opportunities (Ogden *et al.*, 2011). In other cases, however, the increased drainage density can be followed by rapid water flow and even flood the territory. Areas of low drainage may have a low drainage speed and high likelihoods of flooding as the drainage efficiency is low. Flood risk assessment also requires knowledge of drainage density as it defines how effective a region is in dealing with too much water and is important in formulating effective flood management solutions. The line density tool of ArcGIS Pro was used to estimate the drainage density.

**River Distance:** River distance is one of the major predictors of flood risk. The location relative to rivers has a significant influence on the threat of flooding and water moving dynamics within the

localities (O'Neill *et al.*, 2016). The nearer a place is to a river, the vulnerable it becomes to riverine flooding particularly during heavy rains. The floodplain consists of areas that are in close contact with rivers where the water may surpass its banks and flood the nearby area (Fitri, 2019).

**Land Use/Land Cover (LULC):**

Transformations in the land use and land cover can significantly change the hydrological cycle (Brody *et al.*, 2014). Another example is the process of urbanization that tends to augment impermeable surfaces causing a reduction in natural infiltration and augmenting surface runoff, which may cause flooding. On the other hand, properly controlled natural land cover, including forests and wetlands, may help regulate the water circulation, and reduce the risk of floods by increasing the water uptake and reducing the rate of runoff. Knowledge on land use and land cover is essential in achieving flood risk assessment, land use planning and implementation of mitigating methods. The ArcGIS Pro 3.4 was used to create the LULC map of the study area out of Landsat 9. The satellite picture was chosen at random in providing training samples. The principal sources of impervious surfaces are urbanized areas and prevent water absorption, promoting runoffs at high rates compared to agricultural zones that promote infiltration, decrease surface runoff, and minimize flood risks. The LULC map was divided into six (6) main categories and was reformatted by the influence of floods. There was a quantitative evaluation done to adequately investigate the accuracy of and authenticate land use/land cover classification. It is performed through matching of the sampled pixels of LULC map with the right LULC class on the ground. On the basis of the comparison, a confusion matrix was created, and a total accuracy was produced. The total accuracy in each year was calculated using the formula in equation 1.

Total accuracy = (Total number of correctly

categorised pixels)/(Total number of reference pixels) (1)

Rainfall: rain is one of the primary and direct causes of floods that has a significant effect on the surface water runoff (Ariyani *et al.*, 2022). The quantity of rainfall, its intensity, and duration identify the volume of water penetrating the ground and water flowing over the surface. Saturation of ground caused by heavy or prolonged rainfall reduces the capacity of the ground to absorb water and there is a rise in surface runoffs. Thunderstorms or tropical cyclones are associated with intensive precipitation in short periods of time and may lead to flash floods, which are sudden and rapid. The long-periodic rainfalls particularly in areas that have poor drainage systems may contribute towards riverine floods where the water in the river channels gets accumulated and overflows into the flood plains. The patterns of rainfall are also essential to be monitored and comprehended in order to carry out effective flood prediction, mitigation, and response activities. Regions receiving higher rainfalls have more chances of experiencing flooding. The susceptibility assessment was included with an addition of average annual rainfall.

Lineaments:

Magnetic data processing was done to minimize near-surface noise and grid upward continuation was done to 200 m high. This procedure was useful in flattening the Total Magnetic Intensity (TMI) grid by reducing cultural noise, with the mesh cell size of 50. In Oasis Montaj 8.3 software, the experiments tested at filtering stage were done in 50 m, 100 m, and 150 m. Nevertheless, the upward continuation of 200 m gave the most positive results, with a clear and smooth magnetic anomaly, devoid of cultural artifacts.

In structural interpretation, the edge detection methods were used. These were the total horizontal derivative (THD) (Ganguli *et al.*, 2019, 2020, 2021) and the tilt derivative of the total horizontal

derivative (TDR\_THD). To supplement this, depth estimation technique-3D Euler deconvolution was done to detect structures in the subsurface and their depth of occurrence.

Theories and methodologies used to work out the edge detection and the depth estimation can be comprehensively explained in the works of Akinlalu *et al.*, (2021), Amigun *et al.*, (2022), and Oyeniya *et al.*, (2016).

## 2.5 | Multi-Criteria Decision Analysis (MCDA)

MCDA is another decision -making method that incorporates various criteria, to assess intricate spatial issues. In the research, MCDA has been utilized in which the flood influencing variables are merged into a composite flood susceptibility index.

### 1. Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) was incorporated into the MCDA system to give weights to all factors that affect floods. AHP was created by (Saaty, 1980) and it utilizes the pairwise comparison in order to assess the importance of factors (Table 2).

The process involved:

1. 1.Construction of a pairwise comparison matrix: Every factor was compared to the others depending on the contribution to the susceptibility to floods. The 1-9 scale was used by Saaty (Table 3)..
2. 2. Weight derivation: Eigenvalues were calculated on the matrix to get normalized weights on each factor (Table 4).
3. 3.Check of consistency: Consistency Index (CI) and Consistency Ratio (CR) were determined to make sure that there was logical consistency in the pair-wise tests. Any CR below 0.1 was perceived to be acceptable.
4. 4.Weighted overlay: The derived factor

weights were applied to the standardized factor maps (e.g., slope, rainfall, LULC), and the results were aggregated and interpreted in a geospatial environment using the weighted overlay approach through ArcGIS Pro 3.5 to

produce the final flood susceptibility map.

The susceptibility map was subsequently classified, ranging from very low to very high flood susceptibility.

**Table 2 |** Weights of sub-classes using AHP comparison matrix

<b>Flood Influencing Factors</b>	<b>Class</b>	<b>Susceptibility Class Ranges and Ratings</b>	<b>Susceptibility Class Ratings</b>
Elevation	32 – 90	Very High	5
	90 – 158	High	4
	158 – 235	Moderate	3
	235 – 337	Low	2
	337 – 608	Very Low	1
Slope	0 – 2.766	Very High	5
	2.767 – 7.042	High	4
	7.043 – 13.077	Moderate	3
	13.078 – 21.125	Low	2
	21.126 - 64.13	Very Low	1
Drainage Density	0 – 0.373	Very Low	1
	0.374 – 0.909	Low	2
	0.910 – 1.509	Moderate	3
	1.510 – 2.320	High	4
	2.321 – 4.137	Very High	5
Distance from River	0 – 443.842	Very High	5
	443.843 – 1014.497	High	4
	1014.498 – 1648.557	Moderate	3
	1648.558 – 2324.888	Low	2
	2324.889 – 5389.514	Very Low	1
Lineament Density	0 – 0.517	Very Low	1
	0.518 – 1.033	Low	2
	1.034 – 1.550	Moderate	3
	1.551 – 2.066	High	4
	2.067 – 2.583	Very High	5
Land Use Land Cover	Water Body	Very High	5
	Wetland	High	4
	Built Up	High	4
	Bare Land	Moderate	3
	Arable land	Low	2
	Vegetation	Very Low	1
Precipitation	526.835 – 580.434	Very Low	1
	580.435 – 610.033	Low	2
	610.034 – 645.232	Moderate	3
	645.233- 685.231	High	4
	685.232 – 730.830	Very High	5

**Table 3 |** Pair-wise Comparison Matrix

Factors	Elevation	Slope	Drainage density	Distance From River	Lineament density	LULC	Precipitation
Elevation	1	2.00	2.00	0.50	5.00	2.00	0.33
Slope	0.50	1	0.50	0.33	3.00	0.50	0.25
Drainage density	1.00	2.00	1	0.50	4.00	0.50	0.33
Distance From River	2.00	3.00	2.00	1	5.00	2.00	0.50
Lineament density	0.20	0.33	0.25	0.20	1	0.33	0.17
LULC	0.50	2.00	2.00	0.50	3.00	1	0.33
Precipitation	3.00	4.00	3.00	2.00	6.00	3.00	1

**Table 4 |** The Eigen vector weights of each flood factors obtained after the pairwise comparison

Factors	Factor Weight	Factor Weight (%)
<b>Elevation</b>	0.140	14
<b>Slope</b>	0.700	7
<b>Drainage density</b>	0.110	11
<b>Distance From River</b>	0.205	21
<b>Lineament density</b>	0.340	3
<b>LULC</b>	0.119	12
<b>Precipitation</b>	0.321	32
	<b>1.0000</b>	<b>100</b>

### 2.6 | Evaluation of the Flood Susceptibility Map Model

The performance of the result of the flood susceptibility map model (AHP) was evaluated to assess its predictive accuracy. The consistency ratio (CR) of AHP pairwise comparison matrix was identified to be 0.029 which is highly acceptably consistent meaning that the weights assigned are logically consistent. The flood susceptibility map is juxtaposed to a flood inventory based on the data of the previous years regarding floods. The information on inventory (the places of flooded and non-flooded zones) were obtained at the Dartmouth Flood Observatory archive (DFO). This inventory data was superimposed on the susceptibility map

to identify the spatial relationship that existed between observed high and very high susceptibility areas and observed floods. The evaluation was done using the over accuracy and the receiver operating characteristic (ROC) curve and area under the curve (AUC) measures to assess the accuracy of the flood susceptibility map. Accuracy metric measures the general level of accuracy of a model result, which is determined by the number of correct results divided by the number of results. The ROC-AUC measure separates the positive and negative cases (Adeyemi & Komolafe, 2025). The ROC curve is then plotted by using the positive rate as the x-axis and the false positive rate as the y-axis.

### 3. | Results and Discussion

#### 3.1 | Elevation

The Sub-Niger River Basin, Lokoja had an elevation of 32m to 608m (Figure 2). Areas lower than 90m were registered as very high susceptibility zones, which are also in line with the Niger-Benue floodplains whereas uplands above 337m were also recorded as very low susceptibility. The low elevation areas serve as natural flood storage, which deposits the runoff during peak runoffs. This is not a novel finding, as Adeyemi and Komolafe (2025) found elevation to be one of the major predictors of flood susceptibility in the Lower Niger Basin, and

Nguyen *et al.*, (2020) found that low-lying plains in Vietnamese basins are always associated with higher hazard levels.

#### 3.2 | Slope

The slope was ranging 0deg to 64deg (Figure 3). Slopes of 0-2.7deg were coincidental with very high susceptibility and slopes of steeper than 21deg were coincidental with very low susceptibility. The flat terrains promote ponding and poor drainage whereas steep terrains promote rapid run off. The same trends were noticed in the Lam River Basin, Vietnam, where flat slopes were considered one of the strongest factors of floods (Nguyen *et al.*, 2020). In Nigeria, slope was also identified by Komolafe *et al.*, (2015) as one of the key factors of surface runoff and flood intensity.

#### 3.3 | Drainage Density

The drains density was 0-4.14 km/km<sup>2</sup> (Figure 4). Very high flood susceptibility zones were categorized as high drainage density zones (>2.3 km/km<sup>2</sup>) since when the high runoff is converged, the level of floods becomes high. The low drainage density areas (below 0.9 km/km<sup>2</sup>) were coded as low susceptibility areas. This result justifies (Mudashiru *et al.*, 2022) who determined that high drainage density increases the speed of concentration of runoff, and thus flood risks.

#### 3.4 | Distance from River

The farther one was to rivers the less susceptible to flooding (Figure 5). Areas between 0-443 m were determined to constitute very high

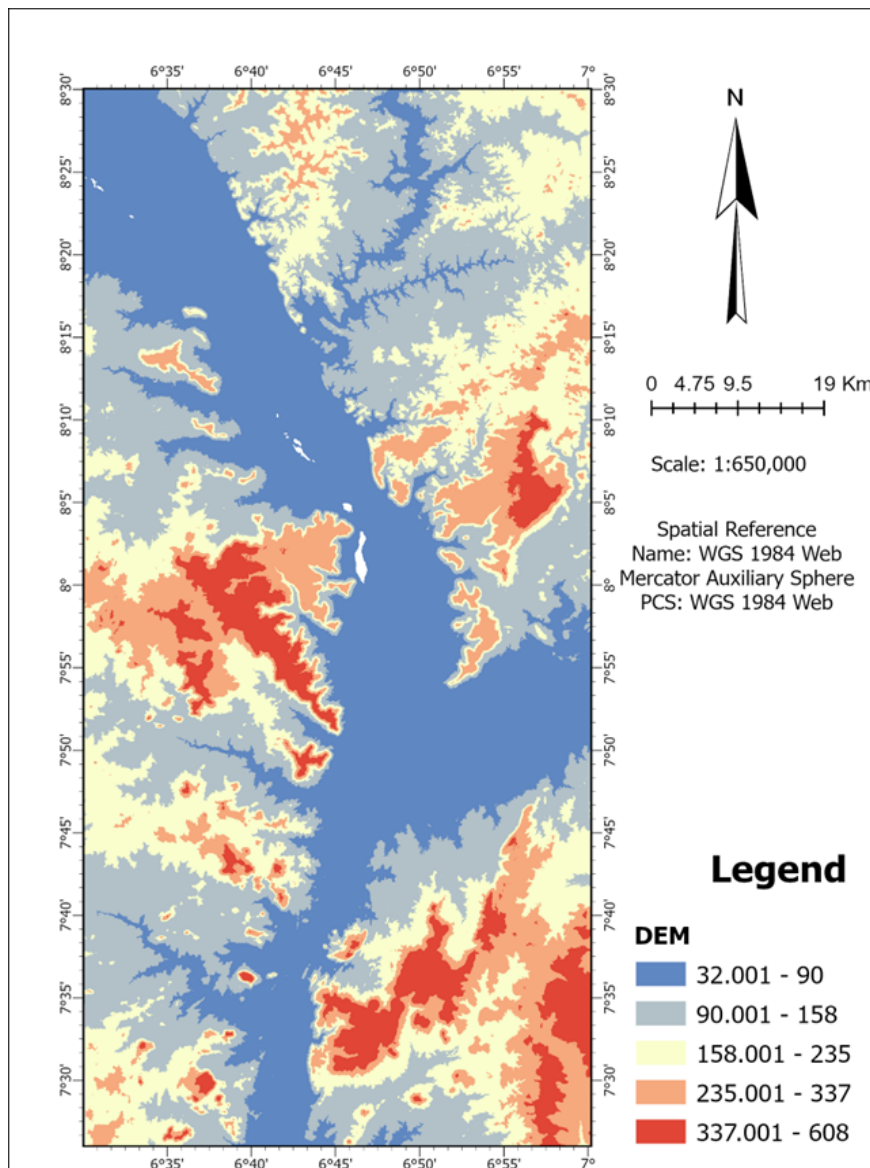
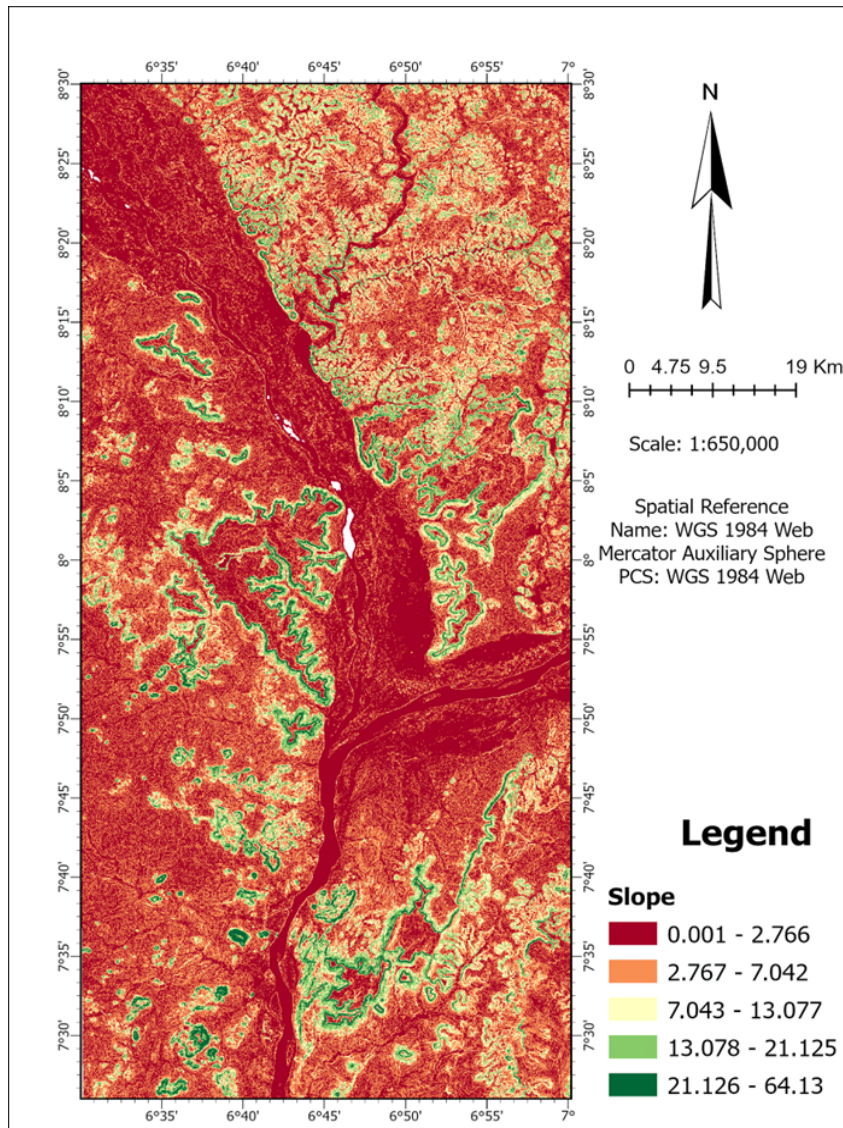


Figure 2 | Elevation Map



**Figure 3 | Slope Map**

susceptibility zones whereas areas above 2.3 km were known to be very low susceptibility zones. This trend is characteristic of the classical floodplain inundation process as it was defined by O'Neill *et al.*, (2016), and coincides with the research conducted in Nigeria where settlements located further along rivers are always characterized by greater flood losses (Adelekan, 2016).

**3.5 | Lineament Density**

The values of lineament density were between 0 and 2.58 km/km<sup>2</sup> (Figure 6). High density (>2.0 km/km<sup>2</sup>) areas were observed as very high susceptibility, which is the zone of structural weaknesses that

can accommodate a preferential water course. This combination of geophysical indicators enhances the Nigerian flood modeling because (Obiora & Ibuot, 2023) have found that the predictive effect and the strength of hazard models are restricted by the absence of subsurface parameters.

**3.6 | Land Use/Land Cover (LULC)**

The LULC classification came up with six (Figure 7; Table 2). Arable land was the main one (60.22), the second one was vegetation (28.22), and the third one was built-up areas (4.27). There was a high level of exposure to high to very high susceptibility zones of built-up and wetland classes. The same was observed in Lagos and Calabar where the urban spread into floodplains exacerbated the flood risk (Ayeni *et al.*, 2025; Eze and Efiog, 2010). Even Adeyemi and Komolafe (2025) affirmed that the presence of built-up surfaces in floodplains increases the exposure risks because of poor infiltration ability.

**3.7 | Annual Precipitation**

The basin received 527 to 731mm of rainfall annually (Figure 8). Areas with 685mm or more rainfall per year are classified as very high susceptibility, and precipitation is the most significant (Table 2). This aligns with the AHP weighting (Table 4), where rainfall contributed the highest influence (32%). It also supports the findings of (Adeyemi & Komolafe, 2025; Mudashiru *et al.*, 2022), who ranked rainfall among the most critical determinants of flood hazard in Nigerian basins.

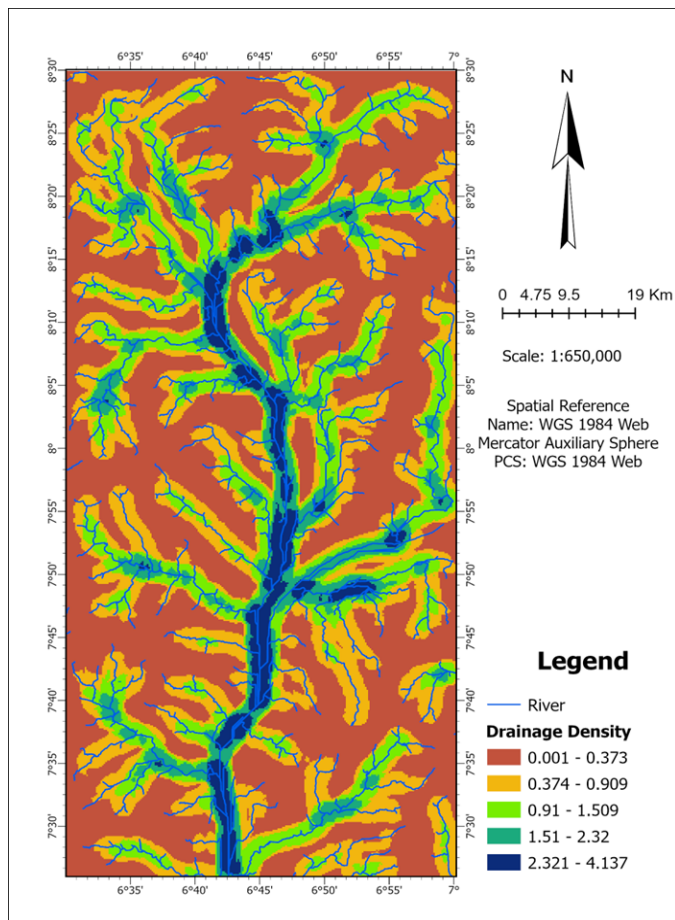


Figure 4 | Drainage Density Map

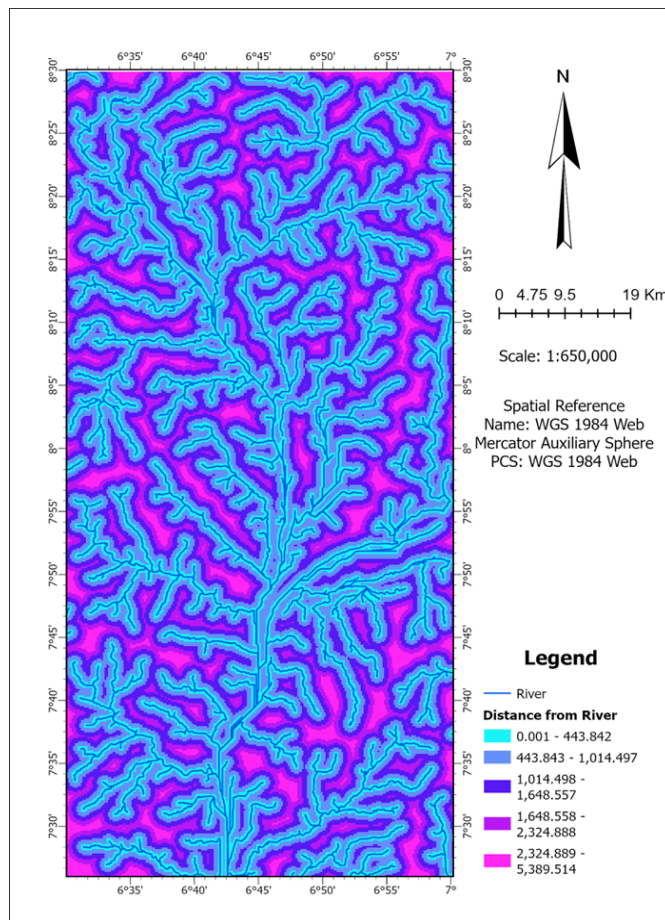


Figure 5 | Distance from River Map

Table 5 | Area coverage of LULC classes

LULC Classes	LULC Area Extent	
	Km <sup>2</sup>	%
Waterbody	169.25	2.56
Built-up	282.13	4.27
Vegetation	1866.70	28.22
Wetland	38.94	0.59
Arable land	3983.70	60.22
Bare land	274.19	4.15

### 3.8 | LULC Accuracy Assessment

#### *Flood Susceptibility Model Map*

The integrated flood susceptibility map (Figure 9) shows five susceptibility classes in the Sub-Niger River Basin, Lokoja, based on the weighted overlay of factors including elevation, slope, drainage

density, distance from rivers, lineament density, land use/land cover (LULC), and precipitation. From the spatial arrangement of these susceptibility classes as indicated in Table 6, it is clear that there are differences in the level of vulnerability in the study area. Very high susceptibility areas cover 744.53 km<sup>2</sup>, which is 13.14% of the study area. These areas

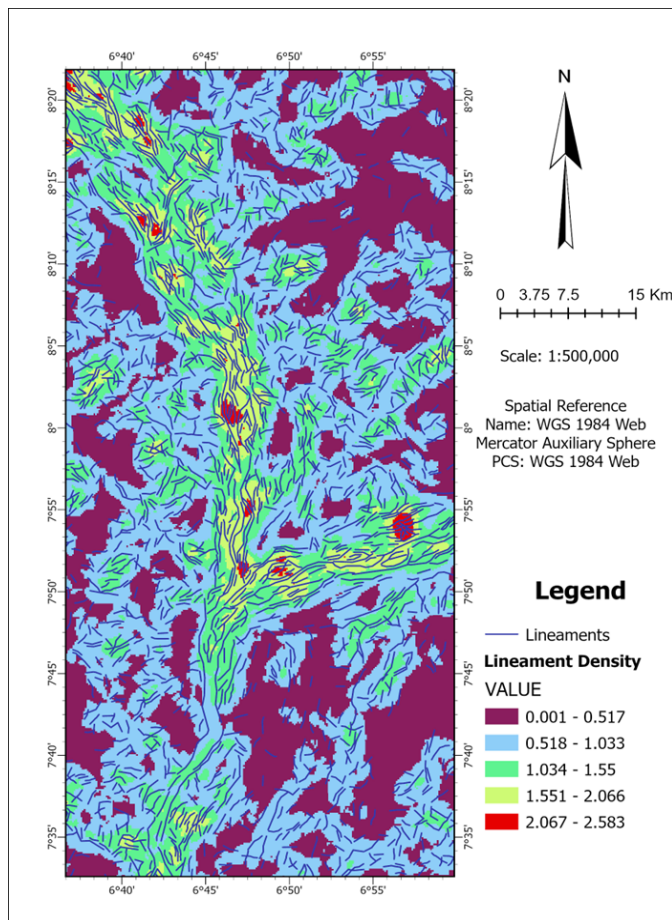


Figure 6 | Lineament Density Map

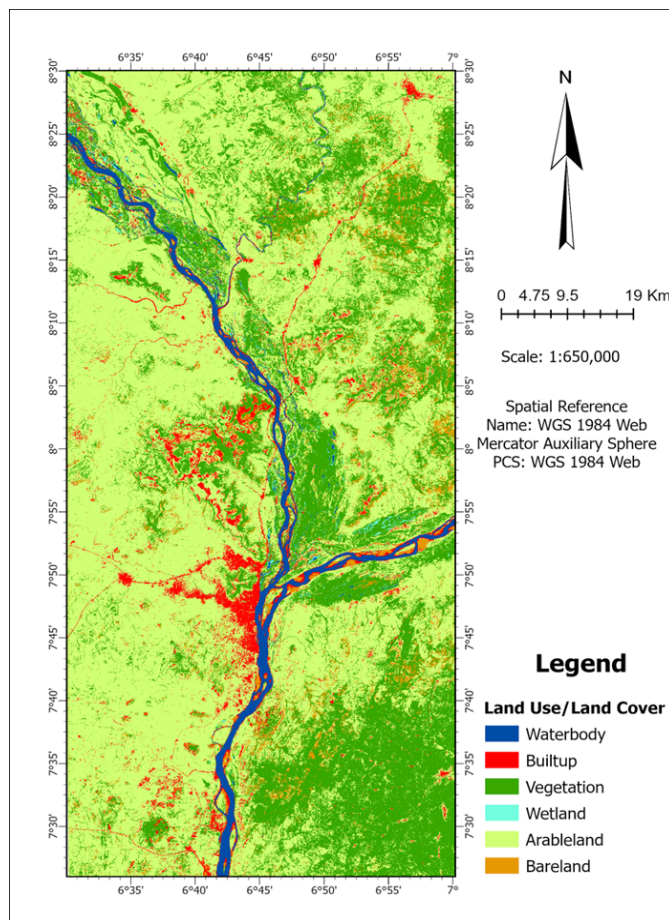


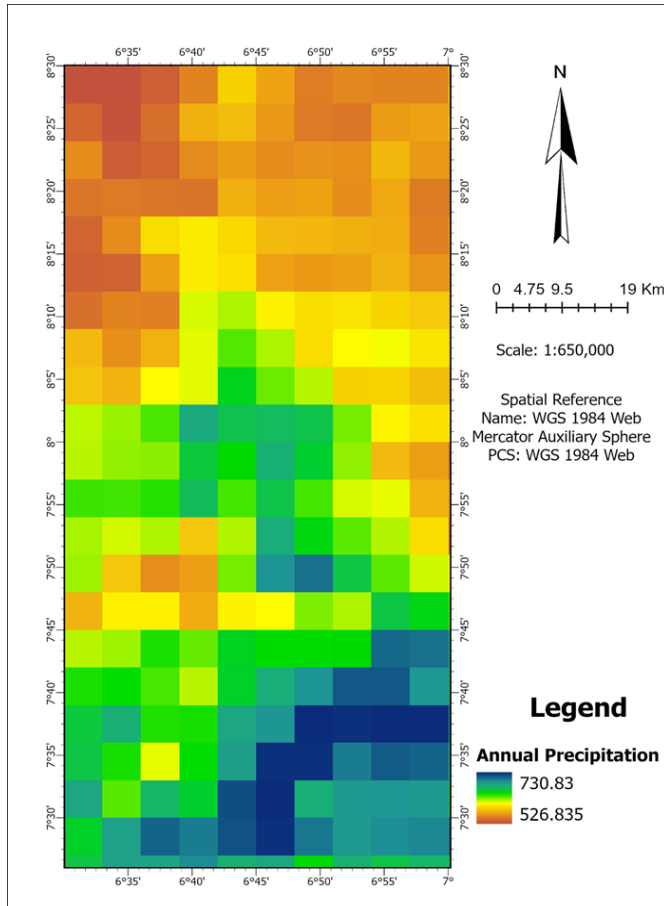
Figure 7 | Land Use/Land Cover Map

Table 6 | Confusion matrix

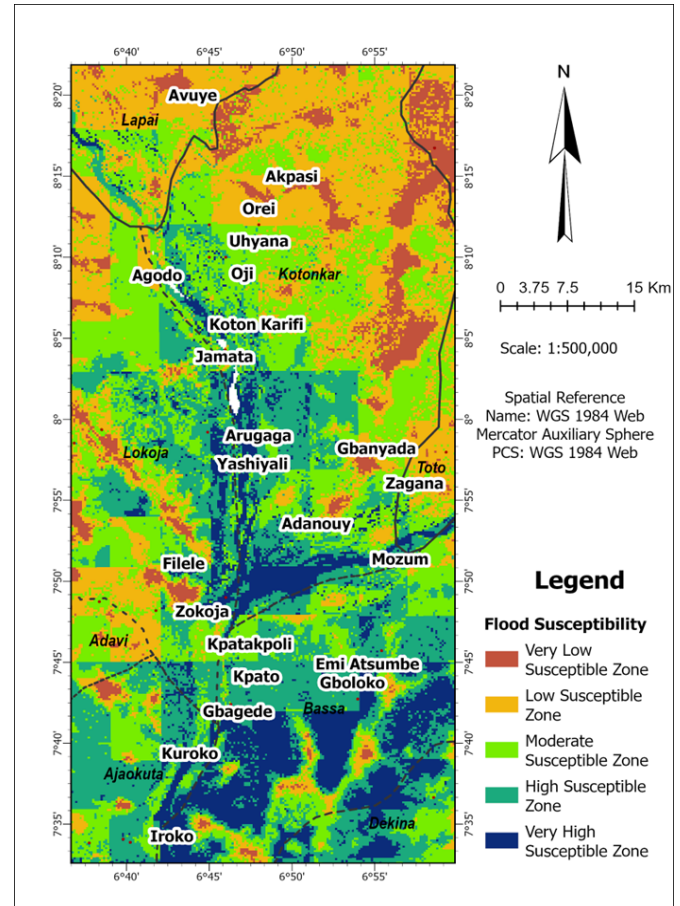
Classes	Waterbody	Built-up	Vegetation	Wetland	Arable land	Bare land	Total (User)	User Accuracy
Waterbody	7	0	0	0	0	0	7	1
Built-up	1	10	1	1	3	1	17	0.588235
Vegetation	0	0	26	0	1	0	27	0.962963
Wetland	0	0	1	10	0	0	11	0.909091
Arable land	0	1	3	0	20	1	25	0.800000
Bare land	1	0	1	0	1	10	13	0.769231
Total (Producer)	9	11	32	11	25	12	100	0
Producer Accuracy	0.777778	0.909091	0.812500	0.909091	0.800000	0.833333	0	0.830

are mostly found along the floodplains of the Niger River and the Benue River, particularly at Ganaja, Sarkin-Noma, Kabawa, and Gadumo. These areas

are characterized by low elevations of 32–90 m, flat slopes of less than 2.7° as indicated in Table 2, high drainage density, and proximity to major



**Figure 8 | Annual Precipitation Map**



**Figure 9 | Flood Susceptibility Map**

river channels, which are less than 500 m away. In these areas, the built-up areas are very vulnerable to flooding as thousands of people are frequently affected by flooding as indicated in Ishaya *et al.*, (2014). The zone agricultural land is also affected by floods that occur repeatedly and this impacts on food security. The high density of lineaments in these areas is an indication that where weaknesses are present, it is easier to have a higher rate of infiltration and runoff thereby escalating the flood problem.

About 1,342.69 km<sup>2</sup> which makes about 23.71 percent of the total area of study is under the high susceptibility zones. These areas occupy a wide radius of the very high areas all the way up to the neighboring settlements and farms. The zones are characterized by moderate drainage density, the slope of between 2.7deg to 7deg, and annual precipitation of above 645 mm, hence, the farming

activities are prone to seasonal flooding. This is justified by Komolafe *et al.*, (2015) who noted that floodplain agriculture in Nigeria is among the most vulnerable land use activities to flooding since it experiences frequent floods. The proximity of the high and very high zones indicates that the flood can spread fast to reach the high and very high zones including the urban and rural regions.

The middle terrain that consists of moderate susceptibility areas have a height of 158 m to 235 m and a slope of 7deg to 13deg. These regions occupy an area of 1,428.48km<sup>2</sup> which constitutes 25.22 of the total. They are intermediaries of flood prone regions and uplands. The agricultural land, bare ground and vegetation constitute a blend of the land use in the area. Flooding of these places is not common, but heavy rains may lead to flash flooding in the low-lying regions.

**Table 6:** Area coverage of Flood Susceptibility Zones

Name	Area Extent (km <sup>2</sup> )	Percent (%)
<b>Very Low Susceptible Zone</b>	465.415	8.22
<b>Low Susceptible Zone</b>	1682.875	29.71
<b>Moderately Susceptible Zone</b>	1428.484	25.22
<b>High Susceptible Zone</b>	1342.690	23.71
<b>Very High Susceptible Zone</b>	744.531	13.14

The susceptibility regions that are low are located predominantly within elevated and sloping regions over a distance of more than 1.6 km of rivers. It is predominantly covered by plants and farmlands. Floods may also be experienced when there is heavy rain that may result in runoff despite the fact that the susceptibility is low, it will eventually reach the moderate and high susceptibility areas.

The very low susceptibility zones occupy an area of 465.42 km<sup>2</sup> which is 8.22% of the total area. These are upland regions that have an elevation of above 337m, slopes of more than 21deg and are mainly composed of natural vegetation. These are buffers that facilitate the uptake of water and water run off. It is not common that the floods in these regions occur, and therefore, the susceptibility classification is justified.

This discussion indicates that the basin is under high and very high susceptibility in 36.85 percent of the total land area of 2,087.22 km<sup>2</sup>. This is an explicit illustration of the flooding issues that are encountered in Lokoja. The most prone to flooding in Lokoja are the places near the Niger and Benue rivers. It is evident that flood prone areas and those with high settlement and agricultural practices are related. The connection shows why the flood disasters in Lokoja usually lead to displacement and formation of infrastructure and livelihoods (Adelekan, 2016; Ishola *et al.*, 2021). The findings of the study also agree with the findings of the study conducted by Komolafe *et al.*, (2020) that found that

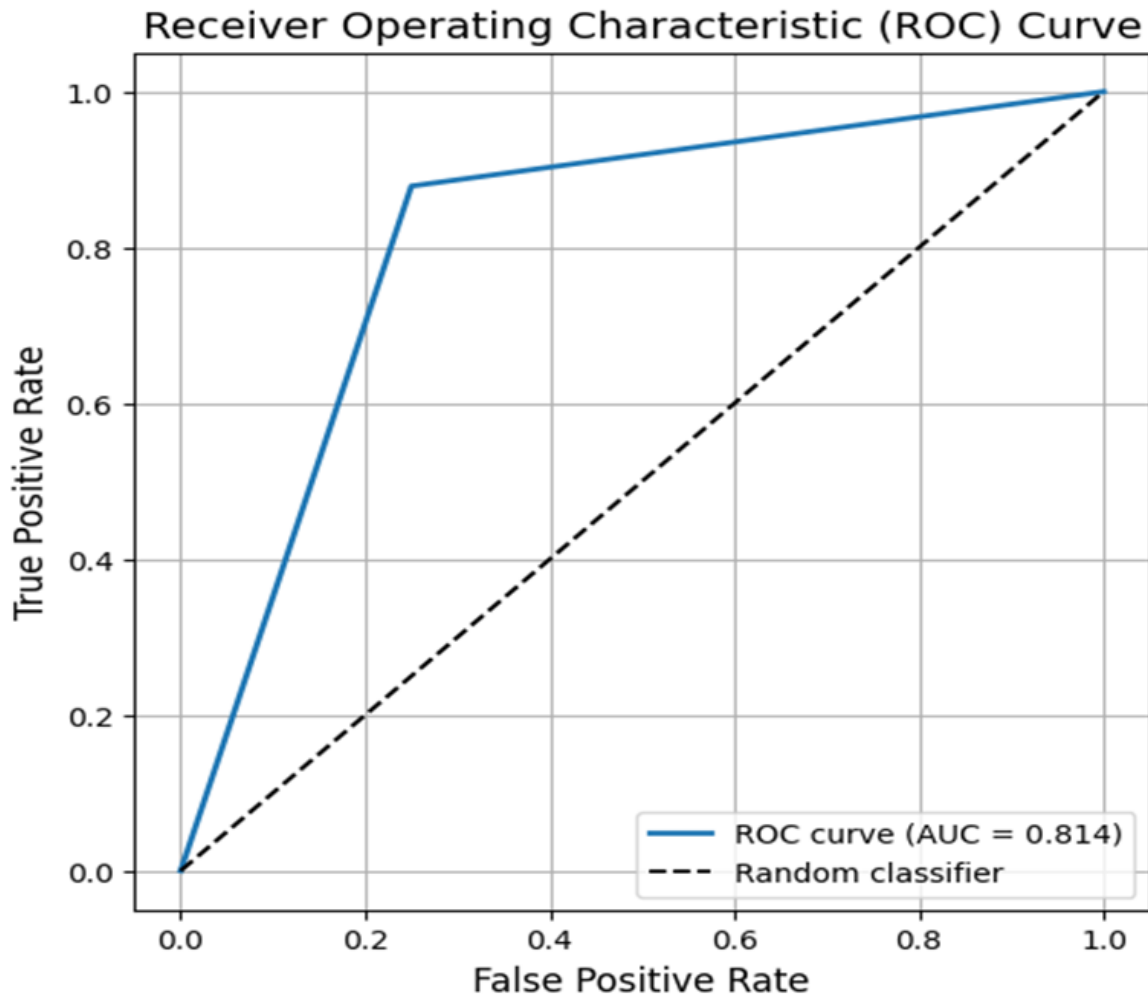
flood susceptibility is increasing in Nigeria due to the development of settlement areas in floodplains. In Lokoja, for instance, there is rapid urbanization and growth without adequate planning. As a result, critical infrastructure is being developed in areas with high flood susceptibility. The relationship between flood susceptibility and land use is a clear demonstration of the need for policy changes.

***Flood Susceptibility Map Model Validation***

The generated map of flood susceptibility of the study area showed a good performance in identifying flood-prone regions. The consistency ratio of the pairwise comparison matrix is calculated to be 0.029, which is less than the acceptable threshold of 0.1, thus ensuring the logical consistency of the weights assigned to the flood-influencing variables by the AHP model. The analysis of the performance of the AHP model in terms of overall accuracy and ROC-AUC curve scores showed an accuracy of 0.78 and an AUC of 0.81, respectively, which is an indication of a good predictive ability of the model (Figure 10).

**4 | Discussion**

This study adopted an integrated geospatial geophysical technique that incorporated remote sensing and GIS coupled with lineaments in determining flood susceptibility zones in the Sub-Niger River Basin in Lokoja. The results of the multi-criteria analysis revealed that 36.85% of the



**Figure 10 |** ROC-AUC Curve

basin, corresponding to 2,087.22 km<sup>2</sup>, falls under high and very high susceptibility zones, mostly along the Niger and Benue floodplains. The affected zones include Ganaja, Kabawa, Sarkin-Noma, and Gadumo, where low elevations below 90 meters, low slopes of less than 2.7 degrees, high drainage densities, proximity of less than 500 meters to rivers, and high human activities are observed. Conversely, zones with elevations of more than 337 meters and slopes of more than 21 degrees are classified as very low susceptibility zones.

This is further highlighted in the results that show the importance of natural factors and human exposure. Although developed areas cover only 4.27% of the basin, they are concentrated in areas of high and very high susceptibility zones, where there is a

potential for flooding. Similarly, agricultural areas that cover 60.22% of the basin are also at great risk of flood hazards. Rainfall is considered the most critical factor that increases flood susceptibility in these areas that are already highly susceptible to flood hazards.

These results are similar to previous research carried out in Nigeria (Adeyemi & Komolafe, 2025; Komolafe *et al.*, 2015; Mudashiru *et al.*, 2022). The importance of topography, proximity to rivers, and rainfall has been highlighted in flood hazard assessment in Nigeria. However, this research has improved on previous methods of flood hazard assessment by considering geophysical factors such as lineament density, thus improving on the shortcomings highlighted in (Obiora & Ibut,

2023) that flood models do not consider subsurface conditions.

Flood susceptibility mapping of the Sub-Niger River Basin in Lokoja indicates variations based on elevation, slope, drainage density, distance to river, lineament density, land use/land cover, and rainfall. The results show that more than one-third of the basin, i.e., 36.85%, is located in areas of high and very high susceptibility zones. These areas are located along the floodplains of the Niger and Benue Rivers. The results show the relationship between natural factors and human activities.

Elevation and slope show the relationship between natural factors and flood susceptibility. Areas with low elevation, ranging from 32 to 90 meters and slopes of less than 2.7 degrees, show strong relationships with areas of very high susceptibility zones. These areas are located along river valleys and floodplains, which collect water during heavy rainfall and river overflow. Adeyemi & Komolafe (2025) also showed that elevation and slope play a crucial role in identifying flood-prone areas in the Lower Niger Basin by applying machine learning algorithms. The authors confirmed that flood risks reduce with an increase in elevation, as also noted globally by Nguyen *et al.*, (2020).

Steep slopes, which are greater than 21 degrees, are also common in the upland regions of Lokoja and are classified as very low susceptibility zones because of their ability to produce quick runoff. Nevertheless, upland areas are less prone to river flooding still they are vulnerable to flash flooding and erosion caused by heavy rains. In their article on the flood factors in Malaysia and Nigeria, (Mudashiru *et al.*, 2022) also pointed this out.

Another parameter which influences susceptibility is the drainage density. Very high susceptibility areas are those that have a high drainage density of greater than 2.3 km/km<sup>2</sup>. This is in line with (Mudashiru *et al.*, 2022), who clarified that areas that had a high drainage density led to the creation of

rapid surface runoff, which amplified the magnitude of floods. These areas are present in the Niger and Benue River floodplains in Lokoja.

The distance to river also has a high level of influence on the susceptibility. Areas less than 443 meters along river channels are always indicated as very high susceptibility areas. This is backed up by earlier works by Adelekan (2016); O'Neill *et al.*, (2016), who argued that communities located along riverside are at high risk of flood because they are close to floodplain. This is visible in Lokoja, Ganaja and Sarkin-Noma, among other places, where thousands of people have been forced by floods in the past (Ishaya *et al.*, 2014).

The major aspect of this paper was inclusion of geophysical data, that is, lineament density based on aeromagnetic data. Areas with high density of lineament above 2.0 km/km<sup>2</sup> were observed to be the areas with very high susceptibility. This implies that weaknesses in the underground structure allow for the flow of water and increase the level of soil saturation. According to Komolafe (2024), the flood damage models used in areas with inadequate data often fail to consider the underground structure. This study therefore filled an important gap noted in previous Nigerian research on susceptibility mapping.

Land use and land cover play a critical role in the assessment and estimation of the level of exposure to flood hazards. Built-up areas, contributing 4.27% to the land cover, are found mainly in areas with high and very high susceptibility. This therefore points to a high level of vulnerability for human settlements (Table 2; Figure 6). Ayeni *et al.*, (2025); Eze & Efiog (2010) noted in the Osun River Basin study that areas with built-up land use are prone to flood hazards. Adeyemi & Komolafe (2025) noted that impermeable land use surfaces are key indicators of susceptibility in the Lower Niger Basin.

Agricultural lands, which covered more than 60% of the study area, were mostly classified as moderate

and high susceptibility zones. This implies that floods directly affect agricultural activities in Lokoja. Komolafe *et al.*, (2015) reported that agriculture is susceptible to floods in Nigeria. Wetland and water bodies were classified as high susceptibility zones based on their natural hydrological characteristics. The vegetated upland was the least affected area, implying that it is useful in the promotion of water absorption and reduction of runoff.

The most prominent factor in the Analytical Hierarchy Process is rainfall, which has a weight of 32%. Regions where rainfall exceeds 685 mm on an annual basis are classified in the very high susceptibility zones, as depicted in Figure 7. Rainfall is therefore a major flood predictor in Lokoja, a fact corroborated in the research works of (Adeyemi & Komolafe, 2025; Mudashiru *et al.*, 2022), which concluded rainfall to be the most dominant predictor of flood hazards in Nigerian flood plains. Changes in rainfall resulting from climate change in West Africa are expected to increase flood susceptibility in Lokoja, a fact corroborated in the research work of Babalola *et al.*, (2021).

As indicated in the composite map in Figure 9, 2087.22 km<sup>2</sup>, or 36.85%, of the basin is under high and very high susceptibility zones. These are areas of densely populated riparian settlements and heavily farmed lands. This observation is similar to the findings of (Adeyemi & Komolafe, 2025), which indicated that 40% of the lower Niger Basin is under similar susceptibility categories. This is also in line with the observations of Komolafe *et al.*, (2015), which indicated that increased settlement and agricultural development in floodplains without proper planning are causes of increased vulnerability.

The use of AHP in this study facilitated the weighting of factors, which is also supported by recent developments that propose a hybrid approach to increase accuracy (Azevedo *et al.*, 2024). For instance, machine learning algorithms such as Random Forest, Support Vector Machine, and

Artificial Neural Network have higher predictive accuracy compared to knowledge-driven methods (Adeyemi & Komolafe, 2025). However, the research adds to the existing knowledge with geophysical data, which is a big gap to the flood research in Nigeria (Obiora and Ibuot, 2023).

## 5 | Conclusion

In this research, a combination of Remote Sensing, GIS and aeromagnetic information has been used in mapping the flood risks in Sub-Niger River Basin in Lokoja. The findings indicate that over one-third of this region falls in the high and very high susceptibility areas especially in the Niger-Benue floodplains. The parameters that cause this vulnerability are elevation, slope, drainage density, nearness to rivers, rainfall and lineament density. The most vulnerable areas are the cities and agricultural lands. Policymaking wise, this paper focuses on the importance of managing floods in Lokoja. These floodplains should be zoned and strong regulations introduced in such areas. Drainage systems, de-blocking of drainage systems and adherence to the laws of disposing wastes should also be a focus area in curbing incidences of flooding. In flood prone areas, the agricultural laws ought to promote flood resistant measures like diversification of crops, early planting as well as insuring the farmers. The preparation of disaster preparedness plans should also aim at addressing the vulnerable human populations by enhancing the early warning of disasters, safe havens to the victims and equal access to evacuation routes. This study should be followed by future studies using more precise topographic measurements, e.g., LiDAR or UAV-based DEMs, by checking the flood susceptibility maps against real floods, and by combining multi-criteria decision analysis and machine learning algorithms. To sum up, this research project provides a flood susceptibility map ready to use, which will assist in identifying the regions with the high risk of flooding

in Lokoja, as well as a convenient framework of land use planning and resilience creation in one of the most flood-prone regions of Nigeria.

## 6 | Acknowledgment

In this study, the authors noted that they obtained the Tertiary Education Trust Fund (TETFund) fund-

ing via the Institution-Based Research Fund. The Federal university of technology, Akure, Nigeria is equally recognized to have good environment and facilities support.

## Reference

- Adelekan, I. O. (2016). Flood risk management in the coastal city of Lagos, Nigeria. *Journal of Flood Risk Management*, 9(3), 255–264. <https://doi.org/10.1111/jfr3.12179>
- ACSS, (2024). Record Levels of Flooding in Africa Compounds Stress on Fragile Countries, the Africa Center for Strategic Studies, <https://africacenter.org/spotlight/record-levels-of-flooding-in-africa-compounds-stress-on-fragile-countries/>
- Aderogba, K. A. (2012). *Qualitative Studies of Recent Floods and Sustainable Growth and Development of Cities and Towns in Nigeria*. 1(3).
- Adeyemi, A. B., & Komolafe, A. A. (2025). Flood hazard zones prediction using machine-learning-based geospatial approach in lower Niger River basin, Nigeria. *Natural Hazards Research*, S2666592125000022. <https://doi.org/10.1016/j.nhres.2025.01.002>
- Akinlalu, A. A., Mogaji, K. A., & Adebodun, T. S. (2021). Assessment of aquifer vulnerability using a developed “GODL” method (modified GOD model) in a schist belt environ, Southwestern Nigeria. *Environmental Monitoring and Assessment*, 193(4), 199. <https://doi.org/10.1007/s10661-021-08960-z>
- Amigun, J. O., Sanusi, S. O., & Audu, L. (2022). Geophysical characterisation of rare earth element and gemstone mineralisation in the Ijero-Aramoko pegmatite field, southwestern Nigeria. *Journal of African Earth Sciences*, 188, 104494. <https://doi.org/10.1016/j.jafrearsci.2022.104494>
- Ariyani, D., Mohammad Yanuar Jarwadi Purwanto, Euis Sunarti, & Perdinan. (2022). Contributing Factor Influencing Flood Disaster Using MICMAC (Ciliwung Watershed Case Study). *Jurnal Pengelolaan Sumberdaya Alam Dan Lingkungan (Journal of Natural Resources and Environmental Management)*, 12(2), 268–280. <https://doi.org/10.29244/jpsl.12.2.268-280>
- Ayeni, A. O., Aborisade, A. G., Aiyegbajeje, F. O., & Soneye, A. S. O. (2025). The dynamics of peri-urban expansion in sub-saharan africa: Implications for sustainable development in Nigeria and Ghana. *Discover Sustainability*, 6(1), 290. <https://doi.org/10.1007/s43621-024-00742-0>
- Azevedo, B. F., Rocha, A. M. A. C., & Pereira, A. I. (2024). Hybrid approaches to optimization and machine learning methods: A systematic literature review. *Machine Learning*, 113(7), 4055–4097. <https://doi.org/10.1007/s10994-023-06467-x>
- Babalola, T. E., Gbenro Oguntunde, P., Ebenezer Ajayi, A., & Omowonuola Akinluyi, F. (2021). Future Climate Change Impacts on River Discharge Seasonality for Selected West African River Basins. In M. Saifullah (Ed.), *Weather Forecasting*. IntechOpen. <https://doi.org/10.5772/intechopen.99426>
- Brody, S., Blessing, R., Sebastian, A., & Bedient, P. (2014). Examining the impact of land use/land

- cover characteristics on flood losses. *Journal of Environmental Planning and Management*, 57(8), 1252–1265. <https://doi.org/10.1080/09640568.2013.802228>
- Elkhrachy, I. (2015). Flash Flood Hazard Mapping Using Satellite Images and GIS Tools: A case study of Najran City, Kingdom of Saudi Arabia (KSA). *The Egyptian Journal of Remote Sensing and Space Science*, 18(2), 261–278. <https://doi.org/10.1016/j.ejrs.2015.06.007>
- Eze, B. E., & Efiog, J. (2010). *Morphometric Parameters of the Calabar River Basin: Implication for Hydrologic Processes*. 2(1). [https://www.researchgate.net/profile/Joel-Efiog/publication/46105920\\_Morphometric\\_Parameters\\_of\\_the\\_Calabar\\_River\\_Basin\\_Implication\\_for\\_Hydrologic\\_Processes/links/02e7e5307b0777262b000000/Morphometric-Parameters-of-the-Calabar-River-Basin-Implication-for-Hydrologic-Processes.pdf?origin=journalDetail&\\_tp=eyJwYWdlIjoiam9lcm5hbERldGFpbCJ9](https://www.researchgate.net/profile/Joel-Efiog/publication/46105920_Morphometric_Parameters_of_the_Calabar_River_Basin_Implication_for_Hydrologic_Processes/links/02e7e5307b0777262b000000/Morphometric-Parameters-of-the-Calabar-River-Basin-Implication-for-Hydrologic-Processes.pdf?origin=journalDetail&_tp=eyJwYWdlIjoiam9lcm5hbERldGFpbCJ9)
- Fitri, M. (2019). The settlement morphology along musu river: the influence of river characteristics. *Dimension (Journal of Architecture and Built Environment)*, 45(2), 133–140. <https://doi.org/10.9744/dimensi.45.2.133-140>
- Ganguli, S. S., Pal, S. K., Rama Rao, J. V., & Sunder Raj, B. (2020). Gravity–magnetic appraisal at the interface of Cuddapah Basin and Nellore Schist Belt (NSB) for shallow crustal architecture and tectonic settings. *Journal of Earth System Science*, 129(1), 92. <https://doi.org/10.1007/s12040-020-1354-8>
- Ganguli, S. S., Pal, S. K., Sundaralingam, K., & Kumar, P. (2021). Insights into the crustal architecture from the analysis of gravity and magnetic data across Salem-Attur Shear Zone (SASZ), Southern Granulite Terrane (SGT), India: An evidence of accretional tectonics. *Episodes*, 44(4), 419–442. <https://doi.org/10.18814/epiiugs/2020/020095>
- Ganguli, S. S., Singh, S., Das, N., Maurya, D., Pal, S. K., & Rao, J. V. R. (2019). Gravity and Magnetic Survey in Southwestern Part of Cuddapah Basin, India and its Implication for Shallow Crustal Architecture and Mineralization. *Journal of the Geological Society of India*, 93(4), 419–430. <https://doi.org/10.1007/s12594-019-1196-7>
- Gupta, N., Dahal, S., Kumar, A., Kumar, C., Kumar, M., Maharjan, A., Mishra, D., Mohanty, A., Navaraj, A., Pandey, S., Prakash, A., Prasad, E., Shrestha, K., Shrestha, M. S., Subedi, R., Subedi, T., Tiwary, R., Tuladhar, R., & Unni, A. (2021). Rich water, poor people: Potential for transboundary flood management between Nepal and India. *Current Research in Environmental Sustainability*, 3, 100031. <https://doi.org/10.1016/j.crsust.2021.100031>
- Ishaya, S., Hassan, S., & James, S. (2014). Post-Adaptation vulnerability of cereals to rainfall and temperature variability in the federal capital territory of Nigeria. *Ethiopian Journal of Environmental Studies and Management*, 7(5), 532. <https://doi.org/10.4314/ejesm.v7i5.7>
- Ishola, S. O., Ogunsina, B. I., Alao, B. I., & Adara, C. T. (2021). *Effects of Climate Smart Farming Practices (CSFP) on Food Security Status among Rural Farming Households in Ogun State, Nigeria*. 9(2).
- Komolafe, A. A., Adegboyega, S. A.-A., & Akinluyi, F. O. (2015). A Review of Flood Risk Analysis in Nigeria. *American Journal of Environmental Sciences*, 11(3), 157–166. <https://doi.org/10.3844/ajessp.2015.157.166>
- Komolafe, A. A., Awe, B. S., Olorunfemi, I. E., & Oguntunde, P. G. (2020). Modelling flood-prone area and vulnerability using integration of multi-criteria analysis and HAND model in the Ogun River Basin, Nigeria. *Hydrological Sciences Journal*, 65(10), 1766–1783. <https://doi.org/10.1080/002626667.2020.1764960>

- Merz, B., Blöschl, G., Vorogushyn, S., Dottori, F., Aerts, J. C. J. H., Bates, P., Bertola, M., Kemter, M., Kreibich, H., Lall, U., & Macdonald, E. (2021). Causes, impacts and patterns of disastrous river floods. *Nature Reviews Earth & Environment*, 2(9), 592–609. <https://doi.org/10.1038/s43017-021-00195-3>
- Mudashiru, R. B., Sabtu, N., Abdullah, R., Saleh, A., & Abustan, I. (2022). Optimality of flood influencing factors for flood hazard mapping: An evaluation of two multi-criteria decision-making methods. *Journal of Hydrology*, 612, 128055. <https://doi.org/10.1016/j.jhydrol.2022.128055>
- Nguyen, H.-D., Pham, V.-D., Nguyen, Q.-H., Pham, V.-M., Pham, M. H., Vu, V. M., & Bui, Q.-T. (2020). An optimal search for neural network parameters using the Salp swarm optimization algorithm: A landslide application. *Remote Sensing Letters*, 11(4), 353–362. <https://doi.org/10.1080/2150704X.2020.1716409>
- Nkwunonwo, U. C., Whitworth, M., & Baily, B. (2016). Review article: A review and critical analysis of the efforts towards urban flood risk management in the Lagos region of Nigeria. *Natural Hazards and Earth System Sciences*, 16(2), 349–369. <https://doi.org/10.5194/nhess-16-349-2016>
- Nwanosike, S. O., Mmom, Prince. C., & Weli, V. E. (2021). Impacts of Flooding on Residents of the Niger Delta Region of Nigeria: Deleterious and Beneficial Dimensions. *Journal of Research in Humanities and Social Science*, 9(11), 58–68.
- Obiora, D. N., & Ibuot, J. C. (2023). Electrical geophysical evaluation of susceptibility to flooding in University of Nigeria, Nsukka main campus and its environs, Southeastern Nigeria. *Journal of Groundwater Science and Engineering*, 11(4), 422–434. <https://doi.org/10.26599/JGSE.2023.9280033>
- Ogden, F. L., Raj Pradhan, N., Downer, C. W., & Zahner, J. A. (2011). Relative importance of impervious area, drainage density, width function, and subsurface storm drainage on flood runoff from an urbanized catchment. *Water Resources Research*, 47(12), 2011WR010550. <https://doi.org/10.1029/2011WR010550>
- Olatunde, A. F., & Sullaiman, I. D. (2025). *Wet and Dry Sell Occurrences in Lokoja Area, Kogi State, Nigeria*. 4(1).
- Ologunorisa, T. E., & Abawua, M. J. (2005). Flood risk assessment: A Review. *J. Appl. Sci. Environ. Mgt.*, 9(1), 57–63. <http://www.bioline.org.br/ja05010>
- O'Neill, E., Brereton, F., Shahumyan, H., & Clinch, J. P. (2016). The Impact of Perceived Flood Exposure on Flood-Risk Perception: The Role of Distance. *Risk Analysis*, 36(11), 2158–2186. <https://doi.org/10.1111/risa.12597>
- Oyeniya, T., Adebola, S. A., & Ojo, S. (2016). *Magnetic Surveying as an Aid to Geological Mapping: A Case Study from Obafemi Awolowo University Campus in Ile-Ife, Southwest Nigeria*. 18(2), 331–343.
- Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. New York ; London : McGraw-Hill International Book Co. <https://archive.org/search.php?query=external-identifier%3A%22urn%3Aoclc%3Arecord%3A1330340106%22>