A Multi-Criteria Approach to Flood Risk Assessment in Makurdi Using GIS and the Analytic Hierarchy Process

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ABSTRACT

Flooding in Makurdi, Nigeria, poses a persistent threat, submerging homes, displacing communities, and leaving residents in a constant struggle for survival. Despite numerous flood risk assessments, previous studies have often overlooked critical factors, leading to recurring floods and inadequate tools for preparedness and mitigation. This study presents an integrated approach to flood risk analysis, combining Geographic Information Systems (GIS), Multi-Criteria Decision-Making (MCDM), and the Analytic Hierarchy Process (AHP). Eight critical factors - slope, elevation, rainfall, land use and land cover, river proximity, soil type, drainage density, and road proximity were considered, quantifying their relative importance and validating them using a suitable consistency ratio. Weighted overlay analysis revealed that over 56 % of the region falls within high flood-risk zones. These findings provide actionable insights for enhancing flood preparedness and mitigation planning in Makurdi. Furthermore, the methodology and results apply to similar flood-prone regions globally, offering a framework for scalable and context-specific interventions to inform flood risk management efforts worldwide.

Keywords: Flooding, Geographic Information Systems (GIS), Multi-Criteria Decision-Making (MCDM), Analytic Hierarchy Process (AHP), Makurdi.

INTRODUCTION

Imagine waking up to find your entire community submerged overnight, homes destroyed, farmlands swept away, and families displaced by the unyielding forces of nature. For the people of Makurdi, Nigeria, this is not just a story but an annual tragedy. Each rainy season brings devastating floods, triggering food insecurity, economic losses, and deepening poverty in already vulnerable communities.

Flooding remains a major global hazard, growing in frequency and severity due to intensifying extreme weather events linked to climate change (Tabari, 2020). In 2023 alone, 176 major floods were recorded worldwide (Dyvik, 2024). In Nigeria, the 2024 floods claimed over 300 lives and displaced more than 1.2 million people across 31 states, with Makurdi being among the most severely affected (Office for the Coordination of Humanitarian Affairs [OCHA], 2024).

Flood risk is driven by a complex interplay of environmental, hydrological, and anthropogenic factors. Variables such as terrain elevation, rainfall intensity, land use patterns, soil characteristics, drainage systems, and proximity to rivers and roads interact dynamically to influence flood susceptibility. Understanding these interactions requires a multi-criteria approach capable of objectively assessing the relative influence of each factor and their combined effects.

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The emergence of spatial technologies such as Geographic Information Systems (GIS) and analytical tools like the Analytic Hierarchy Process (AHP) now enables researchers and planners to integrate and visualize these data layers effectively. This integration enhances the clarity of spatial risk patterns and supports more informed, data-driven flood preparation and planning. It allows decision-makers to pinpoint flood-prone areas with greater accuracy and implement proactive mitigation strategies.

With climate change accelerating the intensity and unpredictability of extreme weather events (Hamidifar et al., 2024; Kumar & Jha, 2023; Bhuyan et al., 2024), embedding GIS and multi-criteria decision-making techniques into flood analysis has become not just advantageous, but essential. Such approaches support the development of resilient, adaptive risk management frameworks tailored to local realities like those faced in Makurdi.

LITERATURE GAP AND RESEARCH QUESTIONS

Despite the severity of flood impacts in Makurdi, previous studies have significant limitations. For instance, Ornguze et al. (2023) and Kunda et al. (2021) primarily considered only land use/land cover (LULC), slope, rainfall, and elevation, omitting other influential factors like river and road proximity, which are critical for understanding flood risk and emergency access. Similarly, studies by Acha and Aishetu (2018) and Ndabula (2021) focused on isolated variables, such as soil type or rainfall, without integrating the full spectrum of hydrological and topographical factors. Oyatayo et al. (2021) and Peter et al. (2020) provided partial analyses without a comprehensive multi-criteria framework to assess the combined effects of flood contributors.

These gaps have resulted in incomplete flood risk models and inadequate preparedness tools, leaving communities exposed to recurring flood disasters.

This study aims to address these gaps by answering the following questions:

i. What are the critical factors contributing to flood risk, and what are their levels of influence?
ii. How effectively can Geographic Information Systems (GIS), Multi-Criteria Decision-Making (MCDM), and the Analytic Hierarchy Process (AHP) be integrated to analyze and map flood risk in Makurdi?

Objectives of the Study

i. To identify key flood-contributing factors in Makurdi and determine their relative importance using AHP.
ii. To employ GIS and MCDM to integrate these factors and generate a spatial flood risk map.
iii. To provide actionable insights for improving local flood preparedness and mitigation efforts.

Scope and Significance

Building on Clark's (1998) theory, which highlights the multi-dimensional nature of flooding encompassing topographical, climatic, environmental, hydrological, and anthropogenic factors, this study analyzes key flood risk factors in Makurdi using GIS and MCDM. AHP is employed to assign weights to these factors, ensuring the reliability of the analysis through a robust consistency ratio.

This approach provides a comprehensive understanding of the relative importance of each factor and their combined contributions to flood risks in the region. The findings of this study aim to enhance the understanding of flood risk dynamics in Makurdi, offering actionable insights to improve disaster preparedness and management. By equipping stakeholders and researchers with detailed analyses and reliable data, this research addresses local challenges and establishes a framework that can be adapted for other flood-prone regions. Ultimately, it contributes to global efforts to mitigate the impacts of climate-induced disasters and foster a safer, more sustainable future.

Figure 1 depicts the 2024 flood disaster's extensive damage in Makurdi (Nigerian Hydrological Services Agency [NIHSA], 2024), underscoring the critical need for improved flood risk management.

Figure 1: Impact of the Devastating Floods in Makurdi, Nigeria (NIHSA), 2024

METHODOLOGY

This section briefly introduces the study area, lists the software used, details the data employed for the analysis, and outlines the procedure for generating the flood risk map for Makurdi, revealing the flood severity in the area.

The Study Area

Nigeria, located in West Africa, is the most populous country on the continent, with a population exceeding 200 million as of 2021 (Idogho et al., 2025). Administratively, the country is divided into 36 states and the Federal Capital Territory, Abuja.

This study focuses on Makurdi, the capital of Benue State in central Nigeria. Geographically, Makurdi lies between latitudes 7°38'N and 7°50'N and longitudes 8°24'E and 8°38'E. The town is bisected by the River Benue, Nigeria's second-largest river, and is characterized by low-lying terrain that makes flood-prone neighbourhoods such as Wurukum and Wadata particularly vulnerable during the rainy season.

Covering approximately 937.4 km², Makurdi had an estimated population of 433,700 in 2022 (National Population Commission [NPC], 2022). The area experiences a tropical wet and dry climate, with the rainy season typically occurring between April and October. Agriculture plays a central role in the local economy, supported by three main soil types, including Plinthic Luvisols, Fluvisols, and Ferric Acrisols, as classified by the Food and Agriculture Organization (FAO, n.d.). The study area is illustrated in **Figure 2**.

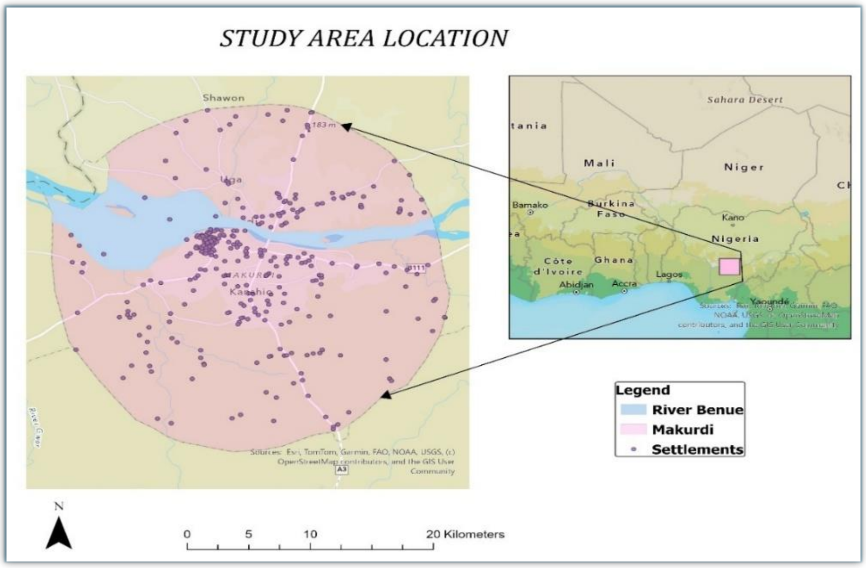

Figure 2: Map Showing the Study Area, Makurdi, Nigeria

Data Collection and Analysis Tools

Table 1 outlines the data used in the study and their respective sources. ArcGIS Pro 3.3 was used for geospatial processing, while Excel was used for data analysis and visualization.

Table 1: Data Acquisition

Data	Source	Details
Administrative Data	- Esri (esri.com) - Geospatial Repository and Data Management (GRiD) System (grid3.gov.ng)	Administrative Maps & Shape Files
Topographical Data	United States Geological Survey (USGS) (earthexplorer.usgs.gov)	Shuttle Radar Topography Mission (SRTM)
Satellite Imagery	United States Geological Survey (USGS) (earthexplorer.usgs.gov)	Landsat 8
Hydrological Data	Centre for Hydrometeorology and Remote Sensing (CHRS) (chrsdata.eng.uci.edu)	Rainfall Yearly data (2001 to 2020)
Soil Data	Food and Agriculture Organization (FAO) (fao.org)	Harmonized World Soil Database (HWSD v2.0)

Footnote: Breakdown of data used in the flood risk analysis for Makurdi, Nigeria, including the relevant websites from which the data were sourced.

Spatial Assessment to Generate Thematic Maps

This study assesses flood risk by analyzing eight key factors - elevation, slope, rainfall, drainage density, land use and land cover (LULC), proximity to rivers, proximity to roads, and soil type using Geographic Information System (GIS) technology. These factors were chosen based on their demonstrated relevance to flood vulnerability, as documented in several related studies (Abah & Clement, 2013; Acha & Aishetu, 2018; Azua et al., 2019; Cabrera & Lee, 2019; Danumah et al., 2016; Kumar & Jha, 2023; Peter et al., 2020).

Elevation is a fundamental factor in flood risk, as lower-lying areas are generally more susceptible to flooding. Shuttle Radar Topography Mission (SRTM) data in TIFF format was imported into the ArcGIS environment to generate a Digital Elevation Model (DEM), which provided a detailed representation of elevation across the study area. Using this DEM, slope values were calculated with the ArcGIS "Slope" tool. The resulting slope map illustrated the steepness of the terrain, which plays a critical role in determining runoff velocity and accumulation.

Land use and land cover patterns were mapped using Landsat 8 satellite imagery. A composite of seven spectral bands was created, and a natural color composite using bands 4, 3, and 2 was selected to reflect true-colour land features. An unsupervised classification method grouped pixels into land cover types based on their spectral similarities, providing insight into how different land uses, such as urban areas, vegetation, water bodies and bare land, affect flood dynamics.

Rainfall data spanning twenty years was compiled and averaged using the “Raster Calculator” tool, which aggregated annual values and divided the total by the number of years. To capture spatial variation, the “Inverse Distance Weighted (IDW)” interpolation method was used, resulting in a rainfall distribution map that visualized precipitation intensity across the study area.

Proximity to rivers was analyzed by applying the “Euclidean Distance” tool to river datasets, generating a continuous surface that showed the distance of each cell from the nearest river. This analysis was crucial for identifying areas at increased flood risk due to their closeness to water bodies. A similar approach was used for assessing road proximity; the Euclidean Distance tool calculated the distance from each location to the nearest road segment, offering insights into how road networks might influence both vulnerability and accessibility during flood events.

Drainage density was derived through a series of hydrological analyses. The DEM was pre-processed using the "Fill" tool to correct imperfections, and flow direction and flow accumulation rasters were generated to model the movement of water. Thresholds were applied to define stream channels, which were then converted to vector features. The density of these drainage lines was calculated using the "Line Density" tool, producing a map that reflects the intensity of drainage networks and their capacity to manage runoff.

Finally, soil characteristics were evaluated by importing soil data in shapefile format and clipping it to the study boundary. The polygon features were converted into point data, enabling an assessment of soil types based on their permeability and water retention properties, both of which significantly influence flood potential.

To enable integrated analysis and comparison across these diverse factors, all eight thematic maps were reclassified into five standardized categories, ranging from very low to very high flood risk. This reclassification process ensured uniformity and allowed for a comprehensive spatial analysis of flood vulnerability across the study area.

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a structured multi-criteria decision-making method that simplifies complex decision problems by organizing them into a hierarchy of criteria and alternatives (Hamidifar et al., 2024). In this study, AHP was used to determine the relative importance of the eight flood risk factors by systematically comparing them in pairs. The pairwise comparison matrix used for this evaluation is presented in **Table 2**.

Weights were assigned to each criterion based on their perceived influence on flood risk in the study area. These pairwise comparisons were carried out using Saaty's 1–9 importance scale, as outlined in **Table 3**, where a value of 1 indicates equal importance, and 9 indicates extreme importance of one criterion over another. Each factor was compared with every other factor, and the results were entered into an Excel-based AHP tool developed by Goepel (2018). This software calculated the normalized weights (principal eigenvector), and the Consistency Ratio (CR).

The final weights derived from the AHP process were integrated into the GIS-based weighted overlay analysis, allowing for the consideration of both spatial variability and the relative influence of flood-contributing factors. This matrix served as the foundation for spatial decision-making using the Multi-Criteria Decision-Making (MCDM) approach, ultimately supporting the development of the flood risk map.

Table 2: Multi-Criteria Decision-Making (MCDM) Matrix

Weights:	$\boldsymbol{w_1}$	$\boldsymbol{w_2}$	...	$\boldsymbol{wn}$
Criteria:	$\boldsymbol{C_1}$	$\boldsymbol{C_2}$	...	$\boldsymbol{C_n}$
$\boldsymbol{A_1}$	X_{11}	X_{12}	...	X_{1n}
$\boldsymbol{A_2}$	X_{21}	X_{22}	...	X_{2n}
...	...	...	Xij	...
$\boldsymbol{A_m}$	X_{m1}	X_{m2}	...	X_{mn}

Source: Saaty, (2008)

Footnote: The matrix presents decision alternatives (A_1 to A_m), representing spatial locations or zones within the Makurdi study area, evaluated against multiple flood risk criteria (C_1 to C_n), such as elevation, slope, rainfall, drainage density, LULC, river proximity, road proximity, and soil texture. The weights (w_1 to w_n) assigned to each criterion were derived using the AHP as proposed by Saaty (2008), based on expert judgment

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and literature. Each cell value X_{ij} represents the suitability or risk score of a given location A_i with respect to criterion C_j.

Table 3: Scales of Pairwise Comparisons

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgement slightly favour one activity over another
5	Strong importance	Experience and judgement strongly favour one activity over another
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation

Source: Saaty, (2008)

Footnote: Pairwise comparison scales used in the AHP for flood risk analysis in Makurdi, Nigeria, based on Saaty's scale, ranging from 1 (equal importance) to 9 (extremely more important)

Weighted Overlay and Flood Risk Mapping

The weights derived from the AHP analysis were applied to generate a flood risk map. The "weighted overlay" geoprocessing tool integrated the weighted factors, creating a comprehensive spatial representation of flood risk across the study area. The resulting spatial data was then reclassified into five flood risk zones: very-low risk, low risk, moderate risk, high risk, and very high risk. This map was used to depict flood-prone areas and the severity of flooding within the region.

Figure 3 displays the workflow for the entire process.

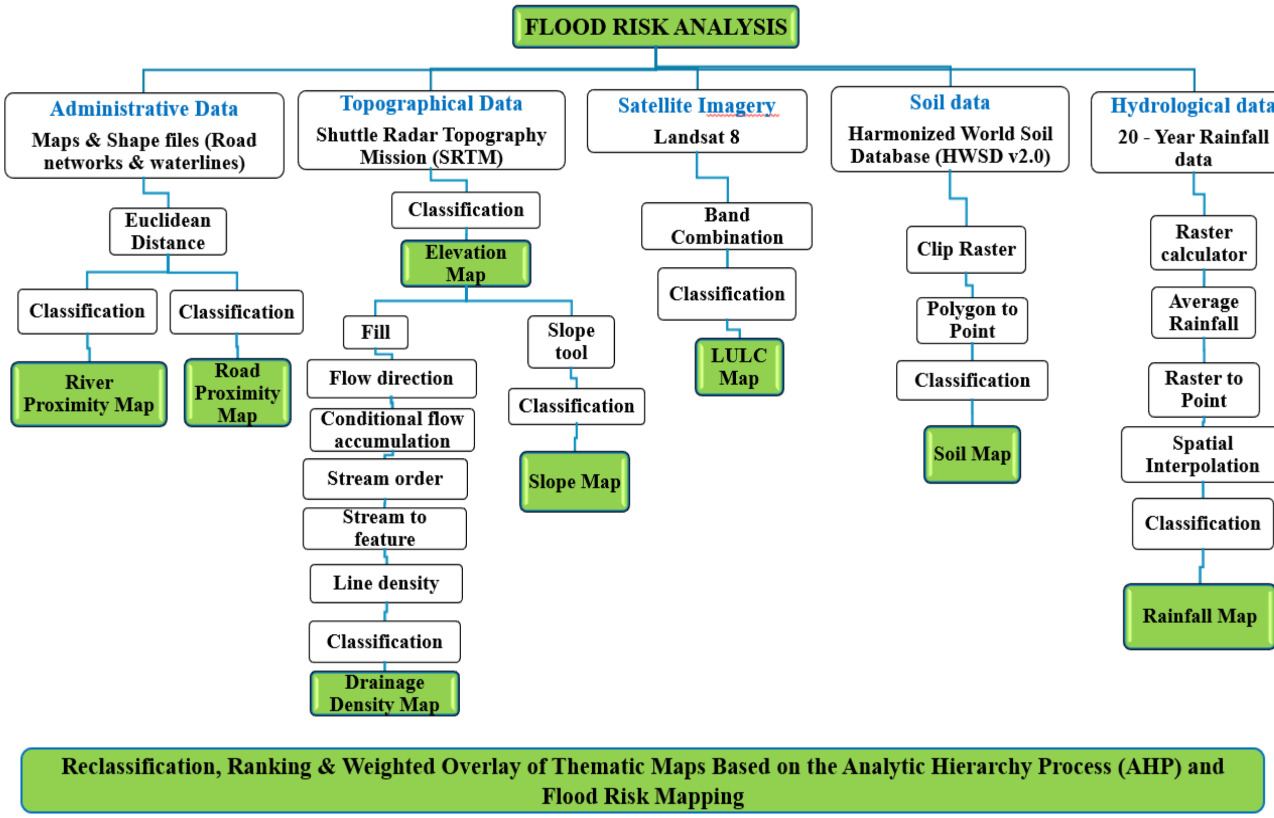

Figure 3: Methodological Flowchart for Flood Risk Analysis in Makurdi

RESULTS

This section presents the findings of the flood risk analysis for Makurdi, highlighting its spatial distribution. The results, displayed through maps and statistical summaries, offer an overview of flood susceptibility across the study area.

Thematic Maps

Table 4 provides a summary of the classification and associated flood risk ratings used in the analysis. Figures 4 to 11 display the eight thematic maps employed in the study, representing key flood risk factors such as elevation, slope, rainfall, drainage density, LULC, river proximity, road proximity, and soil type. These maps depict the spatial variability of each factor and their potential influence on flood susceptibility across the study area. A standardized flood risk scale was applied uniformly across all maps, where a value of 1 indicates very low risk, 2 represents low risk, 3 corresponds to moderate risk, 4 signifies high risk, and 5 denotes very high flood risk. This classification enabled consistent interpretation and integration into the flood risk modeling framework.

Table 4: Results of Thematic Maps and Classification Based on Flood Risk

Flood-Risk Rating	Elevation (m)	Slope (%)	LULC	Rainfall (mm)	River Proximity (m)	Road Proximity (m)	Drainage Density (m/m^2)	Soil
5	83.0	2.360	Water Bodies	1935.70	2424.47	4134.31	0.004285	Ferric Acrisols
4	103.0	4.47	Built-up areas	1908.33	5865.66	2204.97	0.002537	-
3	124.0	6.83	Farmland	1888.13	9541.47	1491.60	0.001647	Fluvisols
2	149.0	10.19	Vegetation	1866.59	13686.53	956.57	0.001126	-
1	204.0	31.67	Bare surface	1845.49	19943.23	405.32	0.000639	Plinthic Luvisols

Footnote: The flood risk category ratings were derived from spatial analysis of the thematic maps. These reflect the relative influence of each contributing factor on flood risk, as determined through GIS-based classification and multi-criteria evaluation. The risk ratings range from 1 to 5, where 1 represents very low risk and 5 represents very high risk.

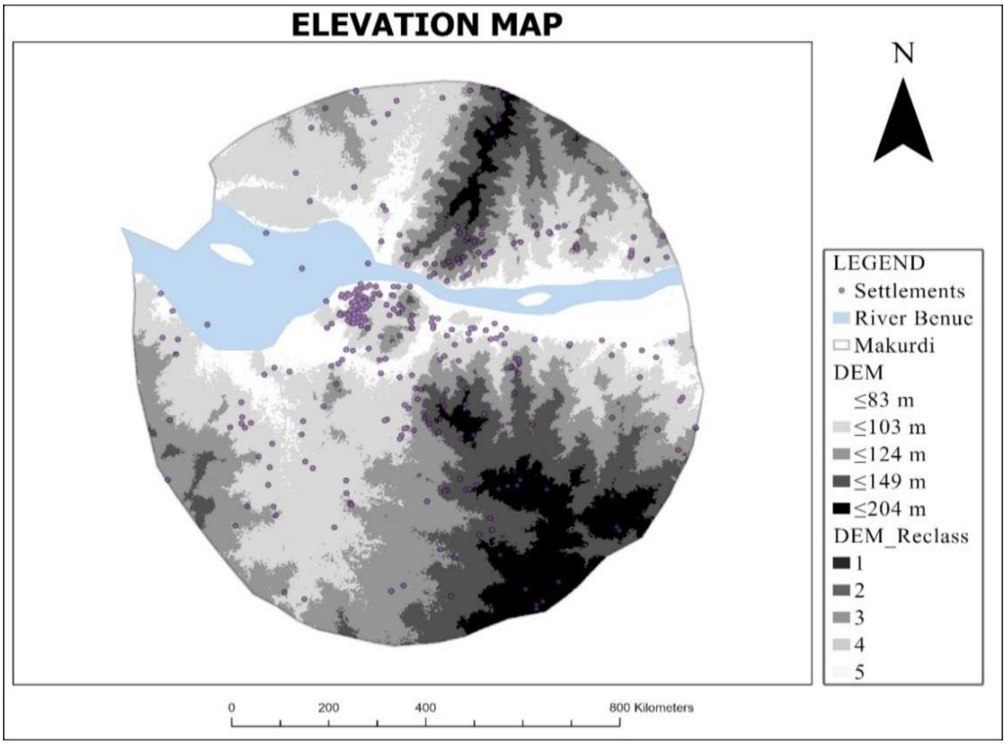

Figure 4: Elevation Map for Makurdi, Nigeria

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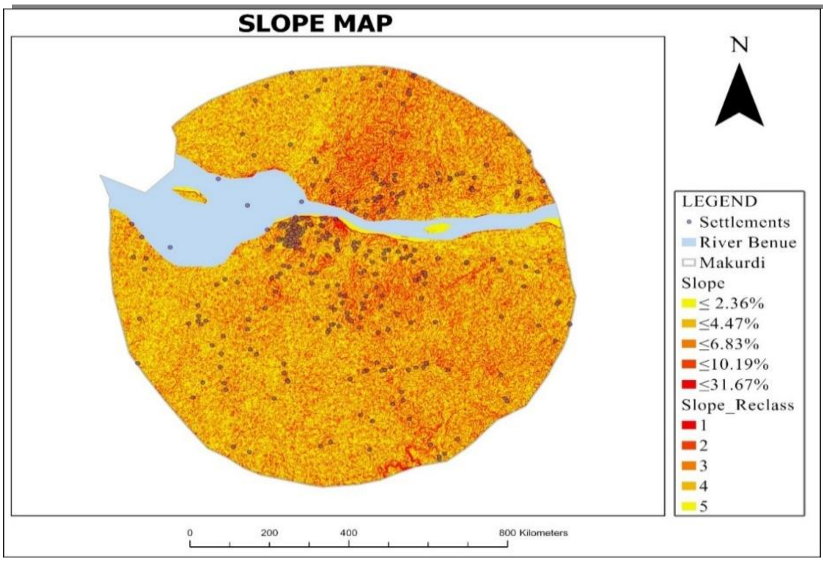

Figure 5: Slope Map for Makurdi, Nigeria

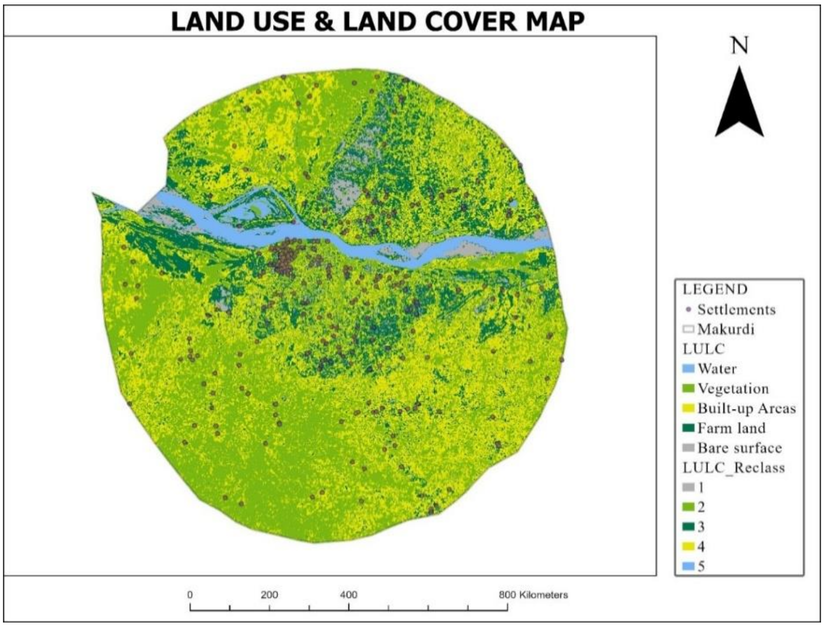

Figure 6: LULC Map for Makurdi, Nigeria

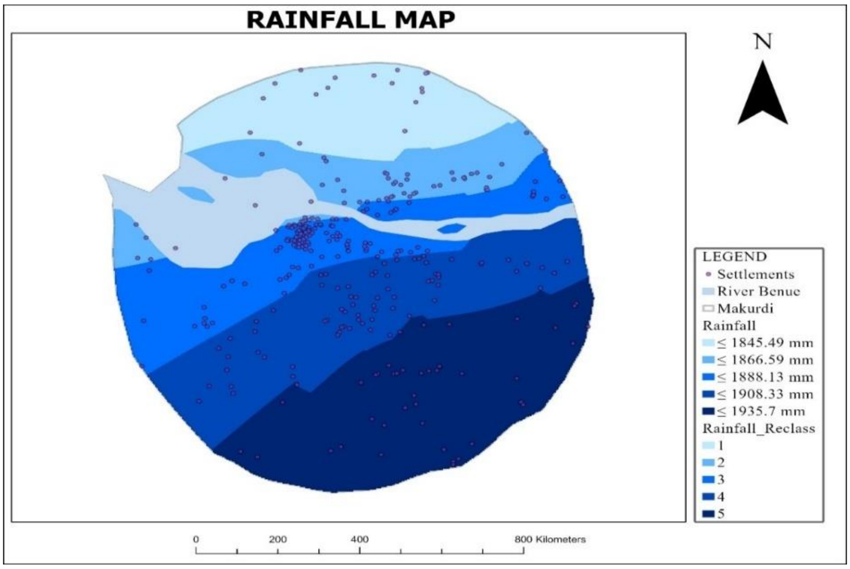

Figure 7: Rainfall Distribution Map for Makurdi, Nigeria

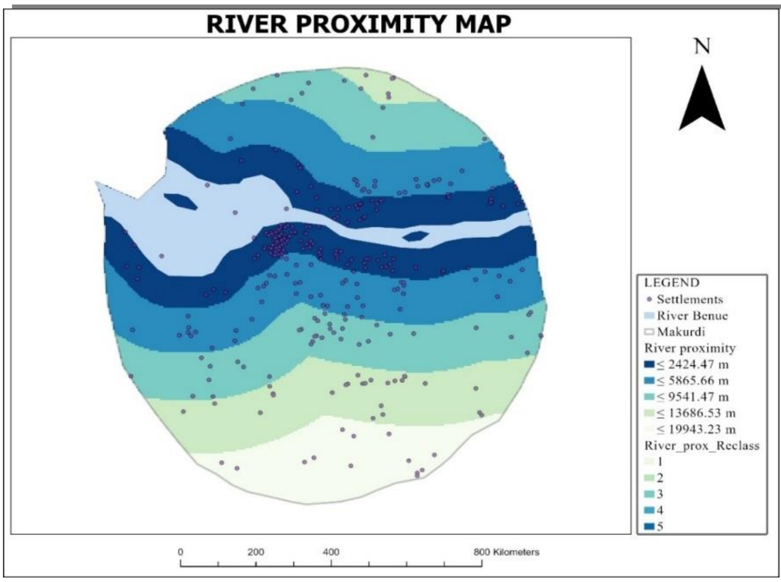

Figure 8: River Proximity Map for Makurdi, Nigeria

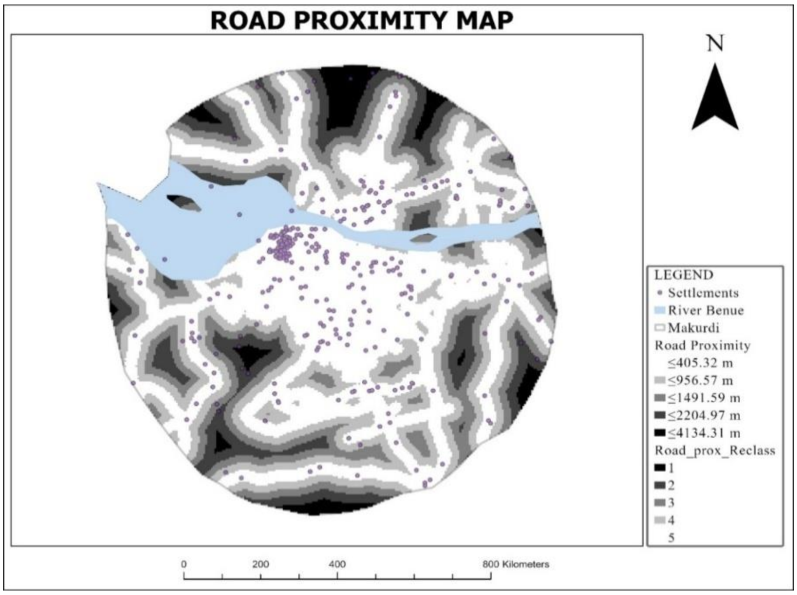

Figure 9: Road Proximity Map for Makurdi, Nigeria

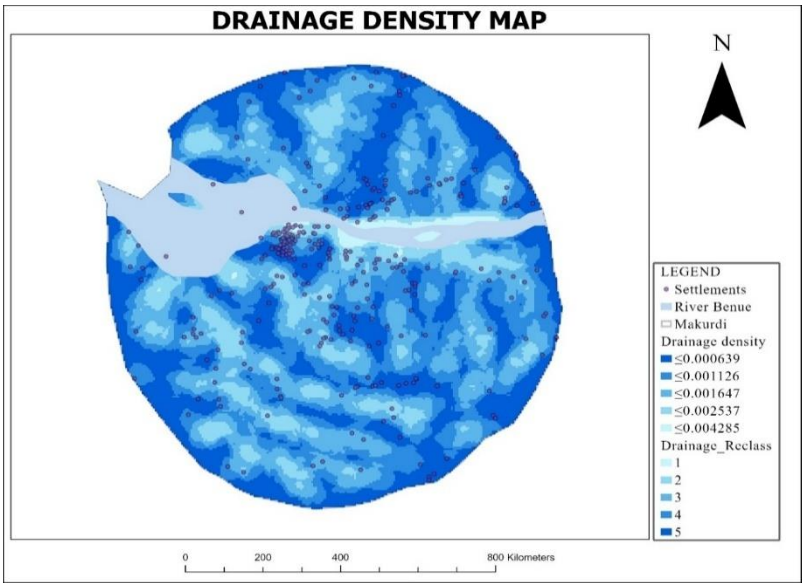

Figure 10: Drainage Density Map for Makurdi, Nigeria

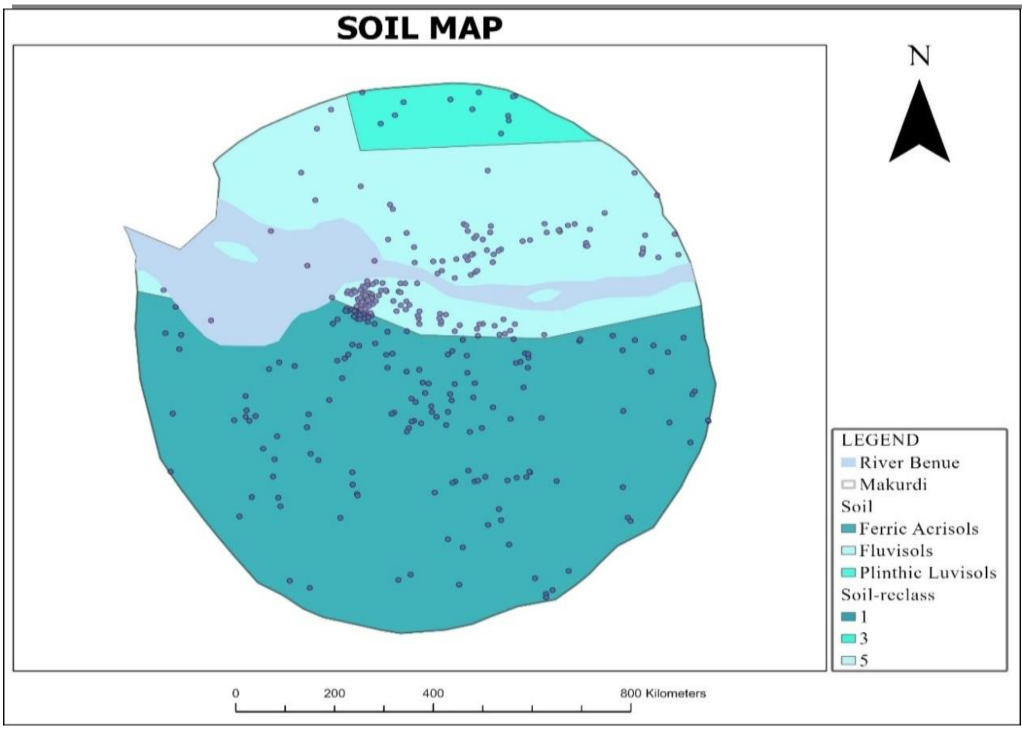

Figure 11: Soil Map for Makurdi, Nigeria

Analytical Hierarchy Process (AHP)

Table 5 shows the AHP pairwise comparison process of the flood risk factors, while **Figure 12** displays the result of the pairwise comparison matrix and the normalized weights (principal eigenvector) assigned to each flood risk factor. **Figure 13** provides a graphical representation of these weights, illustrating the relative importance of each factor in the overall flood risk assessment.

Table 5: Pairwise Comparison of Flood Risk Factors Using AHP Software by Goepel (2018)

Criteria		More Important?	Scale
A	**B**	**A or B**	**(1-9)**
Rainfall	DEM	A	1
	Slope	A	1
	Drainage density	A	3
	LULC	A	5
	River Proximity	A	3
	Soil Type	A	3
	Road Proximity	A	9
DEM	Slope	B	1
	Drainage density	A	3
	LULC	A	5
	River Proximity	A	3
	Soil Type	A	5
	Road Proximity	A	9
Slope	Drainage density	A	7
	LULC	A	7
	River Proximity	B	3
	Soil Type	A	5
	Road Proximity	A	9

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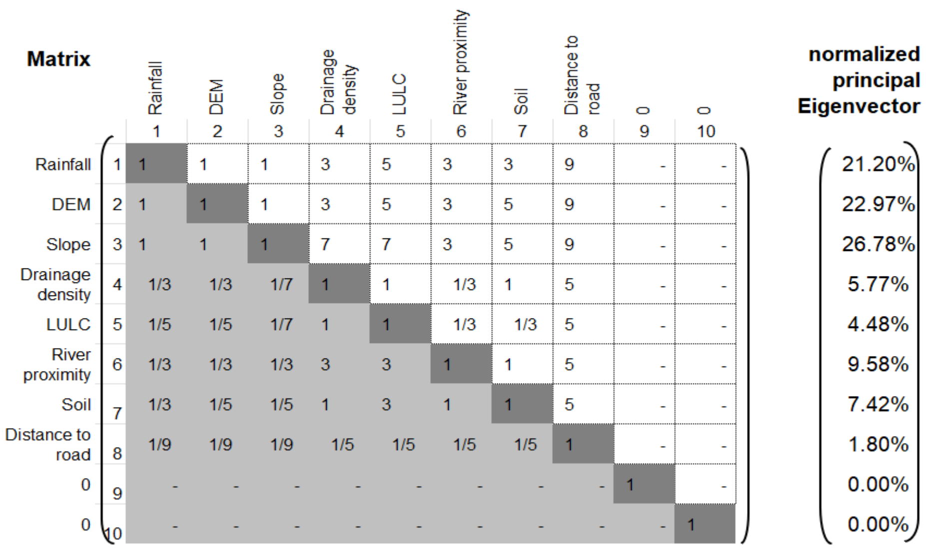
Drainage Density	LULC	A	1
	River Proximity	A	3
	Soil Type	A	1
	Road Proximity	A	5
LULC	River Proximity	B	3
	Soil	B	3
	Road Proximity	A	5
River Proximity	Soil Type	A	1
	Road Proximity	A	5
Soil Type	Road Proximity	A	5

Footnote: Footnote: This table illustrates the pairwise comparison process used to assign relative weights to flood risk criteria. Each pair of criteria (A and B) is compared to determine which is more important and by how much, using Saaty's 1–9 scale. A value of 1 denotes equal importance, while 9 indicates one criterion is extremely more important than the other. This systematic approach ensures consistent and quantifiable weights for the flood risk analysis.



Matrix		1 Rainfall	2 DEM	3 Slope	4 Drainage density	5 LULC	6 River proximity	7 Soil	8 Distance to road	9 0	10 0	normalized principal Eigenvector
Rainfall	1	1	1	1	3	5	3	3	9	-	-	21.20%
DEM	2	1	1	1	3	5	3	5	9	-	-	22.97%
Slope	3	1	1	1	7	7	3	5	9	-	-	26.78%
Drainage density	4	1/3	1/3	1/7	1	1	1/3	1	5	-	-	5.77%
LULC	5	1/5	1/5	1/7	1	1	1/3	1/3	5	-	-	4.48%
River proximity	6	1/3	1/3	1/3	3	3	1	1	5	-	-	9.58%
Soil	7	1/3	1/5	1/5	1	3	1	1	5	-	-	7.42%
Distance to road	8	1/9	1/9	1/9	1/5	1/5	1/5	1/5	1	-	-	1.80%
0	9	-	-	-	-	-	-	-	-	1	-	0.00%
0	10	-	-	-	-	-	-	-	-	-	1	0.00%

Figure 12: Pairwise Comparison Matrix for Flood Risk Analysis in Makurdi, using AHP Software Designed by Goepel (2018)

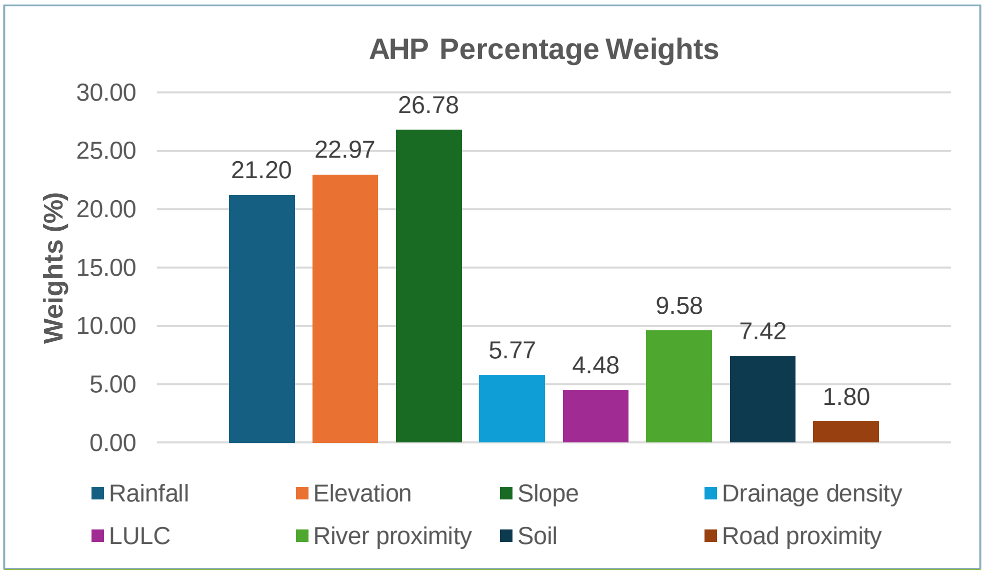


Figure 13: AHP-Generated Weights Based on Pairwise Comparison of Flood-Contributing Factors

Weighted Overlay and Flood-Risk Mapping

Figures 14 and 15 present the flood risk map and data visualization derived from the weighted overlay process. This map categorizes communities within the study area into five flood risk zones ranging from very low to very high risk.

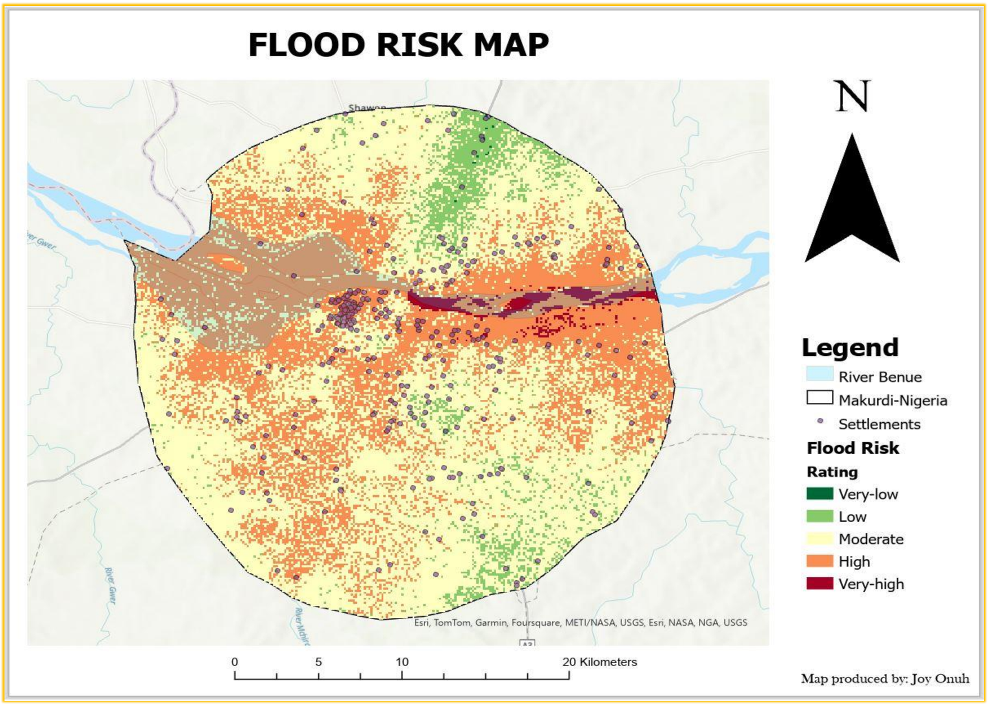


Figure 14: Flood Risk Map of Makurdi, Nigeria, derived from GIS Weighted Overlay Analysis Using AHP-Generated Weights

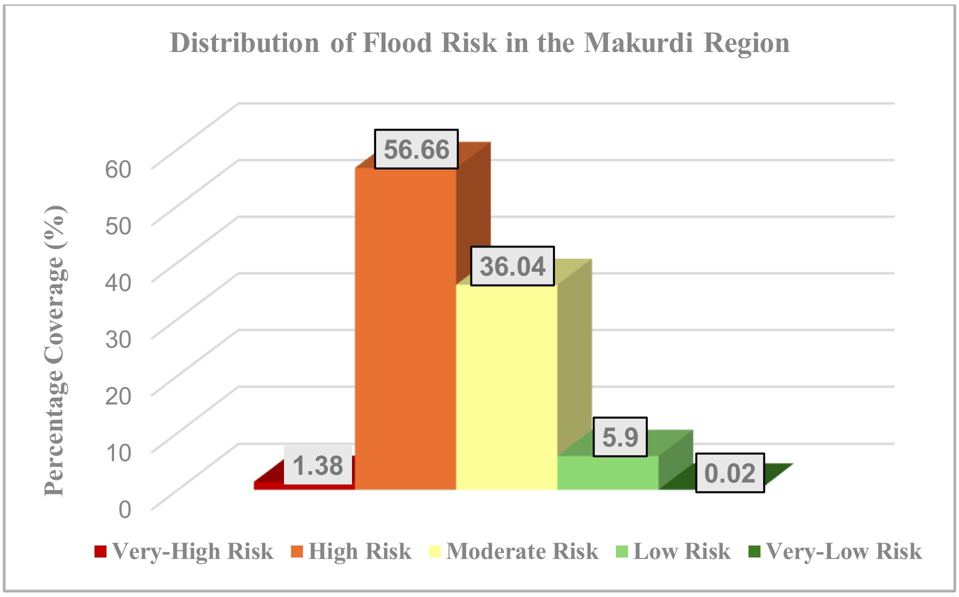


Figure 15: Percentage Breakdown of Flood Risk Categories in Makurdi Based on GIS Analysis Results

DISCUSSIONS

Flooding is a multifaceted issue driven by the interaction of various natural and human-induced factors. This chapter builds on the results from Section 3, examining how the AHP integrates multiple flood-contributing factors to classify flood risk in Makurdi. Key factors include topography and slope, where low-lying areas face higher vulnerability, and land use changes, such as urbanization, which increase surface runoff. Climate change exacerbates these risks by intensifying rainfall patterns. Drainage density affects water management capacity, while soil type influences water absorption and retention, impacting flood severity. Proximity to rivers heightens risk due to overflow potential, and well-designed road networks can reduce flood impact by channelling excess water to drainage outlets. Studying how these factors combine to increase flood risk is essential for devising effective strategies to mitigate it.

Thematic Maps

Thematic maps serve as powerful tools for visualizing these flood-contributing elements, enabling stakeholders to identify high-risk areas and make data-driven decisions for mitigation and planning. A detailed discussion of the eight contributing factors analyzed in this study is presented below.

Elevation plays a foundational role in flood behavior. Water naturally moves downhill, and during periods of heavy rainfall, low-lying regions tend to accumulate runoff. These areas often become natural catchments, making them more susceptible to inundation. The thematic elevation map produced for the study reflects this pattern, emphasizing how lower terrain elevations correlate with higher flood risk. This relationship is consistent with findings from previous research, such as those by Abah and Clement (2013), Kunda et al. (2021), and Ornguze et al. (2023), which underscore elevation as a primary determinant in flood vulnerability assessments.

Closely related to elevation is **slope**, which influences both the speed and volume of surface runoff. Steeper slopes tend to facilitate faster water movement, reducing the chances of accumulation, whereas flatter areas slow down runoff, increasing the potential for waterlogging and flooding. The slope map developed for the study illustrates how flatter areas often coincide with flood-prone zones. These observations are in line with earlier work by Kunda et al. (2021) and Ornguze et al. (2023), who have noted similar trends in other geographic contexts.

Land use and land cover further complicate the flood risk profile. Urban areas, with their extensive impervious surfaces such as concrete and asphalt, significantly limit water infiltration, resulting in higher runoff volumes. In contrast, areas dominated by vegetation allow for greater water absorption, thereby reducing runoff. Bare soil areas, while potentially vulnerable to erosion, can offer some degree of water absorption depending on texture and composition. The reclassification of LULC categories into flood risk levels reflects this nuanced interaction between land cover types and hydrological response, as observed in previous studies including Acha and Aishetu (2018), Oyatayo et al. (2021), and others.

Rainfall stands out as a direct and dynamic contributor to flooding. Its intensity, duration, and seasonal distribution heavily influence how and when floods occur. The rainfall map generated for this study highlights spatial variability in precipitation levels, reinforcing the idea that areas receiving higher rainfall are at greater risk of flooding. This is supported by Aho et al. (2019) and Ndabula (2021), who emphasize the predictive value of historical rainfall data in identifying flood-prone regions.

Proximity to rivers is another critical consideration. Settlements located near major rivers are naturally more exposed to flooding, especially during peak flow events or when rivers overflow their banks. The thematic river proximity map captures this gradient risk, illustrating how distance from the major river (River Benue) influences flood susceptibility. This insight resonates with Ornguze et al. (2023), who have similarly highlighted the dangers of riverine proximity in flood-prone areas.

Proximity to roads can also shape flood dynamics. Areas close to roads might experience lower flood risk due to engineered drainage and better access to emergency response. However, regions farther from road networks may face compounded risks due to both poor drainage and delayed assistance. The thematic analysis captures this duality, providing spatial evidence of the influence of transportation networks on flood vulnerability.

Drainage density, which refers to the concentration of stream channels in a given area, offers another perspective on flood potential. While a well-developed drainage system can aid in the efficient removal of excess water, an overly dense network may result in faster overflow and increased flooding. The drainage density map developed in this study reflects this balance and supports findings by Kunda et al. (2021), who have observed the complex role of drainage networks in modulating flood behavior.

Finally, **soil type** plays a subtle but important role in flood risk. The infiltration capacity of soil determines how much water can be absorbed before surface runoff begins. Sandy soils, like Plinthic Luvisols, allow for higher infiltration rates and thus present lower flood risk. In contrast, clay-rich soils, such as Ferric Acrisols, retain water near the surface, increasing the likelihood of flooding. The soil map produced for the study demonstrates these distinctions, aligning with observations from Acha and Aishetu (2018), Cabrera and Lee (2019), and Ndabula (2021).

Together, these thematic maps and their interpretations offer a comprehensive framework for understanding the spatial variability of flood risk across the study area. They highlight the importance of integrating physical geography, land use, infrastructure, and climatic data into a cohesive flood risk management strategy.

AHP Pairwise Comparison

The Analytic Hierarchy Process (AHP) systematically evaluates and ranks the relative importance of multiple criteria. During the comparison process, as seen in **Table 3**, the more important factor in each pair was assigned the label "A", while the less important one was labelled "B." For example, when Rainfall and Elevation were compared, Rainfall was rated as more important (A), but with a scale of 1, indicating that both factors contribute equally to flood risk. Rainfall received stronger preferences over LULC, River Proximity, Soil Type, and especially Road Proximity, where it was rated 9 times more important. These comparisons underscore the significant role of precipitation in flood occurrence in the study area.

Elevation (DEM) also emerged as a critical factor. It was consistently rated higher than Soil Type, LULC, and Road Proximity, often with scale values of 5 or 9, indicating a strong influence on runoff potential and water flow accumulation. Slope showed similar dominance, especially over Drainage Density, LULC, and Road Proximity, with values as high as 7 or 9, reflecting its importance in determining flow direction and speed.

Conversely, Road Proximity was the least influential factor across most comparisons, consistently receiving the lowest ratings. This suggests that while proximity to roads may affect local drainage and access, its overall contribution to flood generation in the study area is minimal when compared to more direct hydrological or topographic variables.

The completed pairwise comparison matrix was processed using an Excel-based AHP tool developed by Goepel (2018), which calculated the normalized principal eigenvector (weights) and the Consistency Ratio (CR). A CR value of 0.04 confirmed acceptable consistency in the judgments and validated the reliability of the matrix.

The resulting weights ranked Slope (26.8%), Elevation (23%), and Rainfall (21.2%) as the most influential factors. These were followed by River Proximity (9.6%), Soil Type (7.4%), Drainage Density (5.8%), LULC (4.5%), and Road Proximity (1.8%). These findings align with flood dynamics in the region, where terrain and rainfall patterns are known to play a critical role in determining flood risk levels.

Weighted Overlay and Flood Risk Mapping

The weights derived from the AHP process **(Figure 12)** were applied within the GIS environment using the weighted overlay analysis tool to produce a comprehensive flood risk map for Makurdi. This method facilitated the integration of spatial and statistical data, allowing for a visual representation of flood vulnerability based on the relative importance of each contributing factor.

The resulting flood risk map **(Figure 14)** reveals that 56.66% of the study area is classified as high risk, with these zones concentrated primarily in low-lying, built-up regions adjacent to the River Benue. These areas tend to exhibit low elevation and gentle slopes, which significantly increase their susceptibility to surface water accumulation and riverine flooding.

Other risk categories across the region include:

- 1.38% of the area, marked as very high risk.

- 36.04% as moderate risk
- 5.90% as low risk, and
- only 0.02% as very low risk.

Specific neighbourhoods falling within the very high-risk category include Judges Quarters, Gyado Villa, Banada Quarters, and parts of Wurukum. High-risk areas encompass Wadata, Akpehe, Logo 1 & 2, Assembly Quarters, Ankpa Quarters, Lobi Quarters, Court 5, and Welfare Quarters. These locations are known for frequent flood incidents, particularly during peak rainfall periods, leading to disrupted livelihoods and property damage.

Moderate-risk zones cover Federal Housing, Kwararafa Quarters, Kanshio, Yaikyo, and the Airforce Base. In contrast, low-risk areas include Lower Benue, Ikpayango, Mbasonbo, and Mbaageba, while very low-risk zones, potentially suitable for planned development or emergency sheltering are found in Mbakine, Agan, and Abagena.

Overall, the flood risk map provides a valuable decision-support tool for urban planners, disaster management agencies, and local authorities. It clearly delineates areas requiring urgent mitigation interventions such as improved drainage, early warning systems, or land-use regulation, while also identifying safer zones that could be prioritized for future development or emergency response infrastructure.

CONCLUSION AND RECOMMENDATIONS

Flooding in Makurdi poses severe challenges, including displacement, infrastructure damage, and disruption of livelihoods. This study integrated Geographic Information System (GIS), Multi-Criteria Decision-Making (MCDM), and the Analytic Hierarchy Process (AHP) to assess flood risk in Makurdi, Nigeria. Eight key factors were analyzed, with Slope (26.8%), Elevation (23%), and Rainfall (21.2%) emerging as the most significant contributors to flood risk. The flood risk map revealed that over 56 % of the area falls within high-risk zones, particularly in low-lying, built-up areas near the River Benue.

The AHP method enabled a structured comparison of multiple flood risk factors based on their perceived importance, yielding consistent and validated results (CR = 0.04). These outcomes informed the generation of a comprehensive flood risk map that highlights areas requiring urgent intervention. However, the accuracy of the outcomes remains dependent on the quality and currency of the spatial datasets used. Limitations of the study include potential inaccuracies in spatial data, variations in data timeliness, and subjectivity in assigning weights to the factors. These factors could influence the final output and should be considered when interpreting.

Recommendations:

i. Prioritize flood mitigation in high-risk zones by improving drainage infrastructure, enforcing land use regulations, and strengthening preparedness strategies.
ii. Use the risk map to inform planning and zoning decisions, emergency response plans, and community awareness efforts.
iii. Future research could assess the impact of different weighting schemes or AHP structures to determine whether the results remain consistent.
iv. Ensure regular updates to input data to maintain relevance and improve spatial accuracy over time.

This approach offers a flexible and scalable framework that can be adapted to flood-prone areas globally. By adjusting the input factors and weights to reflect local environmental and socio-economic conditions, stakeholders in other regions can apply this method to support evidence-based flood risk assessment and planning.

Conflict of Interest Statement

The author(s) declare that there is no conflict of interest regarding the publication of this article. No financial, personal, or professional relationships have influenced the content or findings presented in this study.

Data Availability Statement

The data supporting this study's findings are available from the corresponding author upon reasonable request. Additional data used in the analysis can be accessed through the specified data sources cited throughout the publication.

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