

Geospatial-Based Multi-Criteria Decision Making for Flood Hazard Assessment in Ala-River Basin, Akure, Southwest Nigeria

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ABSTRACT

Flooding poses a significant environmental challenge in Akure, Ondo State, Nigeria, particularly within the Ala River Basin where rapid urbanization and inadequate drainage systems have increased vulnerability. This study presents a geospatial assessment of flood hazard using a Geographic Information System (GIS)-based Multi-Criteria Decision Making (MCDM) approach. Primary data from Differential Global Positioning System (DGPS) surveys and secondary datasets, including Landsat imagery, SRTM Digital Elevation Model, soil, and rainfall data, were integrated for analysis. Key factors such as rainfall, slope, elevation, drainage density, distance to river, soil type, and land use/land cover were evaluated using the Analytic Hierarchy Process (AHP) and combined through weighted overlay analysis. The results show that rainfall, proximity to river channels, and slope are the most significant contributors to flooding. Approximately 68% of the study area falls within moderate to high flood vulnerability zones. The study provides a spatial decision-support framework for flood risk management and highlights the need for improved drainage infrastructure and sustainable land-use planning.

KEYWORDS: Drainage Density, Flood Hazard Management, Multi-Criteria Analysis (MCA), Geographic Information Science, Remote sensing.

I. INTRODUCTION

Flooding is widely recognized as one of the most devastating natural hazards globally, affecting over 200 million people annually and resulting in significant socio-economic losses, particularly in developing countries (UNDRR, 2023; World Bank, 2022). In recent decades, the frequency and intensity of flood events have increased markedly due to the combined effects of climate change, rapid urbanization, and unsustainable land-use practices (IPCC, 2021; Tellman *et al.*, 2021). These trends are especially pronounced in sub-Saharan Africa, where weak urban planning systems and inadequate drainage infrastructure exacerbate flood risks (Douglas *et al.*, 2023). In Nigeria, flooding remains a recurrent and escalating environmental challenge, with severe impacts on lives, infrastructure, and agricultural productivity. Major flood events, such as those recorded in 2012 and 2022, have highlighted the country's vulnerability and the urgent need for improved flood risk management strategies (Adelekan, 2022; Nkwunonwo *et al.*, 2020). Recent annual flood outlooks released by the Nigeria Hydrological Services Agency consistently identify several states, including Ondo State, as highly susceptible to flooding. Despite these early warnings, flood occurrences continue to pose significant threats to both urban and rural communities, suggesting gaps in preparedness, planning, and spatial risk assessment.

Akure, the capital of Ondo State in southwestern Nigeria, has experienced repeated flood incidents, particularly within the Ala River Basin. The increasing rate of urban expansion, encroachment on floodplains, inadequate drainage systems, and changing rainfall patterns have significantly heightened flood vulnerability in the area (Oladokun & Proverbs, 2016; Bello *et al.*, 2024). These factors, combined with limited availability of detailed flood hazard maps, have made it increasingly difficult for policymakers and planners to effectively manage flood risks within the metropolis. Flood risk is inherently multi-dimensional, influenced by a combination of hydrological, topographical, environmental, and anthropogenic factors such as rainfall intensity, slope, elevation, soil characteristics, drainage density, and land use/land cover (LULC) (Tehrany *et al.*, 2015; Khosravi *et al.*, 2019). The complex interaction of these variables necessitates the use of integrated and spatially explicit analytical approaches capable of capturing their relative contributions to flood susceptibility. Advancements in geospatial technologies, particularly Geographic Information Systems (GIS) and remote sensing, have significantly enhanced the capability to assess and map flood-prone areas with improved accuracy and efficiency (Pham *et al.*, 2021; Rahmati *et al.*, 2020). These technologies facilitate the integration of multi-source spatial datasets, enabling comprehensive analysis of flood conditioning factors. Furthermore, Multi-Criteria Decision Making (MCDM) techniques, especially the Analytic Hierarchy Process (AHP), have been widely adopted for flood hazard assessment due to their robustness in handling multiple criteria and incorporating expert judgment into spatial decision-making processes (Saaty, 1980; Malczewski, 2006; Gigović *et al.*, 2017).

Recent studies (2020–2025) have demonstrated the effectiveness of integrating GIS with MCDM approaches in flood vulnerability mapping across different geographic contexts (Bui *et al.*, 2020; Arabameri *et al.*, 2021; Chen *et al.*, 2023). However, many of these studies rely on generalized modeling frameworks or lack sufficient incorporation of local environmental conditions and decision-support mechanisms tailored to specific regions. In the context of Nigeria, and particularly within the Ala River Basin in Akure, there remains a paucity of detailed, location-specific studies that integrate GIS and MCDM techniques for flood hazard assessment. This gap limits the availability of reliable spatial information required for effective flood risk management and urban planning. This study addresses this gap by employing a GIS-based Multi-Criteria Decision Making approach to assess flood hazard vulnerability within the Ala River Basin, Akure. The study integrates key environmental and hydrological factors, including rainfall, slope, elevation, soil type, drainage density, distance to river, and land use/land cover, to develop a comprehensive flood vulnerability model. Specifically, the objectives are to: (i) analyze land use and land cover dynamics within the study area; (ii) evaluate the influence of environmental factors on flood susceptibility; and (iii) generate a flood hazard vulnerability map using integrated geospatial techniques. The significance of this research lies in its potential to provide a robust, spatially explicit decision-support framework for flood risk management in Akure and similar urban environments. The findings are expected to assist policymakers, urban planners, and disaster management agencies in identifying high-risk zones, improving preparedness, and implementing targeted mitigation strategies. Additionally, this study contributes to the growing body of knowledge on geospatial flood hazard assessment by demonstrating the applicability of GIS and MCDM techniques in data-scarce and rapidly urbanizing regions.

This study contributes to the field of flood hazard assessment by demonstrating the effectiveness of integrating GIS and Multi-Criteria Decision Making techniques in identifying and mapping flood-prone areas within a data-scarce urban environment. Unlike conventional approaches, this study provides a location-specific and multi-factor analysis tailored to the Ala River Basin,

thereby enhancing the accuracy and applicability of flood vulnerability mapping. The outcomes of this research offer a reliable spatial decision-support framework that can be adopted for flood risk management and sustainable urban planning in similar developing regions.

II. LITERATURE REVIEW

Flood hazard assessment has attracted significant research attention globally, with various methodological approaches developed to improve the identification and mapping of flood-prone areas. Early studies primarily relied on hydrological and topographical analyses, utilizing Digital Elevation Models (DEMs) such as the Shuttle Radar Topography Mission (SRTM) data to enhance terrain representation and floodplain delineation (Prinos, 2008; Ani *et al.*, 2020). While these approaches improved spatial accuracy, they were often limited by their inability to integrate multiple influencing factors simultaneously. With advancements in geospatial technologies, Geographic Information Systems (GIS) and remote sensing have become fundamental tools in flood vulnerability assessment. These technologies enable the integration of spatial datasets such as rainfall, slope, elevation, soil type, drainage density, and land use/land cover (LULC) for comprehensive flood risk analysis (Khosravi *et al.*, 2019; Rahmati *et al.*, 2020). GIS-based overlay techniques have been widely applied to combine these factors and produce flood susceptibility maps; however, such approaches often assign equal importance to all variables, thereby limiting their analytical robustness.

To address this limitation, Multi-Criteria Decision Making (MCDM) techniques have been increasingly adopted in flood hazard studies. Methods such as the Analytic Hierarchy Process (AHP) allow for the assignment of relative weights to different flood conditioning factors based on their significance (Saaty, 1980; Malczewski, 2006). Several studies have demonstrated the effectiveness of GIS-MCDM integration in improving flood vulnerability mapping accuracy (Gigović *et al.*, 2017; Arabameri *et al.*, 2021). These approaches provide a structured framework for incorporating expert judgment and handling complex environmental interactions. Recent studies have further advanced flood risk assessment through the integration of GIS and MCDM techniques. For instance, Osman and Das (2023) applied a GIS-based MCDM model to assess flood susceptibility in the Shebelle River Basin, demonstrating improved spatial accuracy compared to conventional overlay methods. Similarly, Shawky and Hassan (2023) employed AHP within a geospatial framework to delineate flood-prone zones, highlighting the importance of factor weighting in decision-making processes. More recent work by Li *et al.* (2025) introduced probabilistic GIS-based models to enhance flood risk prediction, while Gün and Yılmaz (2026) developed a dynamic MCDM framework capable of addressing non-stationary environmental conditions. These studies underscore the growing importance of integrating spatial analysis with decision-support models for improved flood hazard assessment.

In addition to MCDM approaches, machine learning and artificial intelligence techniques have been explored for flood vulnerability mapping. Studies such as Habtamu and Megersa (2021) and Pham *et al.* (2021) have demonstrated the potential of models such as Random Forest and Support Vector Machines (SVM) in predicting flood susceptibility with high accuracy. However, these methods often require large datasets and extensive computational resources, which may not be readily available in data-scarce environments such as many regions in Nigeria. Despite these advancements, several limitations remain in existing studies. Many flood vulnerability assessments rely on generalized models that do not adequately account for local environmental conditions, particularly in rapidly urbanizing regions. Furthermore, limited attention has been given to integrating localized datasets, such as field-based observations and region-specific

hydrological characteristics, into flood risk models. In Nigeria, and specifically within the Ala River Basin in Akure, there is a scarcity of studies that combine GIS, remote sensing, and MCDM techniques to produce detailed and reliable flood vulnerability maps. Therefore, this study addresses these gaps by developing a GIS-based Multi-Criteria Decision Making framework tailored to the unique environmental and hydrological characteristics of the Ala River Basin. By integrating multiple spatial factors and applying a structured weighting approach, this research aims to provide a more accurate and location-specific assessment of flood hazard vulnerability, thereby contributing to improved flood risk management and urban planning.

III. METHODOLOGY

A. Study Area

Akure (Akure South and Akure North) was where this research was conducted and it is one of the eighteen Local Government area of Ondo State. Geographically, Akure is positioned between longitudes 5° 06'E and 5° 28'E and latitudes 7° 07' N and 7° 37'N. The study area is bordered by Ifedore, Ile-Oluji/Oke-Igbo, Owo and Idanre Local Governments Areas in the North, West, East and South respectively (Figure 1). The study area experiences sparse rainfall in April while significant downpour occurred in July but there is a brief hiatus in August, before inconsequential showering and drizzling from September upward and end with scattered rainfall in November yearly. The temperature of Akure fluctuates, but it ranges from 65°F to 88°F in wet season and is rarely below 58°F or above 93°F during the dry seasons (Weather Spark, 2025). Typically, the hottest and coldest months in Akure are March and August respectively. The landscape of Akure is characterized by tropical rainforest vegetation while the current estimated population of Akure is 803,062 (World Population Review, 2025) and it is still counting on daily basis.

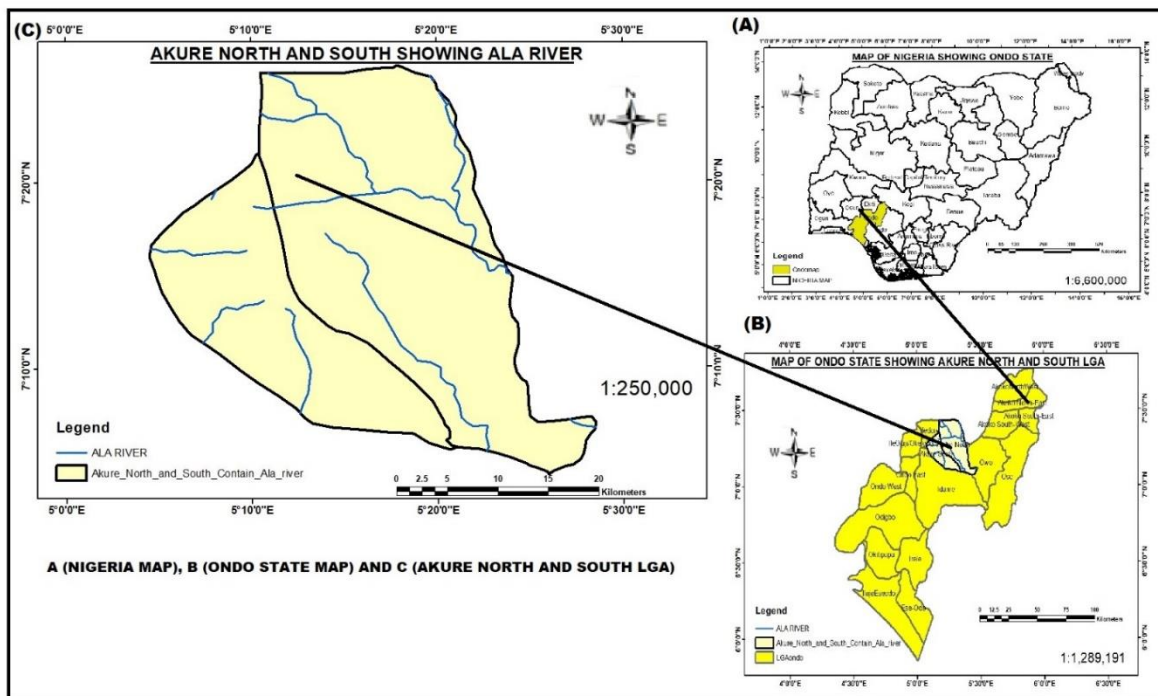


Figure 1: Study Area Map of Akure (Obiora-Okeke *et al.*, 2025).

B. Data Collection and Processing

The flood hazard assessment of the Ala River Basin was based on a systematic approach that integrates both primary (raw) and secondary (existing) data. Primary data were acquired using a Differential Global Positioning System (DGPS) receiver to determine and record the coordinates of Points of Interest (POIs) along the riverbank. These coordinates were obtained through extensive fieldwork, which involved the identification and documentation of locations visually observed to be susceptible to flooding within the study area. The field survey further involved systematic traversal of flood-prone zones along the Ala River corridor to capture precise spatial positions of vulnerable points. The DGPS-derived coordinates provided a reliable basis for spatial analysis, enabling accurate mapping and assessment of flood hazard areas. In addition to the primary data, the study utilized several secondary datasets, including high-resolution satellite imagery of the Ala River, Landsat 8 OLI imagery (2019), Digital Elevation Model (DEM), soil data, and historical rainfall records. The integration of these datasets enhanced the understanding of the topographical and environmental characteristics of the study area. Data processing was carried out through a multi-step procedure within a GIS environment (Suzanne-Boden, 2026). The field-acquired DGPS coordinates were imported into ArcGIS and used to generate spatial reference layers. Similarly, satellite imagery and other datasets were processed and analyzed within the GIS platform. Key GIS operations performed included vectorization of geographical features (Figure 2), creation of shapefiles, buffering (distance to river analysis), stream order determination, and reclassification of thematic layers. These processes facilitated the identification of flood-prone areas and the evaluation of flood severity across the study area.



Figure 2: Digitize Map using each of the vector elements (Author's work).

The research design adopted a rigorous and methodical framework, combining spatial analysis with environmental assessment techniques (Saul, 2024). The methodology was grounded in the principles of Geographic Information Science, ensuring accuracy and reliability of results. Data quality was maintained through careful preprocessing, validation of spatial inputs, and adherence to standard geospatial procedures. The study utilized both hardware and software tools for data acquisition and analysis. The hardware components included high-precision DGPS receivers for field data collection and computer systems for data processing. The software tools comprised ArcGIS for spatial analysis, Google Earth for satellite image visualization, and Microsoft Office for data organization and presentation. Ethical considerations were observed through proper data sourcing, accuracy in analysis, and appropriate acknowledgment of all data sources. Overall, this integrated approach enabled a comprehensive spatial analysis of flood risk, providing valuable

insights into the most vulnerable areas and the potential severity of flood events within the Ala River Basin.

C. Multi-Criteria Decision Making (MCDM) Using AHP

Flood hazard assessment in this study was conducted using the Multi-Criteria Decision Making (MCDM) approach, specifically the Analytic Hierarchy Process (AHP) developed by Thomas Saaty (1980). There are four steps in AHP. These are: i. developing a model ii. derive priorities (weights) for the criteria, iii. consistency check (weights assigned correct or not?) and derive overall priorities (model synthesis) and final decision. AHP is widely used for spatial decision-making because of its ability to incorporate multiple criteria and assign relative importance based on their contribution to a given phenomenon.

D. Criteria Selection

The selection of flood conditioning factors was based on an extensive review of relevant literature (e.g., Rahmati *et al.*, 2020; Khosravi *et al.*, 2019; Pham *et al.*, 2021) and the physical characteristics of the study area. The selected criteria include: Rainfall, Elevation, Slope, Soil type, Drainage density, Distance to river and Land use/land cover. These factors were chosen due to their significant influence on flood occurrence and have been widely validated in previous studies.

E. Weight Determination Using AHP

The relative importance of each criterion was determined using pairwise comparison within the AHP framework. A comparison matrix was constructed based on Saaty's 1–9 scale, where values represent the relative importance of one factor over another. The weights were derived through: Construction of pairwise comparison matrix, Normalization of the matrix, Computation of eigenvector (priority weights). To improve methodological transparency and address reviewer concerns, the weighting process was informed by: existing literature and expert judgment (Surveyors and GIS specialists familiar with flood dynamics in the study area).

F. Consistency Ratio (CR) Check

To ensure the reliability of the pairwise comparisons, the Consistency Ratio (CR) was computed using: Consistency Index (CI) and Random Index (RI). A CR value of less than 0.1 was considered acceptable (Saaty, 1980). This confirms that the judgments used in assigning weights were consistent and reliable.

G. Weighted Overlay Analysis

The standardized raster layers were combined using a weighted linear combination approach in GIS. The flood vulnerability index (FVI) was computed using equation 1 according to Saaty, (1980):

$$FVI = \sum (W_i \times X_i) \quad (1)$$

Where: W_i = weight of each factor, X_i = standardized score of each factor. The resulting map was classified into flood vulnerability zones: Very Low, Low, Moderate, High, and Very High.

H. Validation of Flood Hazard Map.

The generated flood vulnerability map was validated using field observations and DGPS-collected flood-prone locations. The validation process involved overlaying the observed flood points on the generated flood hazard map to assess the degree of agreement. Additionally, a qualitative validation approach was adopted by comparing the results with known flood-prone areas identified through local knowledge and historical flood occurrence patterns. Due to limited availability of long-term flood records in the study area, this study acknowledges the constraint of quantitative validation and recommends future studies to incorporate historical flood datasets and statistical validation techniques such as Receiver Operating Characteristic (ROC) analysis.

IV. RESULTS AND DISCUSSION

This section presents the spatial analysis results of flood conditioning factors and their integration using a Multi-Criteria Decision Making (MCDM) approach. The discussion emphasizes the influence of each factor on flood vulnerability and provides a quantitative interpretation of the resulting flood hazard map.

A. Influence of Topographic Factors: Slope and Distance to River

The slope map derived from SRTM DEM (Figure 3a) reveals a clear variation in terrain steepness across the study area. Steeper slopes (19.22–52.69 m), represented by red and orange colors, facilitate rapid surface runoff, thereby increasing the likelihood of downstream flooding rather than localized water accumulation. Conversely, low-lying and gentle slopes (0–2.27 m), shown in green shades, promote water stagnation and infiltration, making them more susceptible to prolonged inundation.

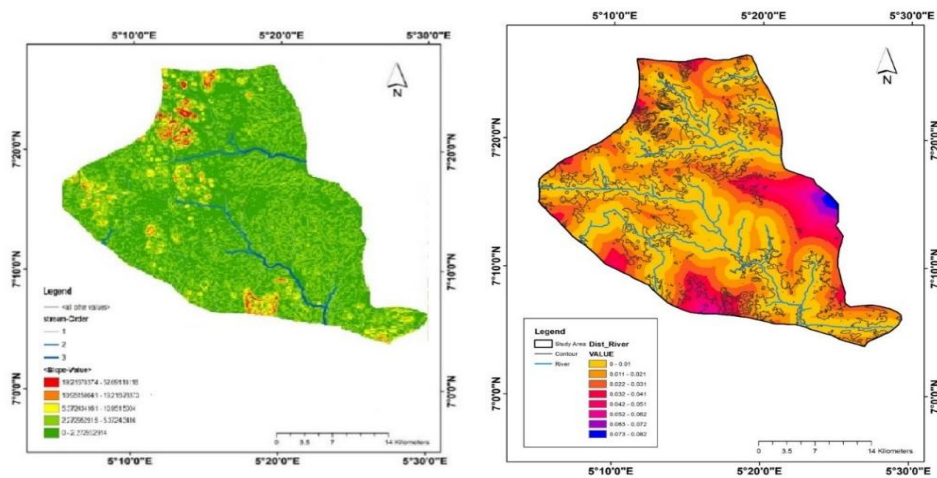


Figure 3: Slope Map of Ala River (a) and Distance to River (b) (Author's work)

This finding aligns with previous studies (Rahmati *et al.*, 2020), which emphasize that low-gradient terrains are more vulnerable to flood accumulation, particularly in urban environments. Similarly, the distance-to-river analysis (Figure 3b) demonstrates that areas closer to the Ala River are significantly more prone to flooding. Proximity to river channels increases exposure to overflow during peak discharge events. This spatial relationship highlights the critical role of river adjacency in determining flood susceptibility, consistent with findings by Osman and Das (2023).

B. Hydrological and Soil Factors: Drainage Density and Soil Type

The drainage density map (Figure 4a) indicates that areas with high drainage density (58.7–132.0 m/km²) exhibit increased flood vulnerability due to the concentration of runoff within closely spaced stream networks. High drainage density enhances rapid water movement and reduces infiltration time, thereby increasing flood peaks.

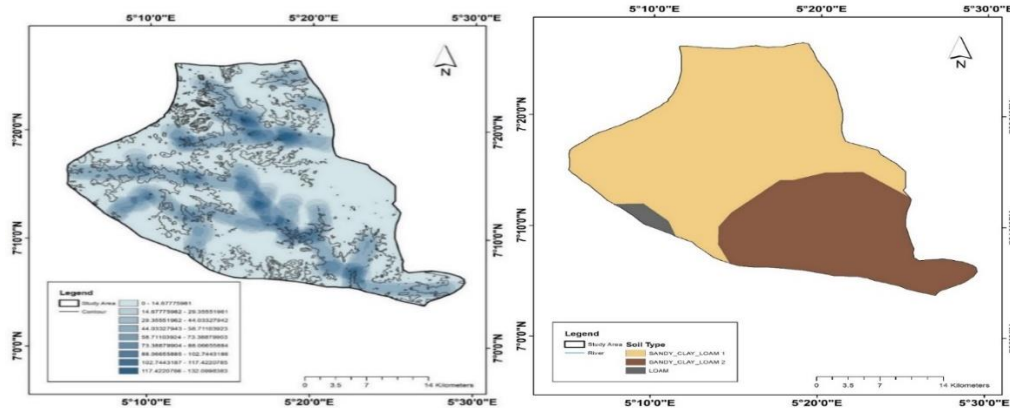


Figure 4: Drainage density map of the study area (a) and Soil type of the study area (b) (Author’s work)

In contrast, areas with low drainage density (0–14.6 m/km²) tend to have reduced runoff concentration and lower flood susceptibility. This relationship supports the assertion that drainage density is a key determinant of flood intensity (Khosravi *et al.*, 2019). The soil map (figure 4b) further illustrates the influence of soil properties on flood dynamics. Sandy clay loam dominates the study area, suggesting moderate infiltration capacity. However, areas with higher clay content may exhibit reduced permeability, leading to increased surface runoff and flood risk. This highlights the importance of soil characteristics in controlling infiltration-runoff processes.

C. Rainfall Distribution and Flood Implications

The rainfall distribution map (figure 5) shows spatial variability ranging from 1300 mm to over 1800 mm annually. Areas with higher rainfall intensity correspond to zones of increased flood susceptibility due to higher runoff generation.

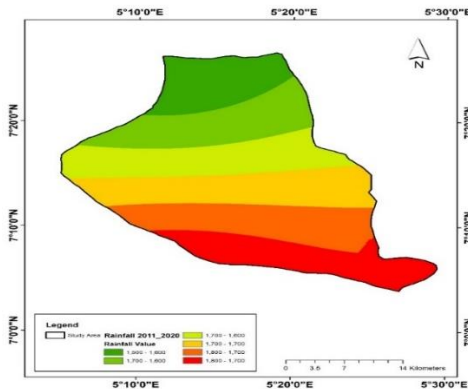


Figure 5: Showing the Rainfall pattern of the Study Area (Author’s work).

When combined with other factors such as drainage density and slope, high rainfall significantly amplifies flood risk. For instance, regions experiencing both high rainfall and high drainage density are more likely to experience frequent and severe flooding events. This observation is consistent with studies by Pham *et al.* (2021), which identified rainfall as a dominant factor in flood hazard modeling.

D. Land Use/Land Cover and Flood Dynamics

The land use/land cover (LULC) analysis (figure 6 and figure 7) reveals that bare land (44.99%) and built-up areas (17.04%) dominate the study area. The high proportion of bare land contributes to increased surface runoff due to limited vegetation cover, while built-up areas reduce infiltration due to impervious surfaces. Vegetated areas (20.53%) play a mitigating role by enhancing infiltration and reducing runoff velocity. However, ongoing urban expansion in Akure is likely to increase flood vulnerability due to the replacement of permeable surfaces with impermeable structures.

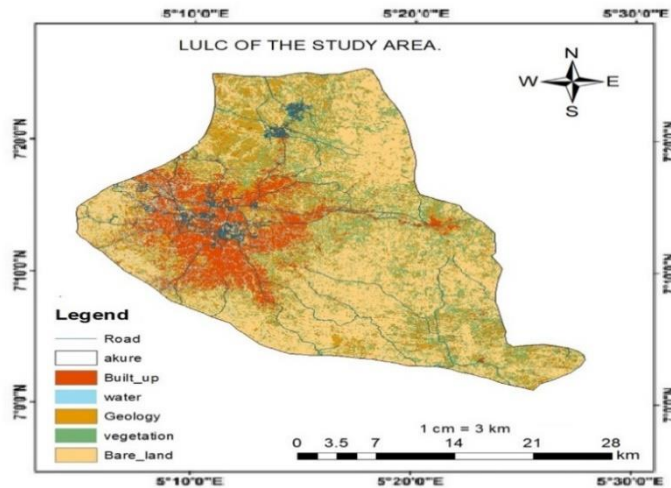


Figure 6: Showing Land Use Land Cover Map (Author’s work).

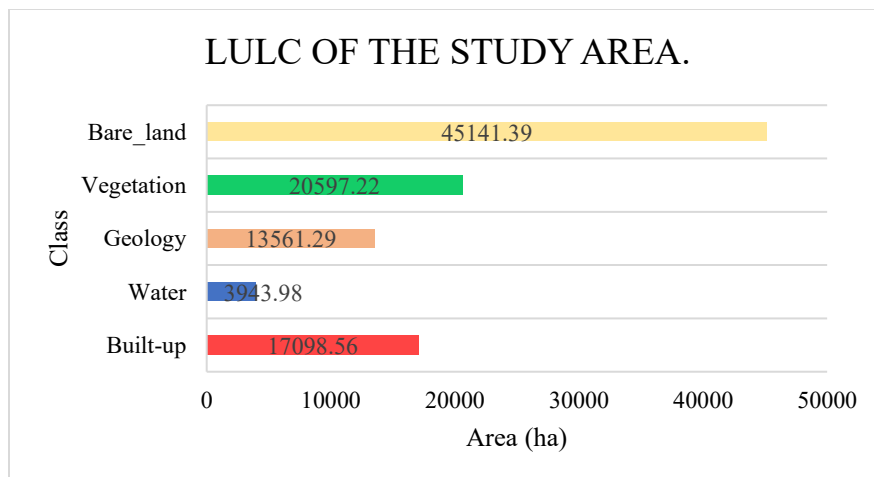


Figure 7: Land use land cover map Bar chart of the study area (Author’s work).

E. Flood Vulnerability Mapping Using MCDM

The integration of all flood conditioning factors using the AHP-based weighted overlay technique resulted in the flood vulnerability map (figure 8). The assigned weights indicate that rainfall (34.71%), distance to river (20.69%), and slope (14.38%) are the most influential factors controlling flood occurrence in the study area.

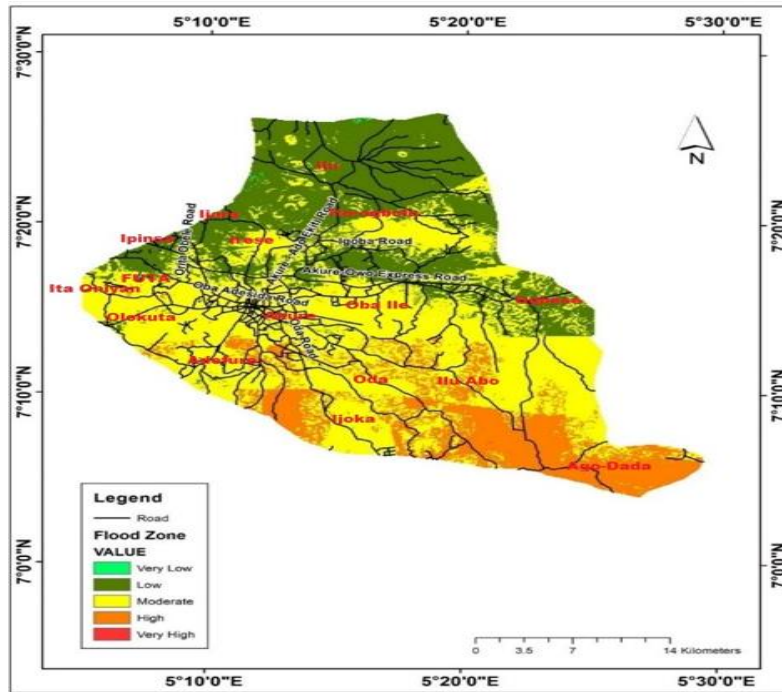


Figure 8: Map of the Flood Risk Areas (Author’s work).

The Consistency Ratio (CR = 0.026) confirms that the pairwise comparison matrix is reliable and within the acceptable threshold (CR < 0.1), indicating a high level of consistency in the weighting process. The flood vulnerability map classifies the study area into five categories as shown in table 1: Very Low: 0.059%, Low: 31.53%, Moderate: 52.12%, High: 16.29%, and Very High: 0.003%. The results indicate that over 68% of the study area falls within moderate to high vulnerability zones, highlighting a significant exposure to flood risk.

Table 1: The Percentage of Flood Vulnerable Zones

VALU	COUNT	AREA_KM ²	FLOOD_ZONE	Land Cover %
1	638	0.5742	Very Low vulnerable	0.059
2	343347	309.0123	Low vulnerable	31.525
3	567643	510.8787	Moderate vulnerable	52.119
4	177456	159.7104	Highly vulnerable	16.294
	33	0.0297	Very Highly vulnerable	0.003
		980.2053		100%

Moderate-risk areas dominate the landscape, suggesting that while flooding may not be extreme in all cases, a large portion of the area remains susceptible under intense rainfall conditions. High-risk zones are primarily concentrated along the river basin, where proximity to water channels, high drainage density, and low elevation combine to increase flood likelihood. Interestingly, the very high vulnerability class accounts for a negligible proportion (0.003%), indicating that extreme flood conditions are spatially limited but potentially severe when they occur. These findings are consistent with recent studies (Gün & Yılmaz, 2026), which emphasize the importance of multi-factor integration in identifying spatial flood risk patterns.

Moreso, the percentage of flood Vulnerable Zones according to table 1, shows that significant portion of the study area that is, about 0.003% is extremely susceptible to flooding while a larger area (Iju and Itaogbolu), roughly 31.5%, is categorized as having a low vulnerability, indicating a minimal overall risk of flooding in the study area. In terms of risk distribution, 52.1% of the area, that is Akure, Obaile, Olokuta, FUTA, Adofure, and Ita-Oniyan falls into the moderate risk category, and 16.3% is in the high-risk zone that is Ilu-Abo and Ago-Dada. Zones with high risk are likely to experience flooding during flood events, while low-risk areas are the least likely to be affected. However, in the case of a major flood, moderate-risk areas, and even some low-risk areas, could be impacted. The data that was utilized in this research points out that the most affected regions are those along the river basin, including residential zones and agricultural lands. This specific outcome stems from several contributing factors, such as the type of data utilized, the process of standardization, the criteria used for standardization, and the selection of standardization methods. These factors collectively define the weighting procedures and the relative significance of each factor. Essentially, the high-risk areas are more prone to flooding in any flood event, whereas the impact on medium and low-risk areas varies based on the flood's intensity and extent. The area's most at risk are located along the river basin, encompassing human settlements and farmlands.

F. Implications and Model Reliability

The spatial distribution of flood vulnerability highlights critical areas requiring immediate attention, particularly along the Ala River corridor where residential and agricultural activities are concentrated. The validation using DGPS field data confirms a strong spatial agreement between observed flood-prone locations and modeled high-risk zones, thereby enhancing confidence in the model output. However, the absence of long-term historical flood data limits the ability to perform advanced statistical validation, which remains a limitation of this study.

V. CONCLUSION AND RECOMMENDATIONS

This study assessed flood hazard vulnerability in the Ala River Basin, Akure, using an integrated Geographic Information System (GIS) and Multi-Criteria Decision Making (MCDM) approach. By incorporating key environmental and hydrological factors including rainfall, slope, elevation, drainage density, soil type, distance to river, and land use/land cover, the study developed a spatially explicit flood vulnerability model for the study area. The results revealed that rainfall, proximity to river channels, and slope are the most influential factors controlling flood occurrence, contributing approximately 34.71%, 20.69%, and 14.38%, respectively. The flood vulnerability map indicated that a significant proportion of the study area (over 68%) falls within moderate to high flood risk zones, with high-risk areas concentrated along the Ala River corridor. These areas are characterized by low elevation, high drainage density, and intense rainfall patterns, making them particularly susceptible to flooding events.

The integration of AHP within a GIS framework proved effective in capturing the relative importance of multiple flood conditioning factors and producing a reliable flood hazard map. The low Consistency Ratio ($CR = 0.026$) further confirms the robustness of the weighting process. Validation using field observations showed a strong spatial agreement between identified high-risk zones and observed flood-prone locations, thereby enhancing confidence in the model outputs. This study contributes to flood risk assessment by providing a location-specific and data-driven approach tailored to the Ala River Basin. Unlike generalized models, the approach adopted in this study integrates local environmental conditions and spatial variability, thereby improving the accuracy and applicability of flood vulnerability mapping in rapidly urbanizing regions. Based on the findings of this study, the following recommendations are proposed:

- i. Ondo State authorities should prioritize the implementation of an integrated flood management plan that will include the development of enhanced flood defenses, particularly in high-risk zones identified in this research.
- ii. the establishment of a community-based early warning system is crucial since such system would leverage the latest in hydrological modeling and forecasting technology to provide real-time alerts, allowing for prompt and effective community response to impending flood events.
- iii. Nigeria Hydrological Services Agency (NIHSA) and Nigerian Meteorological Agency (NIMET) should be well equipped and positioned to combat and mitigate the impact of floods in Ondo State.

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