FLOOD RISK ASSESSMENT AND VULNERABILITY MAPPING USING ANALYTICAL HIERARCHY PROCESS AND GEOGRAPHIC INFORMATION SYSTEM: A CASE STUDY OF MINNA, NIGER STATE

Mubaraq, ALI[1*], Ibrahim Olayinka JIMOH[1], Isa Adekunle HAMID-MOSAKU[2], Emmanuel G. AYODELE[2], Abidemi Waheed ATOYEBI[2], Kazeem Adewunmi RAHEEM[3]

[1]Department of Civil Engineering, School of Infrastructure, Process Engineering and Technology, Federal University of Technology, Minna, Niger State, Nigeria

[2]Department of Surveying and Geoinformatics, University of Lagos, Akoka, Yaba, Lagos State, Nigeria.

[3]Department of Civil & Environmental Engineering, University of Port Harcourt, Choba, Port Harcourt, Rivers State, Nigeria.

*Corresponding author's email: alimubaraq84@gmail.com; Phone Number: +2348078217231

ABSTRACT
Flooding is one of the most damaging disasters worldwide, and natural and human activities influence it. It has caused destruction and loss of lives and properties, which calls for spatial scope and mitigation methods for a better understanding. This research aims to map and identify flood risk regions in Minna, Niger State, using a multi-criteria decision-making tool – the Analytical Hierarchy Process (AHP) and Geographic Information System (GIS). The AHP is the foundation for the study in determining and integrating the weighted percentage of flood criteria within the ArcGIS interface. The criteria considered for this research include Elevation, Topographic Wetness Index (TWI), Slope, Precipitation, Drainage Density, Soil Type, Proximity to River, and Land Use Land Cover (LULC). The resultant AHP flood risk map shows that 22.25% of the study area is at high and very high risk of flooding, 53.7% has a moderate susceptibility level, while 24.05% is at low and very low risk of flooding. Low slopes, high drainage density, and built-up regions are observed to be characteristic of these communities, which are at a very high risk of flooding. The result of the analysis urges the authorities in Minna, Niger State, to devise appropriate plans for potential floods in the future, such as proper maintenance of the drainage system and creating awareness of flood risk.

Keywords: Minna, AHP, Flood risk regions, driving criteria, Environmental issues.

1.0 INTRODUCTION

Natural disasters pose significant risks to lives and property. The ability of a community to respond to emergencies is put to the ultimate test during such disasters (March 2002). Millions of people are affected by the consequences of these events, resulting in high death tolls, severe financial impacts, and community displacement (Beth *et al.,* 2017). The increasing frequency and severity of natural disasters, such as flooding, are closely linked to climate change. Factors such as heavy rainfall and river overflow have made these events more common due to shifts in the climate. The significant consequences of these disasters on societies and economies, as noted by Nadeem *et al.* (2022), include the destruction of infrastructure and property, loss of life, and an increased prevalence of poverty and hunger. Ifiok *et al.* (2022) emphasised the fact that these disasters may cause the extinction of species, highlighting the intricate consequences of climate-induced events such as flooding. Musa *et al.* (2015) analysed the causes of flooding in Minna, with the primary goal of proposing solutions to mitigate the adverse effects along the pathways of River Suka. It was reported that the continuous flooding along the banks of the River Suka is primarily due to human activities, including construction in flood-prone areas, inadequate drainage systems, and alterations to the landscape of the region.

The impact of flooding is a global phenomenon, and Minna, in Niger State, is also affected. Researchers have utilised Geographic Information Systems (GIS) to map flood-prone areas worldwide, helping governmental agencies responsible for disaster management to make informed decisions regarding flood preparedness and response. In some regions significantly threatened by floods, survival becomes increasingly difficult, prompting mass migration of residents to already densely populated areas. This migration exacerbates challenges such as poverty and a rising dependency rate, making these issues critical and deserving of serious attention. According to Peduzzi *et al. (*2009), over 800 million people reside in flood-prone areas, and the frequency of floods in recent years has reached unprecedented levels, exposing 70 million people to flooding annually. A catastrophic flooding in Nigeria in March 2012 resulted in over 430 fatalities, 566,466 displaced individuals, and an inundated area measuring more than 4,701 km^2 (Agada & Nirupama, 2015). In another study, Ajumobi *et al. (*2022) assessed the consequences of the 2022 flooding in Nigeria, highlighting severe impacts on property, water, facilities, agriculture, and health. Generally, Nigeria has experienced floods of varying magnitudes over the years. The National Emergency Management Agency (NEMA) announced in January 2023 that flooding is anticipated in the country, underscoring the urgent need for preparedness against potential flood events.

Currently, there is a pressing need to gain a deeper understanding of the factors contributing to flood risk and vulnerability in Minna, Niger State, Nigeria. A systematic approach is essential for identifying and modelling these factors; moreover, they are multifaceted, and the quest for multicriteria evaluation (MCE)/multicriteria decision-making (MCDM) is important. According to Adzandeh et al. (2024), Balogun et al. (2020), and Hamid-Mosaku et al. (2017), among the various available MCE methods, the Analytical Hierarchy Process (AHP) has been chosen for its simplicity and effectiveness in ranking factors based on their importance. Therefore, the modelling was done within a Geographic Information System (GIS) environment using the AHP approach. As part of the study, various human activities were examined, such as urban development and changes in land use, as well as the socio-economic impacts of flooding on the communities in Minna. This analysis aims to provide necessary and adequate mitigation strategies.

Among the objectives of this study are to assess the vulnerable flood risk areas in Minna and create flood risk and vulnerability maps in Minna using the Analytical Hierarchy Process and GIS. Various driving factors were evaluated from diverse sources, whilst mitigation strategies that can assist governmental and non-governmental agencies in enhancing emergency response and flood management initiatives were proposed. Therefore, the remaining sections of the manuscript are arranged as follows: a review of flooding-related studies and approaches adopted is presented in Section 2. The methodology is provided in Section 3. The results and discussion are presented in Section 4, while Section 5 concludes the discussion.

2.0 LITERATURE REVIEW

Flood affects most countries globally and is considered one of the most devastating and frequently occurring natural hazards (Komolafe *et al*., 2015; World Bank Group, 2019), thus necessitating the quest for proactive flood hazard mapping and risk management and mitigation for sustainable economic and urban development strategies (Bouchikhi et al., 2025; Loukili et al., 2025). On the one hand, flooding occurs when water overflows onto previously dry land, indicating that the amount of rainfall the land can absorb has been exceeded (Nwachukwu *et al*., 2018). Flooding occurs when rivers experience exceptionally high flows, causing water overflow into floodplains or areas beyond the main river channels (Raghunath, 2006). The risk associated with floods is determined by their likelihood and the potential extent of damage, which can include loss of life and property within the affected communities (Henry, 2006). Therefore, floods can also serve as indicators of the overall quality of an environment (Ifiok *et al*., 2022).

Nigeria has experienced frequent and severe flooding, particularly in the last few years (Bamidele and Badiora, 2019). Notable incidents with attendant worst scenarios occurred in 2012, 2018, and 2022 - 2024 (Konwea, 2012; Nigeria Hydrological Services Agency, 2020; Okwuashi & Jibunor, 2021; Ayanlade & Omojola, 2022; Dada & Adekoya, 2023). These disasters affected at least 32 out of the 36 States in Nigeria. The floods were mainly caused by prolonged heavy rainfall in various regions and the release of excess water from the Lagdo Dam in Cameroon (Nura and Alison, 2023). Additionally, inadequate policy planning and implementation, blockages of waterways, and activities by residents in flood-prone areas also contributed to the flooding in Nigeria (Ekpoh et al., 2015). These floods have significantly impacted the country's environment and economy (Ifiok et al., 2022).

2.1 Causes and Effects of Flooding

Over the years, various researchers have offered insights into the causes of flooding. In their review of flood risk in Nigeria, Komolafe *et al*. (2015) observed that the floods in Nigeria are primarily caused by a high level of vulnerability among residents and a lack of coping capacity. Nkwunonwo *et al*. (2015), in their study on flooding and flood risk reduction in Nigeria, concluded that major contributing factors include rapid population growth, poor urban planning, and an increase in both the frequency and intensity of rainfall. , Olajuyigbe *et al*. (2012) in assessing the flood hazards in Mile 12, Lagos State, noted that recurring floods pose significant risks to the local economy and ecology. The study identified several causes, including frequent heavy rainfall, water discharged from the Oyan Dam in the nearby Ogun State, obstruction of drainage channels by debris and other materials, narrow river channels, and construction activities along floodplains. Their research methodology included administering questionnaires, interviewing relevant government officials, and conducting participatory observations. Other causes, according to Magami *et al.* (2014) include dam failures, overflowing rivers, poor channel maintenance, neglect of advisories from the Nigerian Meteorological Agency (NIMET), and insufficient evaluation of settlements in flood-prone areas.

Heavy rainfall, alongside inadequate drainage systems on roads and the obstruction of flood channels by refuse dumps, significantly contributes to flooding disasters in Uyo, Akwa Ibom State, Nigeria (Evans *et al.*, 2017). Nnodim and Ezekiel (2020) investigated the impact of chronic flooding on the livelihoods of rural residents in the Orashi region of Rivers State. The causes of flooding identified include prolonged periods of heavy rainfall, river overflow, and the continuous release of excess water from reservoirs. In the work of Tabiri (2015), four main causes were identified as reasons for persistent flooding in the Accra metropolis, Ghana, which are: negligence, poor planning, structures obstructing waterways, and inadequate waste disposal. ,Nwigwe and Embargo (2014) echoed the findings by Tabiri regarding flooding in Nigeria, adding that collapsed dams and the topography of certain areas also contribute to the flooding issues.

Flooding, due to its devastating nature, has significant negative effects on the livelihoods of individuals (Ejem and Ben-Enukora, 2025; Eteh et al., 2025; Jega et al., 2025; Sun et al., 2024). Literature on the impact of flooding indicates that households are losing lives and property. Saleem *et al*. (2013) conducted a study on Muzaffargah - a flood-prone district in Punjab, a case study to analyse the impact of floods on livelihoods and food security in the area. The researchers conducted interviews with 120 flood victims to gather data. The study found that agriculture was the main income source; however, floods severely damaged vital natural resources, including land, irrigation systems, orchards, and livestock, resulting in decreased income for the community. Consequently, the population faced food shortages and food insecurity, as many were forced to consume contaminated goods, particularly water. This disaster ultimately delayed the recovery and prosperity of farmers by several years. Ani *et al*. (2020) also emphasised the fact that floods significantly affect the livelihoods of people and the environment. Similarly, Ojikpong *et al*. (2016), in their assessment of flood risks in residential neighbourhoods of the Calabar metropolis, found that flooding leads to loss of life and property, and the destruction of socio-economic activities. The study noted that the extent of loss and destruction is influenced by factors such as the timing of the flood, the condition of drainage systems, and the location of river encroachments. Okeleye *et al*. (2016) assessed the impact of flood disasters on the livelihoods of farmers in the Oke Ogun region of Oyo State. They collected information through focused group discussions, structured questionnaires, in-depth interviews, and portable GPS technology. The findings from this study revealed that farmers are highly vulnerable to flooding due to its significant effects on their farmland. Most farmers have limited coping mechanisms because they lack access to insurance and reliable early warning systems for floods.

In Ejem and Ben-Enukora (2025), the differential effects of 2022 flood events on men and women were examined and in relation to the devastating destruction of farms, loss of income, health challenges, and longer recovery periods for marginalised groups. Moreover, Eteh *et al.* (2025), assessed the increasing flood frequency from 2018 to 2024 and severity that threatens infrastructure, agriculture, and local livelihoods downstream, highlighting loss of farmland and disruption in ecosystem services, based on machine learning and geospatial techniques. The influence of crop production and income among smallholder farmers was investigated in Jega et al. (2025), revealing a statistically significant negative impact on the livelihoods of the farmers and the community.

Also, Nnodim and Ezekiel (2020) examined the effects of flooding in a catchment area of Rivers State, Nigeria. The analysis focused on the impacts of floods on both crop and fish farming. The study emphasised that flooding has several detrimental effects on agriculture, including the submergence of farmlands, destruction of crops and irrigation systems, and loss of harvested produce. In fish farming, flooding can spread infections that lead to fish diseases, contaminate rivers and streams, and result in the death of fish and other aquatic animals. Ifiok *et al*. (2022) researched the causes and effects of flooding in Nigeria, noting that floods stem from natural and human activities. The outcomes of this study supported the fact that natural causes of floods include topography, soil type, and extreme rainfall. Human activities contributing to flooding involve inadequate environmental planning and monitoring, housing development in flood-prone areas, deforestation, poorly managed construction that clogs drains, improper waste disposal practices, and government negligence in developing and implementing effective policies at all levels.

2.2 Hierarchical Framework and Paired Comparison

The Analytical Hierarchy Process (AHP) is a multicriteria decision-making (MCDM) technique that helps in prioritising, organising, and structuring preferences (Hamid-Mosaku *et al.* 2017). This method aids in comparing various options and making informed decisions based on both qualitative and quantitative factors. By establishing a multilevel hierarchy of criteria and alternatives, AHP systematically evaluates the elements to determine their relative significance in achieving the primary objective. It simplifies the preference-rating process through pairwise comparisons, which contributes to greater consistency in judgment (Rebollo *et al.*, 2016; Hamid-Mosaku *et al.*, 2017; Balogun *et al.*, 2020; Adzandeh *et al*., 2024).

AHP employs hierarchical frameworks to illustrate the problem and subsequently establish preferences for various options through user judgment. This method relies on paired comparisons to derive these priorities. The hierarchical framework consists of three levels: level one, which represents the overall goal is the Flood Risk Assessment, level two, which comprises the criteria is the flood hazard and flood vulnerability, and level three, which relates to the elements for each criterion. The elements are valued for paired comparisons on a scale from 1 (equal importance) to 9 (extreme importance) as presented in Table 1.

Table 1: Fundamental scale for pairwise comparison

Intensity of importance	**Definition**	**Explanation**
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one element over another
5	Strong Importance	Experience and judgment strongly favour one element over another
7	Very strong importance	One element is favoured very strongly over another, its dominance is demonstrated in practice
9	Extreme importance	The evidence favouring one element over another is of the highest possible order of affirmation
2,4,6,8 can be used to express intermediate values		

The pairwise comparisons are made by expressing the judgments of the experts in the form of an n-by-n positive reciprocal decision matrix A, having elements $[x_{ij}]$; where $x_{ii} = 1$ (i.e., the diagonal elements are equal to 1, thus, representing an element being compared to itself). Other elements are represented based on comparisons between two criteria. If the criterion on the column is preferred to that on the row, the inverse of the rating is taken. This ensures consistency in the matrix construction. Thus, $x_{ij} = {}^{1}/_{ji}$ for all $i, j = 1, \dots, n$, such that, the principal eigenvalue of A is λ_{max}.

The Consistency Ratio (CR) is obtained by dividing the Consistency Index (CI) by a Random Index (RI), as shown in Equation 1. CI is calculated using Equation 2 (Alonso and Lamata, 2006; Hamid-Mosaku et al., 2024).

$$Consistency\ Ratio\ (CR) = \frac{Consistency\ Index}{Random\ Index} \quad (1)$$

$$Consistency\ Index\ (C.I) = \frac{\lambda max - n}{n-1} \quad (2)$$

where n is the number of criteria

λ_{max} = Average of Consistency Measure

λ_{max} Is used to calculate the consistency index; based on the condition that $\lambda_{max} \geq n$, with equality if and only if A is consistent. Also, A represents the biggest eigenvalue for the pairwise comparison matrix.

On the other hand, the Random Index (RI) represents the consistency index of a randomly generated reciprocal matrix value generated by Saaty (1980) based on the number of criteria. The average values for orders from 1- 15 matrices generated as in Table 2, and for a sample size of up to 100 (Brent et al., 2007; Saaty, 1980). If CR is less than 10%, then the matrix can be considered as having an acceptable consistency.

Table 2 RI (n) values (Brent et al., 2007; Saaty, 1980)

n	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.5799	0.8921	1.1159	1.236	1.3322	1.3952	1.4537	1.488	1.512	1.5356	1.5571	1.5714	1.5831

2.3 AHP and GIS Method of Flood Assessment

The Geographic Information System (GIS) is a valuable tool for capturing, storing, analysing, managing, and visualising spatial or geographic data. In the context of flood mapping, GIS provides researchers with a framework to identify areas vulnerable to flooding. This tool combines spatial data with analytical capabilities, facilitating the identification and characterisation of regions at risk. GIS is globally recognised for its contribution to disaster preparedness. Researchers often emphasise its importance in providing spatially explicit information that assists policymakers in developing effective strategies to mitigate flood risks (Aichi et al., 2024; Burayu et al., 2023; Mohammed et al., 2024). In addition, GIS-based models help foster community resilience by promoting public awareness and enhancing understanding of the extent of potential hazards.

Over the years, researchers have integrated the Analytic Hierarchy Process (AHP) and Geographic Information Systems (GIS) to map areas vulnerable to flooding. Chukwu *et al*. (2022) employed GIS and AHP methods to assess flood risks in Ethiope, Delta State. They utilised seven GIS elements as criteria, which were weighted and normalised to eliminate bias in judgments. These criteria were instrumental to generating flood hazard and flood vulnerability maps. The flood hazard map was based on physical and hydrological factors, including slope, drainage, soil types, and rainfall. In contrast, the flood vulnerability map incorporated anthropogenic variables such as population density, drainage systems, and land use/land cover (LULC). By combining these two maps, the researchers created an overall flood vulnerability map for the study area, categorising regions from very low susceptibility to very high susceptibility to flooding. The findings indicated that communities at high and very high risk of floods typically exhibit characteristics, such as low slopes, high drainage densities, proximity to rivers, and inadequate drainage systems. Conversely, areas with high slopes, dense forests, low drainage densities, minimal rainfall, and effective drainage systems have an extremely low likelihood of flooding.

Aydin and Birincioğlu (2022) analysed flood hazards in the Bitlis province of Turkey using Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP). It was found that the southwest region of the research area poses a significant flood danger due to high precipitation and stream density. However, the risk is mainly confined to areas surrounding low-elevation streams, owing to the region's harsh terrain and steep slopes. In contrast, the northern areas experience a milder flood risk that extends over a larger region, attributed to average precipitation and comparatively lower slopes. The most dangerous zones are identified as densely populated urban areas. Additionally, regions with low stream density and high elevations were determined to be low-risk areas for flooding.

Danumah *et al*. (2016) utilised multi-criteria analysis and GIS to analyse and map flood-prone areas in Abidjan. The study revealed that eight out of thirteen municipalities in the district are at risk of flooding. The various criteria used within the ArcGIS interface are slope, land use, population density, drainage density, soil type, Isohyet, and sewage system density. The resulting AHP flood risk map indicated that 34% of the study area has high or very high flood risk. Their research demonstrates the validity and significant contribution of geoinformation approaches to evaluating natural disasters.

Waseem *et al.* (2023) assessed the flood hazards, vulnerabilities, and risks in the Shebelle River Basin (SRB) in southern Somalia using the Analytical Hierarchy Process (AHP) and Geographic Information Systems (GIS) using seven significant factors: elevation, slope, drainage density, distance to the river, rainfall, soil type, and geology to create the flood hazard maps. Additionally, they used Global Man-Made Impervious Surface (GMIS), population density, distance to roads, land use/land cover (LULC), and the extent of human-built area settlements (HBASE) to develop the flood vulnerability map. Finally, they produced a flood risk map by integrating the flood hazard and vulnerability maps.

Amen *et al*. (2023) conducted a study to identify flood-prone areas in Duhok, located in the Kurdistan Region of Iraq, using GIS techniques combined with the Analytical Hierarchy Process (AHP). The Flood Hazard Index (FHI) was evaluated by assigning relative weights to 12 factors, including elevation, slope, proximity to rivers, rainfall, and land use. Other parameters considered were land cover, soil type, lithology, topographic roughness, wetness indices, aspect, sediment transport index, and stream power index. These weighted parameters were used to generate a flood susceptibility map, categorising the region into zones with varying flood risk, from very low to very high. The results indicated that 44.72 km^2 of Duhok City is at a very high risk of flooding.

Shawky and Hassan (2023) researched flash flood susceptibility zonation in the Sinai Peninsula, located in the north-eastern part of Egypt, based on GIS and the AHP. The relative weights of nine geographical factors based on their relevance to flash flood occurrence were determined and used to create a flood risk map for the study area. The map indicated that 21% of the evaluated region faces a very high or high risk of flash flooding, 19.8% has a moderate risk, and 59.2% falls under very low or low risk. A GIS and AHP framework were adopted to identify suitable shelter locations in Ubon Ratchathani flood-prone areas in Thailand (Tiangtrong et al. 2925). Meanwhile, Rathod and Ukey (2025), identified twelve factors that contributed to the GIS-AHP flood susceptibility mapping of the Savitri and Vashishti River Basins, Western Maharashtra.

There are studies incorporating MCDM with GIS, remote sensing, geomatics, and hydrological modelling using different machine learning and deep learning classifiers. In Loukili et al. (2025), the evaluation of the performance of Sentinel-1, Sentinel-2, and Landsat satellite data for flood detection was carried out within the Google Earth Engine platform, using Random Forest (RF) and Minimum Distance (MD) classifiers. Babati et al. (2025) examined the application of machine learning in coastal flooding, with different ML classifiers. Novel flood inventory sampling strategies were adopted based on ML for the susceptibility flood mapping (Long et al, 2025).

The literature reviewed demonstrated the effectiveness of GIS and AHP in assessing flood risk areas and producing reliable results, but there is a paucity of such for the case of Minna. Therefore, this study aims to fill this research gap by providing a comprehensive flood risk map for Minna, Niger State, that could help mitigate flood hazards, where such a map is currently lacking.

3.0 RESEARCH METHODOLOGY

3.1 Study Area

The scope of this research is Minna, Niger State, Nigeria, which is located between latitude 9° 36'22"N and longitude 6° 33'l 5"E. It consists of two local governments – Bosso and Chanchaga Local Government Areas (Figure 1). It is located in the North Central Geopolitical Zone of Nigeria and covers an area of around 6,789 sq km (Daniyan and Muhammed, 2018). It is in a tropical climate region characterised by two seasons in a year, the wet and dry seasons. The annual rainfall usually lasts between May and October. The dry season lasts between October and March.

Figure 1: Geographic Map of the Study Area

3.2 Datasets

The datasets utilised in this research consist of a diverse range of geographical, hydrological and demographical Information pertinent to Minna, Niger State. They include Administrative Map, Digital Elevation Map (DEM), Topographic Wetness Index (TWI), Slope, Precipitation, Land Use/ Land Cover (LULC), Proximity to River, Drainage Density, and Soil Type. The dataset is gathered from various sources and serves as the foundation for AHP and GIS methodologies used in conducting the research. Table 3 presents the data types and their corresponding sources.

Table 3: Data and data source

S/N	Dataset	Source
1	Administrative Map	diva-gis.org
2	DEM	earthexplorer.usgs.gov
3	TWI	ArcGIS toolbox (Raster Calculator)
4	Slope	ArcGIS toolbox (Spatial Analyst Tools – Surface – Slope)
5	Precipitation	Crudata.uea.ac.uk
6	LULC	Earthexplorer.usgs.gov
7	Proximity to the river	ArcGIS toolbox (Spatial Analyst Tools – Distance – Euclidean Distance)
8	Soil Type	Fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/

3.3 Analytical Hierarchy Process (AHP)

3.3.1 Expert Opinions

Experts in the field of hydrology, disaster management and environmental science were identified. Their extensive knowledge and experience on flood assessment were utilised to perform the pairwise comparison of selected criteria by comparing each criterion to determine their relative importance.

3.3.2 Development of Pairwise Comparison Matrix

The pairwise comparison matrix is developed by comparing the relative importance of criteria to each other. An 8 x 8 matrix was constructed with all selected alternatives forming its rows and columns. The matrix was then filled based on the rating from the paired comparison between the various criteria.

3.3.3 Development of Normalisation Matrix

The normalisation of the pairwise matrix is a crucial step that aims at matrix consistency and is mathematically suitable for deriving meaningful priorities. Normalisation can be attained by dividing each element in a column of the pairwise comparison matrix by the sum of elements in that column. This process ensures the adjustment of each value within each column to properly represent its relative importance, thereby enabling a consistent comparison across the criteria.

3.3.4 Checking the Consistency Ratio

Checking the consistency ratio is a pivotal step to ensure the reliability of the ratings made during paired comparison.

3.4 Geographic Information System

3.4.1 Terrain Analysis

The Digital Elevation Model was utilised in generating the Slope, Topographic Wetness Index and Drainage Density of the study area. These factors help to understand the terrain, flow pattern, and drainage characteristics, influencing flood behaviour.

3.4.2 Data Reclassification

Integrating the Reclassify toolbox in ArcGIS to categorise data into distinctive classes helps in simplifying data to aid in the assessment and prioritisation of flood-vulnerable areas. Through this process, thematic data were classified into five specific classes ranging from low to extreme vulnerability. The Reclassify toolbox was utilised to define and assign values to these classes, offering a clear and interpretable representation of vulnerability gradients within the study area.

3.4.3 Mapping of Flood Risks

A flood risk map is developed by combining hazard and vulnerability indices. This approach is commonly applied to various natural hazards and follows Equation 3:

$$Risk = Hazard\ Index\ X\ Vulnerability\ Index \tag{3}$$

In this study, weights generated using AHP were assigned to the different criteria based on their relative influence and contribution to the flood in the study area. The Weight overlay tool in ArcGIS was employed to combine multiple thematic layers, incorporating the assigned weight to create a composite index representing flood vulnerability. This process facilitated the generation of a single map showing varying vulnerability levels across the study area and providing a clear and detailed visual representation. This will enable decision makers to identify and prioritise areas for targeted intervention and mitigation strategies based on the degree of vulnerability.

4.0 RESULTS AND DISCUSSION

4.1 Expert Opinion

The expert judgment helped in the final selection of the criteria used for this study. These criteria are: topographic wetness index (TWI), elevation, slope, precipitation, LULC, soil type, drainage density, and proximity to river.

4.2 Hierarchical Framework and Paired Comparison

The selected criteria for assessment of the vulnerability of the study area to flood were combined to form the pairwise matrix in Table 4, while Table 5 presents the normalised version. The flood map, which depends on the eight criteria, was developed using the degree of influence of each criterion from the paired comparison matrix. After summing up the weighted values from all contributing criteria, the final flood susceptibility map was generated with a Consistency Ratio of 0.075, and is less than 0.1 as Saaty (1980) proposed, validating its reliability. Table 6 presents the computed consistency ratio.

Table 4: Pairwise Comparison Matrix

	TWI	Elevation	Slope	Precipitation	LULC	Soil Type	Drainage Density	Proximity to river
TWI	1	1	1	1	3	5	1	2
Elevation	1	1	1	1	2	1	1	1/3
Slope	1	1	1	1	3	3	1/2	1/3
Precipitation	1	1	1	1	3	5	2	1
LULC	1/3	1/2	1/3	1/3	1	3	1/3	1
Soil Type	1/5	1	1/3	1/5	1/3	1	1/5	1/3
Drainage Density	1	1	2	1/2	3	5	1	1

Proximity to river	1/2	3	3	1	1	3	1	1

Table 5: Normalised Matrix

	TWI	Elevation	Slope	Precipitation	LULC	Soil Type	Drainage Density	Proximity to river	Criteria Weight (%)
TWI	0.17	0.11	0.1	0.17	0.18	0.19	0.14	0.29	16.9
Elevation	0.17	0.11	0.1	0.17	0.12	0.04	0.14	0.05	11
Slope	0.17	0.11	0.1	0.17	0.18	0.12	0.07	0.05	12
Precipitation	0.17	0.11	0.1	0.17	0.18	0.19	0.28	0.14	17
LULC	0.06	0.05	0.03	0.06	0.06	0.12	0.05	0.14	7
Soil Type	0.03	0.11	0.03	0.03	0.02	0.04	0.03	0.05	4
Drainage Density	0.17	0.11	0.21	0.08	0.18	0.19	0.14	0.14	15
Proximity to river	0.08	0.32	0.31	0.17	0.06	0.12	0.14	0.14	17

Table 6: Consistency Ratio

	TWI	Elevation	Slope	Precipitation	LULC	Soil Type	Drainage Density	Proximity to river	Total	Average	Consistency Measure
TWI	1	1	1	1	3	5	1	2	1.34	0.17	8.65
Elevation	1	1	1	1	2	1	1	1/3	0.89	0.11	8.70
Slope	1	1	1	1	3	3	1/2	1/3	0.96	0.12	8.60
Precipitation	1	1	1	1	3	5	2	1	1.34	0.17	8.53
LULC	1/3	1/2	1/3	1/3	1	3	1/3	1	0.56	0.07	8.83
Soil Type	1/5	1	1/3	1/5	1/3	1	1/5	1/3	0.34	0.04	9.20
Drainage Density	1	1	2	1/2	3	5	1	1	1.22	0.15	8.90
Proximity to river	1/2	3	3	1	1	3	1	1	1.34	0.17	8.56
Consistency Index											**0.105**
Random Index											**1.41**
Consistency Ratio											**0.075**

4.3 Flood Criteria Maps

The criteria maps were produced within the ArcMap 10.5 software environment, and these maps were subsequently reclassified into five categories of vulnerability ranges (very low, low, moderate, high, and very high) using the natural break method, classifying them based on their potential impact on flooding. The findings reveal that the average annual rainfall in the study area between 1981 and 2022 varies between 1132 mm and 1152 mm. The dataset was prepared using the Inverse Distance Weighted (IDW) method, which revealed that high precipitation represents high vulnerability to flooding. The proximity to the river, generated using the Euclidean distance toolbox, was used to show how areas located closer to rivers are more vulnerable to flooding. During excessive rainfall, rivers might experience overtopping and inundation of adjacent lands when they exceed their carrying capacities.

The elevation, which influences water flow and accumulation patterns, varies between 93 meters and 458 meters. Areas with low elevation serve as natural collection basins for surface water, making them highly vulnerable. The slope ranges between 0 and 10. A 9-degree slope in the region, was used in revealing that areas with high slope angle are more vulnerable to flooding because such area allows high runoff of rainwater with less infiltration.

Moreover, the Land Use/Land Cover dataset that was prepared for the study area using supervised classification, and the spatial characteristics of the region were found to be Built-up Areas, Barren Lands, Vegetation and Water Bodies. Vegetated areas, due to their high rate of infiltration and reduced runoff, were found to be less susceptible to floods compared to built-up areas, which are highly vulnerable, due to their low rate of infiltration and increased runoff.

Also, the drainage density generated from the Digital Elevation Model through the spatial analyst tools ranges between 0.9966 and 1.003 km/km^2. High drainage density represents areas that are highly vulnerable to flooding and increased flood risk, which could trigger runoff and sediment transport.

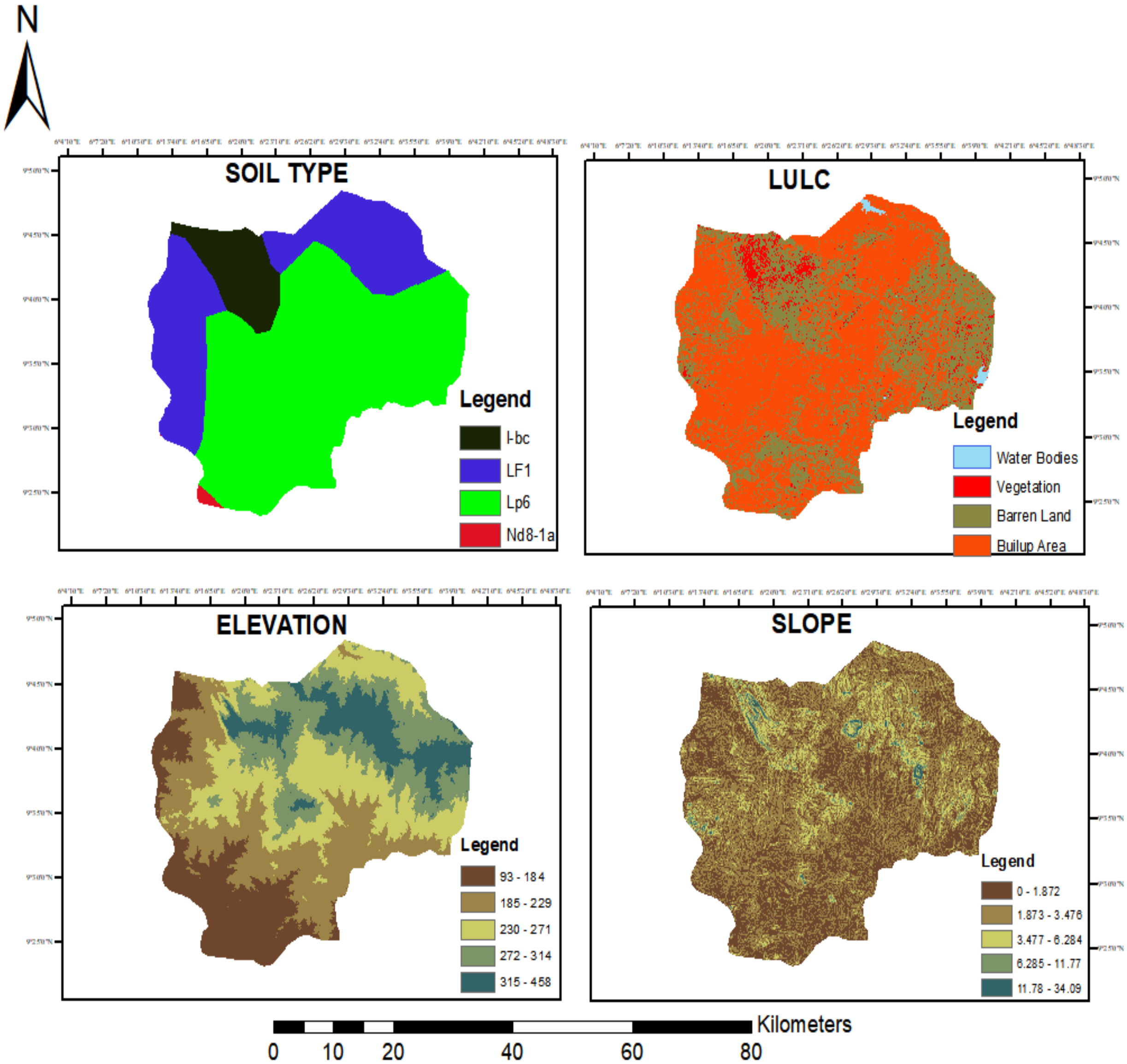

Figure 2: Thematic Maps showing soil types, LULC, elevation, and slope

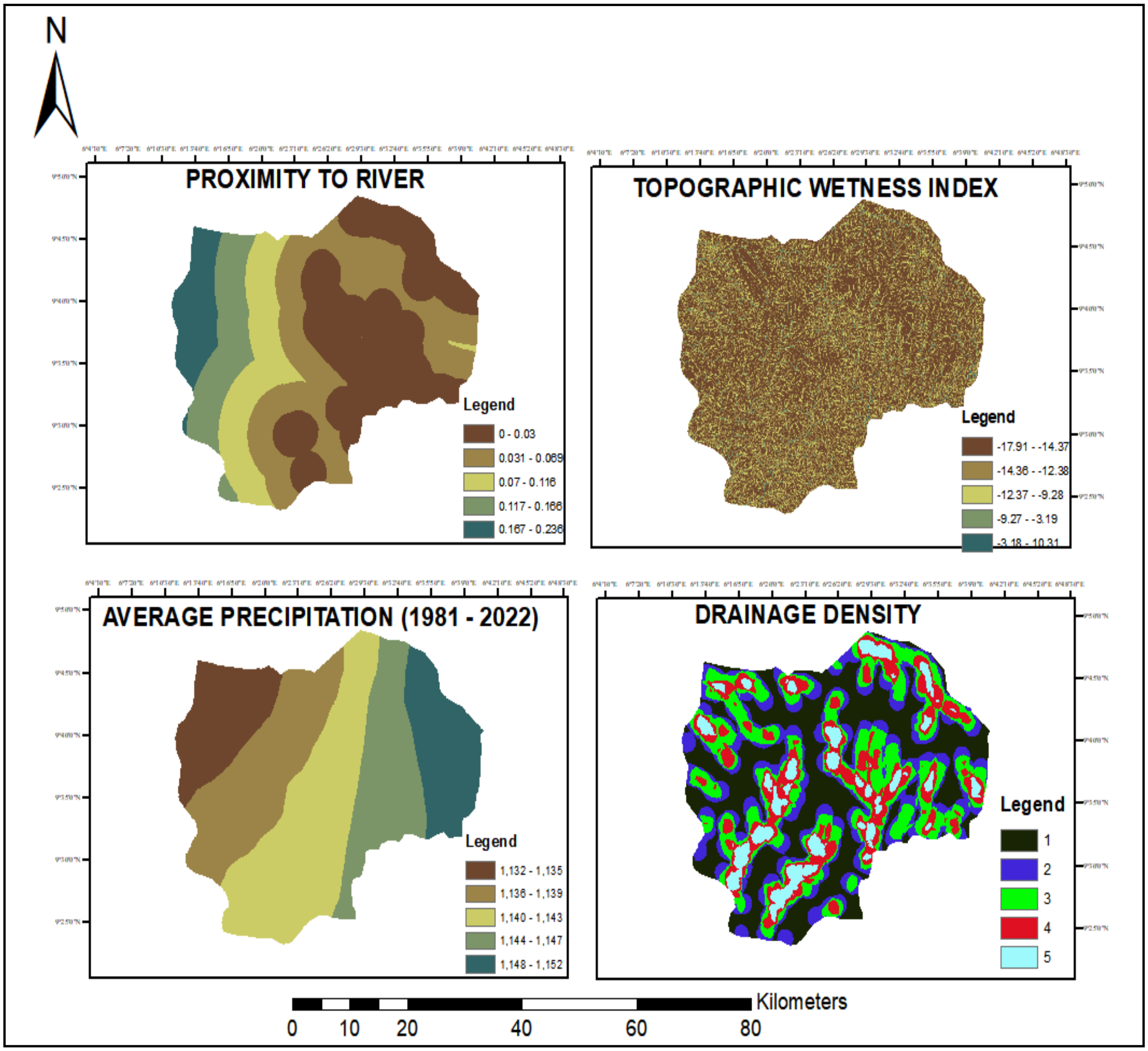

Figure 3: Thematic Maps showing proximity to river, TWI, average precipitation, and drainage density

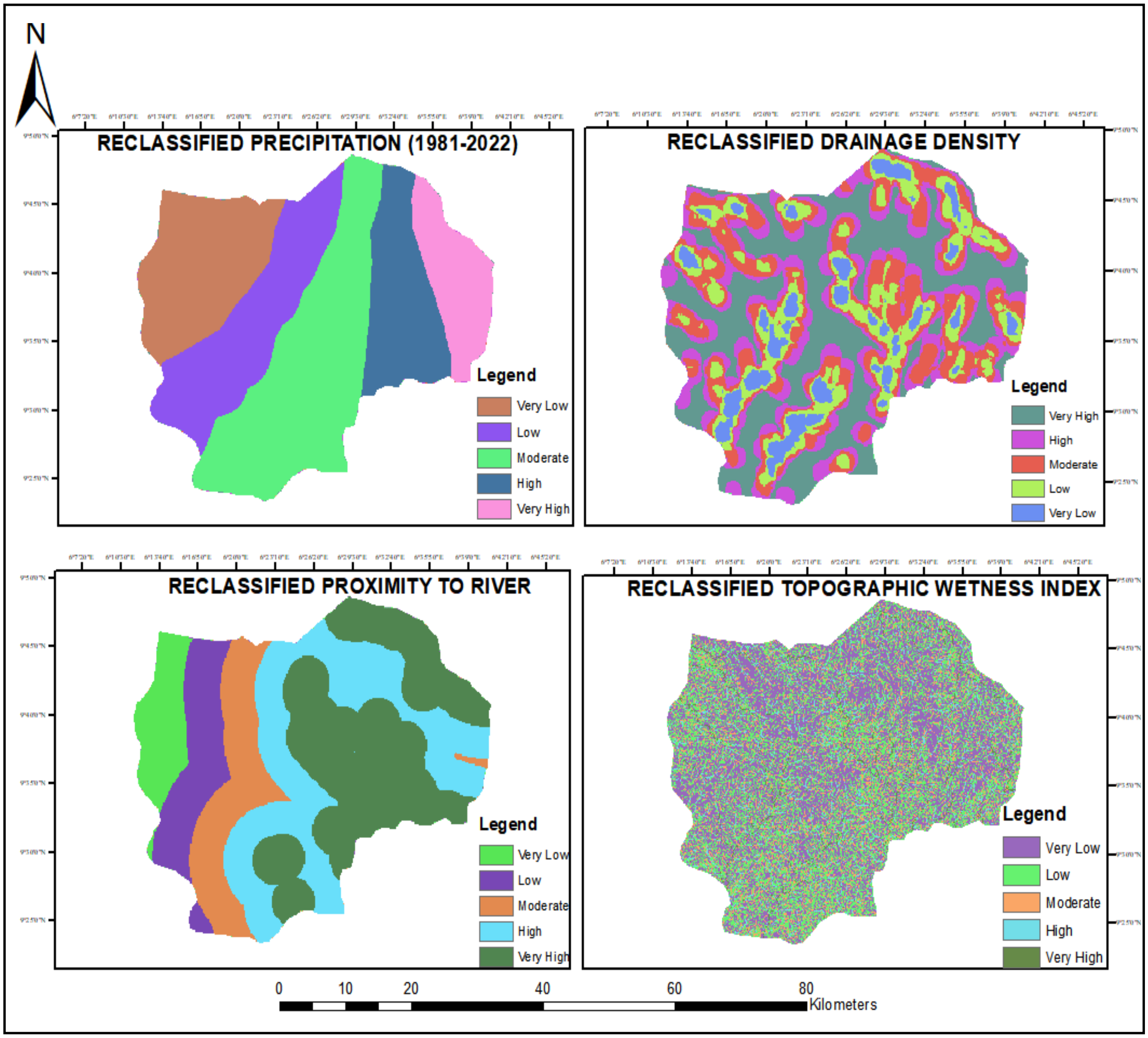

Figure 4: Reclassified Maps

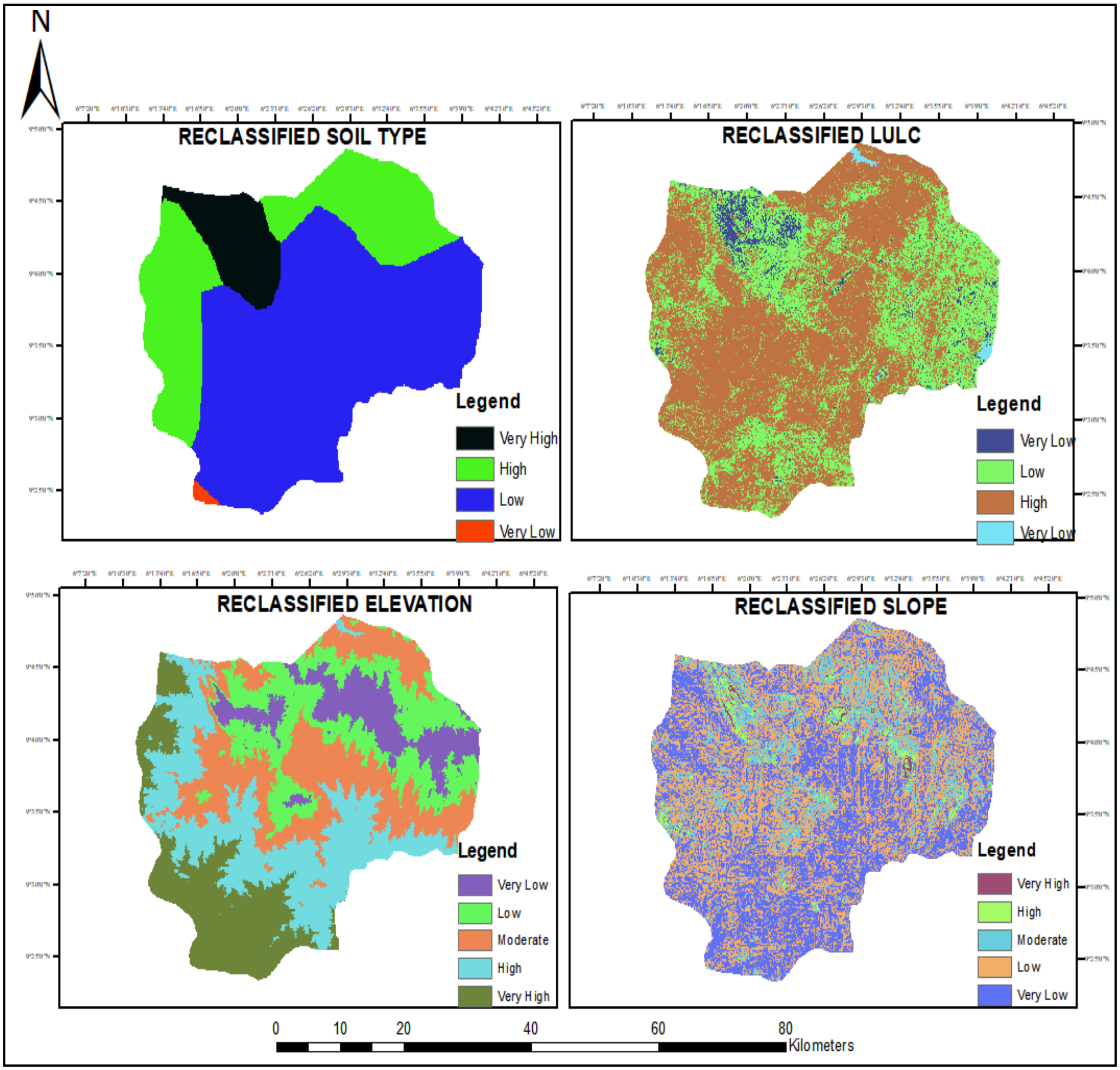

Figure 5: Reclassified Maps Cont'd

4.4 Flood Risk Map

The flood risk map was created through a weighted overlay analysis of flood risk factors, utilising thematic layers in the ArcMap 10.5 software. The spatial analyst tool's weighted overlay function facilitated the analysis. The Analytical Hierarchy Process (AHP) method was used for reclassification, incorporating weightings from eight criteria to produce the final flood susceptibility map classified into five distinct flood risk categories: very low, low, moderate, high, and very high. The findings indicated that 2.14% of the evaluated area is at very low risk, 21.91% at low risk, 53.7% at moderate risk, and 22.25% at high to very high flood risk.

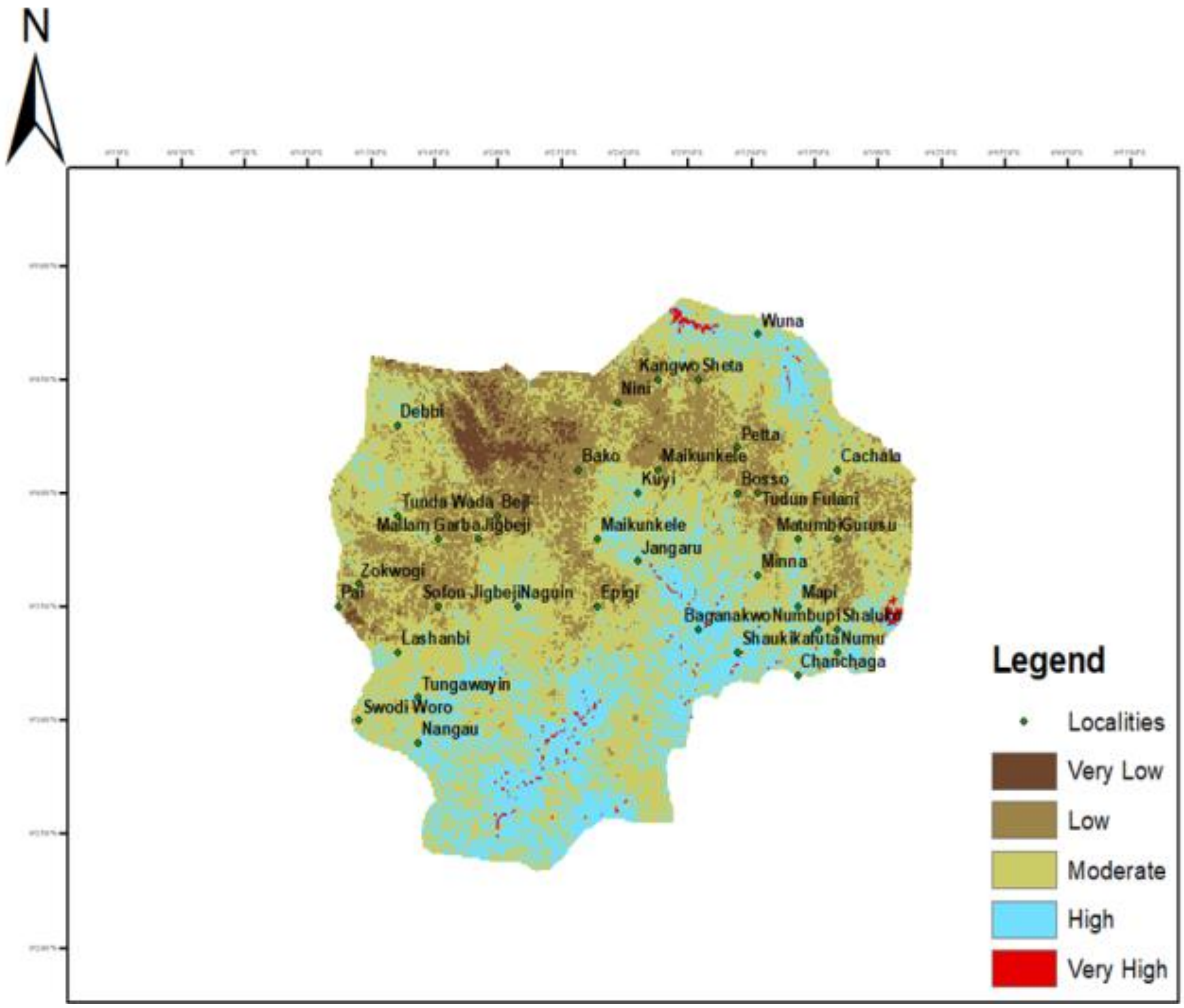

Figure 6: Final Vulnerability Maps

5.0 Conclusion and Recommendation

This study used the AHP model and Geographic Information Systems (GIS) to assess flood susceptibility in Minna, Niger State, Nigeria. Data was collected on eight influential criteria for flood hazard and vulnerability, including TWI, DEM, LULC, precipitation, slope, river proximity, drainage density, and soil type in the study area. Thematic maps were generated for each criterion using ArcGIS software.

The significance of each criterion was evaluated using the AHP model through pairwise comparisons, which were weighted and normalised to minimise bias. A consistency ratio test was conducted, yielding a value of 0.075, which is below the 0.1 threshold suggested by Saaty for reliable judgment.

By overlaying and combining these criteria, a flood vulnerability map was produced, showing that factors such as low slope, high drainage density, and proximity to rivers significantly contribute to identifying areas at elevated flood risk. The flood likelihood was expressed using five indicator classes, ranging from very low to very high.

Given these results, this research encourages regulatory bodies to enhance drainage systems to mitigate the impact of increased runoff resulting from river overtopping. It is essential to restrict development in flood-prone areas, raise awareness about flood risks, and educate vulnerable communities on preparedness measures.

Additionally, future research should explore advanced geomatics techniques, leveraging new capabilities offered by various satellites, including those on the Google Earth Engine platform, which are not limited to the Landsat series. Incorporating AI (machine learning and deep learning), hydrological modelling, and other analytical multi-criteria decision-making (MCDM) methods, such as analytic network process (ANP), fuzzy AHP, fuzzy ANP, and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), FTOPSIS, and structural equation modelling (SEM) will further enhance assessments of flooding drivers.

REFERENCES

Adzandeh, A. E., Hamid-Mosaku, I. A., Ayodele, E. G., Olayinka-Dosunmu, D. N., Badejo, O. T., and Okolie, C. J. (2024). Integrating GIS and AHP for a Multi-Criteria Flood Vulnerability Assessment in the Benue River Basin, Nigeria. *Dutse Journal of Pure and Applied Sciences, 10*(3b), 106-123. doi:https://dx.doi.org/10.4314/dujopas.v10i3b.12

Agada, S., & Nirupama, N. (2015). A serious flooding event in Nigeria in 2012 with specific focus on Benue State: a brief review. Natural Hazards, 77(2), 1405–1414. https://doi.org/10.1007/s11069-015-1639-4

Aichi, A., Ikirri, M., Ait Haddou, M., Quesada-Román, A., Sahoo, S., Singha, C., Sajinkumar, K. S., and Abioui, M. (2024). Integrated GIS and analytic hierarchy process for flood risk assessment in the Dades Wadi watershed (Central High Atlas, Morocco). *Results in Earth Sciences, 2,* 100019. doi:https://doi.org/10.1016/j.rines.2024.100019

Ajumobi, VE, Womboh, SB; Ezem, SB (2023). Impacts of the 2022 Flooding on the Residents of Yenagoa, Bayelsa State, Nigeria. *Greener Journal of Environmental Management and Public Safety, 11(1), 1-6. https://www.researchgate.net/publication/367092515*.

Alonso, J.A. and Lamata, M.T. (2006). Consistency in the analytic hierarchy process: a new approach. International Journal of Uncertainty, Fuzziness, Knowledge-based Systems, 14(4), 445-459.

Ani, C. N., Ezeagu, C. A., Nwaiwu, N. K and Ekenta, E. O. (2020). Analysis of factors influencing flooding and vulnerability assessment of Awka and its environs. *American Journal of Engineering Research, 9(5), 34-45*.

Aydin, M. C., & Sevgi Birincioğlu, E. (2022). Flood risk analysis using GIS-based analytical hierarchy process: a case study of Bitlis Province. Applied Water Science, 12(6), 122. https://doi.org/10.1007/s13201-022-01655-x

Babati, A.-h., Isa, Z., Abdussalam, A.F., Baba, S.U., Mustapha, B.B., and Musa, A.S. (2025). Application of machine learning for coastal flooding. *Discover Cities*, *2*(1), 80. doi:10.1007/s44327-025-00125-8

Balogun, A., Quan, S., Pradhan, B., Dano, U., and Yekeen, S. (2020). An improved flood susceptibility model for assessing the correlation of flood hazard and property prices using geospatial technology and fuzzy-ANP. *Journal of Environmental Informatics*, *37*(2), 107-121.

Bamidele, O. F and Badiora, A. I (2019). Flood disaster vulnerability in North Central Nigeria. International Journal of Research and Innovation in Social Science, 3(12), 364-371.

Beth Barnes, Sarah Dunn, Sean Wilkinson. (2017). Natural hazards, disaster management and simulation: a bibliometric analysis of keyword search. *https://doi.org/10.1007/s11069-019-03677-2*.

Bouchikhi, S., Chourak, M., El Baida, M., and Boushaba, F. (2025). Multi-criteria decision analysis and hydrodynamic modeling for flood-safe urban planning: case study of Oued Merzeg, Casablanca (NW Morocco). *Natural Hazards*. doi:10.1007/s11069-025-07641-1

Brent, A.C., Rogers, D.E.C., Ramabitsa-Siimane, T.S.M., and Rohwer, M.B. (2007). Application of the analytical hierarchy process to establish health care waste management systems that minimise infection risks in developing countries. *European Journal of Operational Research, 181*(1), 403-424. doi:http://dx.doi.org/10.1016/j.ejor.2006.06.015Burayu, D. G., Karuppannan, S., and Shuniye, G. (2023). Identifying flood vulnerable and risk areas using the integration of analytical hierarchy process (AHP), GIS, and remote sensing: A case study of southern Oromia region. *Urban Climate, 51*, 101640. doi:https://doi.org/10.1016/j.uclim.2023.101640

Chukwu, Michaelmary, Huang, Xiao., Peng, Bo, and Oloruntimilehin, Isaac (2023). Flood Risk Evaluation Using AHP-Based Model and GIS Technique: A Case Study of Ethiope East and West Local Government Areas, Nigeria. *J Indian Soc Remote Sens* **51**, 2561–2576 (2023). https://doi.org/10.1007/s12524-023-01786-x

Dada, E. O., & Adekoya, J. A. (2023). "The Impact of 2022 Floods on Displacement and Public Health in Nigeria." Journal of Environmental Management, 312, 114850. [DOI: 10.1016/j.jenvman.2022.114850]

Daniyan, M. N., & Mohammed, M. (2018). Analysis of trend and dynamics of urban sprawl in Minna Niger State Nigeria. *Proceedings of ICGET 2018*, pp.31-34

Danumah, J. H., Odai, S. N., Saley, B. M., Szarzynski, J., Thiel, M., Kwaku, A., Kouame, F. K., & Akpa, L. Y. (2016). Flood risk assessment and mapping in Abidjan district using multi-criteria analysis (AHP) model and geoinformation techniques, (Cote d'ivoire). Geoenvironmental Disasters, 3(1), 10. *https://doi.org/10.1186/s40677-016-0044-y*

Ejem, A.A. and Ben-Enukora, C.A. (2025). Gendered impacts of 2022 floods on livelihoods and health vulnerability of rural communities in select Southern states in Nigeria. *Discover Social Science and Health, 5*(1), 67. doi:10.1007/s44155-025-00211-7

Ekpoh, I. J (2015). Climate change and recent severe flooding in Uyo, Akwa Ibom State, Nigeria. *Global Journal of Social Sciences, 14, 23-3*.

Eteh, D.R., Japheth, B.R., Akajiaku, C.U., Osondu, I., Mene-Ejegi, O.O., Nwachukwu, E.M., Oriasi, M.D., Omietimi, E.J., and Ayo-Bali, A.E. (2025). Assessing the impact of climate change on flood patterns in downstream Nigeria using machine learning and geospatial techniques (2018–2024). *Discover Geoscience, 3*(1), 76. doi:10.1007/s44288-025-00178-7Evans, U. F., Dominic, K. O., Evans, G. U. and Utting, C. (2017). Analysis of the relative contributions of climatic elements and environmental variables to flood disaster in Uyo, AkwaIbom State, Nigeria. *International Journal of Environmental Sciences and Natural Resources, 6(2), 52-56*.

Hamid-Mosaku, A.I., Mahmud, M.R., Mohd, M.S., Balogun, A.-L., and Raheem, K.A. (2024). A Hybrid AHP-TOPIS-Based Marine Economic Activities Evaluation Model for Marine Geospatial Data Infrastructure. *UNILAG Journal of Transport and Logistics, 1*(1), 55-72. Retrieved from http://njms.unilag.edu.ng/index.php/UJTL

Hamid-Mosaku, A. I., Mahmud, M. R., Mohd, M. S., Balogun, A. L., and Raheem, K. A. (2017). Fuzzy Evaluation of Marine Geospatial Data Infrastructure (MGDI) and MGDI Decisions' Criteria. *Journal of Engineering Research, Faculty of Engineering, University of Lagos, 22*(1), 23-37. Retrieved from http://www.jer.unilag.edu.ng

Ifiok Enobong Mfon, Michael Chukwuemeka Oguike, Salvation Ubi Eteng, Ndifreke Moses Eti. (2022). Causes and Effects of Flooding in Nigeria: A Review. DOI:10.47191/ijsshr/v5-i10-16.

Jega, A.A., Umar, S.A., and Hassan, S.U. (2025). Economic Effect of Flood Disaster and its Management among Smallholder Farmers in Kebbi State. *International Journal of Research and Scientific Innovation (IJRSI)*, 15-24. doi:10.51244/IJRSI.2024.1103002

Komolafe, A.A., Adegboyega, S.A., and Akinluyi, F.O., 2015, A review of flood risk analysis in Nigeria. American Journal of Environmental Sciences 11(3), 157–166.
doi:10.3844/ajessp.2015.157.166.

Komolafe, A.A., Adegboyega, S.A., and Akinluyi, F.O., 2015, A review of flood risk analysis in Nigeria. *American Journal of Environmental Sciences 11(3), 157–166.* doi: 10.3844/ ajessp.2015.157.166.Long, G., Tantanee, S., Nusit, K., and Sooraksa, P. (2025). Flood Susceptibility Mapping Using Machine Learning Models with Novel Flood Inventory Sampling Strategies. *Sensors and Materials, 37*(9), 3829-3839.

Loukili, Y., Lakhrissi, Y., Bourian, I., Hassine, L., Kourab, Z., Ali, T., Elaksher, A.F., and Chakrabortty, R. (2025). Enhancing Flood Mapping Accuracy in North and West Africa Using Multi-Sensor Satellite Data and Machine Learning in Google Earth Engine. *Earth Systems and Environment*. doi:10.1007/s41748-025-00796-8

M Amen, A. R., Mustafa, A., Kareem, D. A., Hameed, H. M., Mirza, A. A., Szydłowski, M., & Bala, B. K. (2023). Mapping of Flood-Prone Areas Utilizing GIS Techniques and Remote Sensing: A Case Study of Duhok, Kurdistan Region of Iraq. Remote Sensing, 15(4), 1102. https://doi.org/10.3390/rs15041102

Magami, I. M., Yahaya, S and Mohammed, K. (2014). Causes and consequences of flooding in Nigeria. *Biological and Environmental Sciences Journal for the Tropics. 11(2),154-162*.

March, G (2002). Natural Disasters and the Impacts on Health. University of Western Ontario: London, ON, Canada.

Mohammed, Z. T., Hussein, L. Y., and Abood, M. H. (2024). Potential Flood Hazard Mapping Based on GIS and Analytical Hierarchy Process. *Journal of Water Management Modeling, 32*(C528), 1-25. doi:https://doi.org/10.14796/JWMM.C528

Musa, Nda, H. M., Usman, M. Y., Abdul, H., & Sanni, L. M. (2015). An assessment of flood vulnerability on physical development along drainage channels in Minna, Niger State, Nigeria. African Journal of Environmental Science and Technology, 9(1), 38–46. *https://doi.org/10.5897/ajest2014.1815*

Nadeem, M. U., Waheed, Z., Ghaffar, A. M., Javaid, M. M., Hamza, A., Ayub, Z., Nawaz, M. A., Waseem, W., Hameed, M. F., Zeeshan, A., Qamar, S., & Masood, K. (2022). Application of HEC-HMS for flood forecasting in hazara catchment Pakistan, south Asia. International Journal of Hydrology, 6(1), 7–12. https://doi.org/10.15406/ijh.2022.06.00296

Nigeria Hydrological Services Agency (2020). 2020 Annual flood outlook. Available online at: https://nihsa.gov.ng/wp-content/uploads/2020/06/2020-NIHSA-Annual-Flood-Outlook-AFO-5-2.pdf.

Nkwunonwo, U.C., 2016, A review of flooding and flood risk reduction in Nigeria. *Global Journal of Human Social Science: B Geography, Geo-Sciences, Environmental Science & Disaster Management 16(2), 23–42*.

Nkwunonwo, U.C. (2016). A review of flooding and flood risk reduction in Nigeria. *Global Journal of Human Social Science: B Geography, Geo-Sciences, Environmental Science & Disaster Management 16(2), 23–42.*

Nnodim, A. U and Ezekiel C (2020). Perceived Impact of Perennial Flooding on Livelihood Activities of Rural Dwellers of Orashi Region of Rivers State. *International Journal of Innovative Human Ecology and Nature Studies 8(2),12- 18*.

Nura Umar & Alison Gray (2023). Flooding in Nigeria: a review of its occurrence and impacts and approaches to modelling flood data. International Journal of Environmental Studies, 80(3), 540-561, DOI: 10.1080/00207233.2022.2081471.

Nwigwe, C and Embargo, T. T. (2014). An assessment of causes and effect of flood in Nigeria. *Standard Scientific and Research Essay, 2(7), 307-315.*

Ojikpong, B. E., Ekeng, E. E., Obongha, U. E and Emri, S. I. (2016). Flood risk assessment of residential neighbourhoods in Calabar Metropolis, Cross River State, Nigeria. *Environment and Natural Resources Research, 6(2), 115- 127*.

Okeleye, S. O., Olorunfemi, F. B., Sogbedji, J. M andAziadekey, M (2016). Impact assessment of flood disaster on livelihoods of farmers in selected farming communities in Okeogun Region of Oyo State, Nigeria. *International Journal of Scientific and Engineering Research, 7(8), 2067-2083*.

Okwuashi, O. J., & Jibunor, E. E. (2021). "Flood Risk Assessment and Management in Nigeria: Case of the 2020 Flood Events." Water, 13(5), 674. doi: 10.3390/w13050674

Olajuyigbe, A. E., Rotowa, O. O. and Durojaye, E. (2012). An assessment of flood hazard in Nigeria: The Case of Mile 12, Lagos. *Mediterranean Journal of Social Sciences, 3(2), 367-377*.

Peduzzi, P., Dao, H., Herold, C., and Mouton, F., 2009, Assessing global exposure and vulnerability towards natural hazards: The Disaster Risk Index. Natural Hazards and Earth System Sciences 9(4), 1149–1159. doi: 10.5194/nhess-9-1149-2009.

Rathod, N. and Ukey, M.S. (2025). Flood Susceptibility Mapping of Savitri and Vashishti River Basins, Western Maharashtra: A Comparative GIS-AHP Approach. *Journal of the Indian Society of Remote Sensing*. doi:10.1007/s12524-025-02304-x

Rebollo, M., Palomares, A., & Carrascosa, C. (2016). Decentralized group analytical hierarchical process on multilayer networks by consensus. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial

Intelligence and Lecture Notes in Bioinformatics), 9662, 183–194. https://doi.org/10.1007/978-3-319-39324-7_16

Saaty, T.L. (1980). *The Analytic Hierarchy Process, Planning, Priority Setting, and Resource Allocation*. New York: McGraw-Hill.

Saleem, A., Muhammad, I., Babar, S., Ghazanfar, A. and Muhammad (2013). Impact of flood on livelihood and food security and food security of rural Communities: A case study of Southern Punjab, Pakistan. *Pakistan Journal of Agricultural Science, 50(4): 751-758.*

Shawky, M., & Hassan, Q. K. (2023). Geospatial Modeling Based-Multi-Criteria Decision-Making for Flash Flood Susceptibility Zonation in an Arid Area. Remote Sensing, 15(10). https://doi.org/10.3390/rs15102561.

Sun, W., Huang, H., Sun, P., and Ding, W. (2024). MEMS strapdown inertial attitude measurement system using rotational modulation technology. *PLoS ONE, 19*(2), e0298168. doi:10.1371/journal.pone.0298168

Tabiri, M. O. (2015). Perennial problem of floods in Accra: What is the way forward? *International Journal of Advanced Research in Education & Technology, 2(3): 198-201*.

Tiangtrong, A., Mangmoon, T., Apirak, S., Amornwech, N., Noipow, N., and Jan, C.-D. (2025). Optimized shelter planning in flood-prone areas using geographic information systems (GIS) and the analytical hierarchy process (AHP): an analysis of Ubon Ratchathani, Thailand. *Natural Hazards*. doi:10.1007/s11069-025-07604-6

Waseem, M., Ahmad, S., Ahmad, I., Wahab, H., & Leta, M. K. (2023). Urban flood risk assessment using AHP and geospatial techniques in swat Pakistan. SN Applied Sciences, 5(8). https://doi.org/10.1007/s42452-023-05445-1