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GEOSPATIAL FLOOD RISK MAPPING AND VULNERABILITY ASSESSMENT USING GIS AND AHP IN HADEJIA RIVER BASIN, JIGAWA STATE, NIGERIA

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ABSTRACT
Geographic Information System (GIS) and the Analytic Hierarchy Process (AHP) model within a multi-criteria decision analysis framework is used to map flood susceptibility in a river basin in northern Nigeria. Ten hydro-geomorphological indices, elevation, slope, rainfall, land use, and soil type, were systematically analyzed for their impact on flood hazards. A comprehensive flood susceptibility map was generated by assigning weights and ranks to factors. Areas with heightened vulnerability to flooding are attributed to slope, land use patterns, and proximity to water bodies. This study emphasizes the influence of rainfall patterns, drainage density, distance from rivers, geology, soil composition, topographic wetness, stream power, land use, encroachment onto flood plains, and vegetation cover on flood susceptibility. Additionally, gender considerations in disaster response and resilience efforts are discussed, highlighting challenges in flood-prone areas and advocating for inclusive strategies to bolster community resilience. The findings are pivotal for devising flood management strategies and hold applicability to analogous flood-prone areas globally.

Keywords: Flood susceptibility, Flood mitigation, Flood vulnerability, Flood-prone areas, Gender, Floods

INTRODUCTION
Floods pose a significant and escalating threat in various regions globally, particularly in areas adjacent to wetlands (Casanova and Brock 2000; Kamal et al. 2018; Eli and Bariweni 2020). Nigeria, in particular, has a long history of flood disasters, with the first recorded event dating back to 1948 in Ibadan (Etuonovbe 2011; Abubakar 2020; Nkeki et al. 2022). Since then, floods have become a recurring phenomenon in the country, primarily influenced by climate variations and change (Ekpoh and Nsa 2011; Ogbo et al. 2013; Okafor 2021; Raimi et al. 2021; Ani et al. 2022). These floods have resulted in immense human and economic losses, including fatalities, injuries, illnesses, property damages, and mass displacements of populations (Abdulkarim et al., 2021). While the impact of floods is widespread across Nigeria, certain areas bear a disproportionately high risk, such as the riparian zones along the Hadejia River basin in Jigawa state (Zakaria et al., 2022). Communities in this region, including Kafin Hausa, Auyo, Guri, and Ringim, face annual flood incidents that lead to the loss of homes, properties, and lives (Daily Trust, 2022). Over the years, devastating floods have ravaged these areas, leaving a trail of destruction, including the destruction of villages and extensive damage to houses and farmland (Vanguard, 2022). The frequency and severity of these floods necessitate a deeper understanding of their causative factors and the development of effective flood management strategies (Abubakar, 2020).
Previous studies conducted in the Hadejia River basin have shed light on various aspects related to floods, including their causes, frequency, surface water management, impact on diseases, and the influence of climate change (Thomas 1996; Olalekan 2014; Abdullahi et al. 2016; Ahmed et al. 2018; Umara et al. 2019). Additionally, researchers have explored flood vulnerability, risk assessment, water resources, hydrology, land use, and sustainability in the basin (Adams and Thomas 1996; Thomas and Adams 1997; Sobowale et al. 2010; Yahaya et al. 2010; Sabo et al. 2016; Odewole et al. 2020; Tudunwada and Abbas 2022). These studies have provided valuable insights into the dynamics of floods in the Hadejia River Basin, contributing to improved water management schemes and disaster preparedness.
However, a comprehensive understanding of flood susceptibility and the spatial distribution of flood-prone areas in the Hadejia River basin is still lacking. To address this gap, this study aimed to map flood susceptibility using Geographic Information System (GIS) and the Analytic Hierarchy Process (AHP) multi-criteria decision analysis model. They integrate hydrogeomorphological indices, such as elevation, slope, rainfall, land use, soil type, etc. This study assesses the factors contributing to flood susceptibility in this region. The resulting flood susceptibility maps can serve as a valuable tool for effective water management schemes, risk assessment, and decision-making to mitigate the impact of floods in the Hadejia River basin.

MATERIALS AND METHODS
The Study Area
The Hadejia River Basin is a part of the larger Komadugu-Yobe River Basin in the semi-arid northern region of Nigeria (Umar et al., 2018). It is located between latitudes 110 32' 08.4"N to 120 26' 24.8"N and longitudes 80 07' 50.0"E to 100 01' 50.9"E (Figure 1). With a catchment area of 24,687 km2, this river basin is mainly situated in the northwestern semi-arid zone of Nigeria (Figure 1). The basin's hydrology is dendritic in nature. The average annual flow, peak flow, and mean date of peak flow range from 1,396 mm3/s to 43 mm/s to 38 mm3/s, respectively, with the peak flow occurring on August 10th and September 16th in different parts of the basin

(Umar et al., 2018). The mean annual rainfall exhibits variation across different regions of the basin. The upstream basement complex area averages around 1100 mm. Moving towards the middle section of the basin, the mean annual rainfall decreases to approximately 400 mm. Finally, near Lake Chad, the mean yearly rainfall drops further to less than 300 mm (Odunuga et al., 2011). Figure 1 presents the study area map, and Table 1 presents data types and their respective sources.

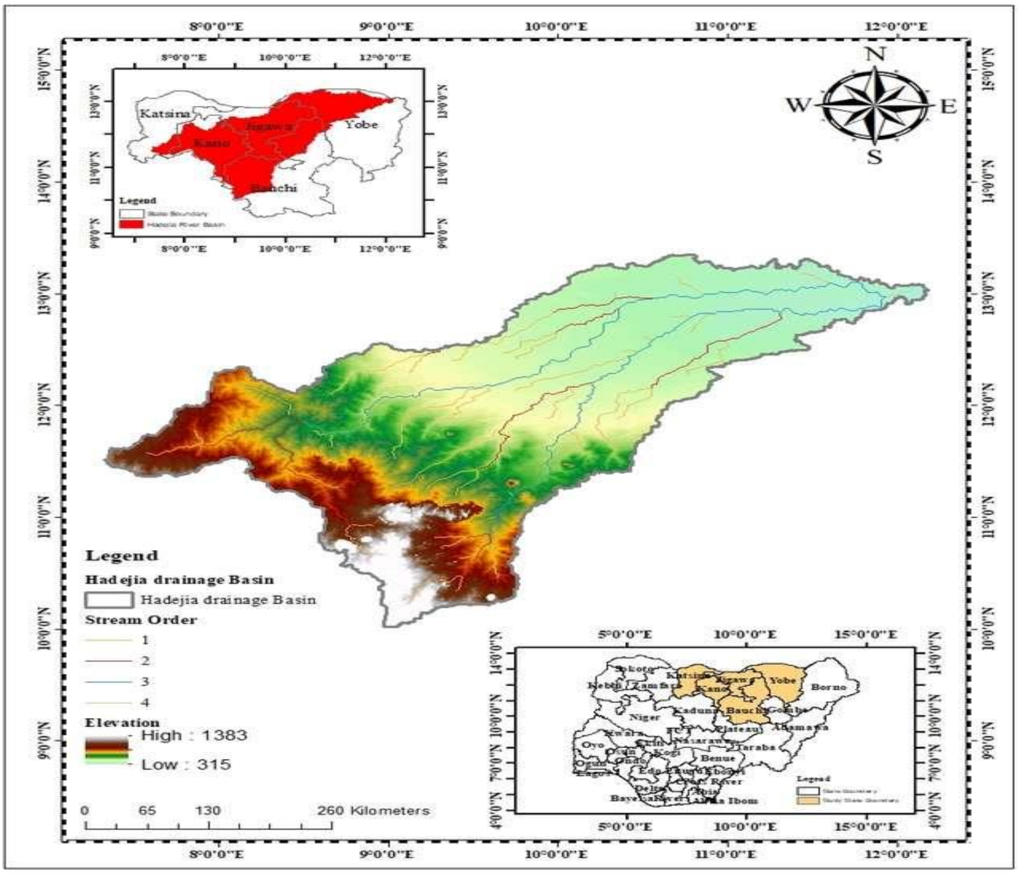

Figure 1: Map of the study area

Table 1: Data Type and Sources

Data	Data Type	Unit/Format	Resolution	Period/year	Source
Hydrological Data	Average monthly rainfall and Stream flow data	mm month-1/Raster	30 arc-seconds (~1km)	1991 - 2021	Tropical Rainfall Measuring Mission website (TRMM). NiMeT and Hadejia-Jama'are River Basin Development Authority Accessed 20/06/2025
Digital Elevation Model (DEM) of Shuttle Radar Topography Mission (SRTM)	Elevation	Meters (above sea level)	3 arc-seconds (~100m)		https://srtm.csi.cgiar.org/srtmdata/ Accessed on 20/06/2025
Soil Properties	Soil type	Unit/Shapefile	-	2015	https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/ Accessed 18/11/2025
Sentinel 2A	Land use Land Cover	-/Raster	10m		https://scihub.copernicus.eu/dhus/#/homeAccessed 12/02/2022

Data	Data Type	Unit/Format	Resolution	Period/year	Source
MODIS Terra NDVI data (MOD 13)	NDVI	Raster	1km		Land Processes Distributed Active Archive Center (LP DAAC), NASA. Accessed 18/02/2025
Geology	Geology	Vector Shapefile			
Landsat	Land use Land Cover	Raster	30m	2024	United State Geological Survey (USGS) https://earthexplorer.usgs.gov/ Accessed 18/02/2025
Road Network	Road	Vector Shapefile			www.divagis.com
Water Line and Water Ways	River	Vector Shapefile			www.divagis.com
Socio-economic factors		Questionnaire			Respondents

Data Collection

Satellite Image Acquisition and Processing

Sentinel 2A satellite images were acquired at different spatial resolutions of 10m, 20m, and 60m. These images were obtained from the United States Geological Survey (USGS) Earth Explorer website (http://earthexplorer.usgs.gov/). The images were resampled to a uniform spatial resolution of 10m using sen2core software to ensure consistency. Before further analysis, preprocessing steps were performed to mitigate the issue of cloud cover present in all images within the study area. This involved substituting composite areas affected by cloud cover with suitable alternatives. Figure 2 illustrates the flowchart of the Land Use and Land Cover methodology.

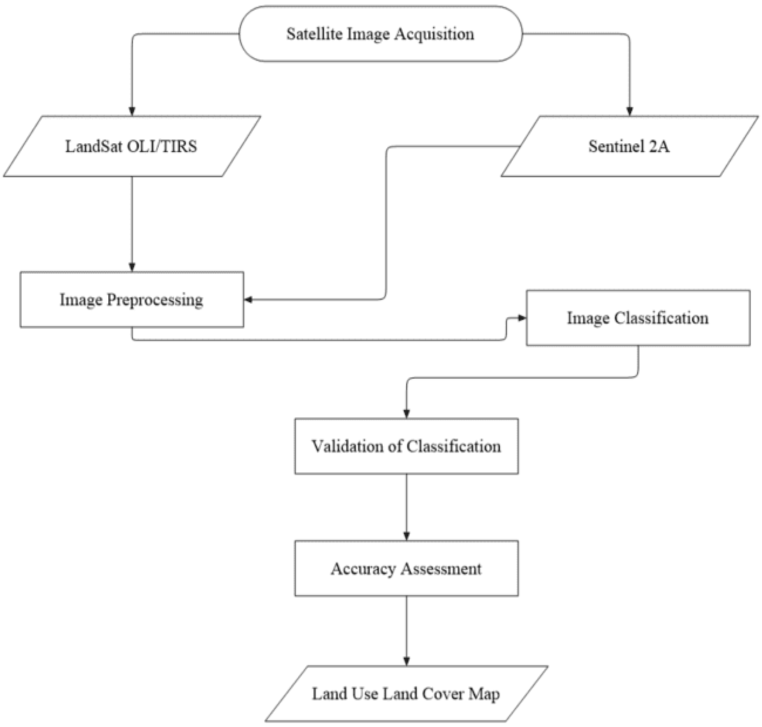

Figure 2: Flow Chart of Land Use Land Cover Methodology

Image Pre-Processing

The images underwent radiometric calibration and atmospheric correction using the sen2cor plugin in SNAP software. This process produced at-sensor radiance images and surface reflectance images, respectively. The enhanced images were then stacked and mosaicked using ERDAS 2014 software after applying haze removal, noise reduction, and histogram equalization. The study area was defined by clipping the mosaicked data in ArcGIS 10.8 software. A supervised image classification was conducted using the Maximum Likelihood algorithm, with seven classes utilized for training: water-body, built-up areas, riparian vegetation, dense vegetation, bareland, shrubland, and farmlands. Accuracy assessment and validation were performed using a stratified sampling method in ArcGIS Pro 2.4 software. The result was a final land use and land cover (LULC) map. In addition to the LULC map, ten additional layers were derived to represent flood causative factors. These layers included elevation, slope, topographic wetness index (TWI), rainfall, distance from the river, normalized difference vegetation index (NDVI), drainage density, stream power index (SPI), geology, and soil.

Flood Criteria Ranking and Pair-wise Comparison using the AHP Model

The implementation of the Analytic Hierarchy Process (AHP) model within the Multi-Criteria Evaluation (MCE) framework was pursued to construct a comprehensive flood susceptibility map for the designated study area. The identification of criteria and factors influencing flooding in the study area was derived from a literature synthesis. This empirical input and insights from relevant scholarly sources collectively form the basis for establishing the fundamental criteria for operationalizing the AHP model. This methodological approach is designed to amalgamate empirical evidence with theoretical underpinnings, thereby augmenting the precision and dependability of the flood susceptibility mapping process.

Analytical Hierarchy Process (AHP)

The methodology for rigorously evaluating flood susceptibility areas within the study area extensively utilizes ranking and pair-wise comparison techniques. This method investigates three primary and eleven subordinate criteria, subjecting them to meticulous pair-wise analyses to unveil their relative significance in determining flood susceptibility areas within the study's domain. Within this framework, a comprehensive recalibration and hierarchical ranking of the subordinate criteria are conducted, contextualizing their perceived impact on flood susceptibility areas within the study area.

Assessing the relative importance of flood causative factors involves translating respondent judgments into a Pair-wise Comparison matrix, adhering to the Saaty Scale: a preference evaluation system facilitating comparative judgments among criteria (Saaty, 1997). Subsequently, a normalized matrix computation technique was employed to ascertain the weight attributed to each criterion. This process entails dividing each criterion within every column by the sum of that column, ultimately resulting in the computation of criterion weights through row averaging.

Applying the Analytical Hierarchy Process (AHP), as outlined in Equations 1 to 7, represents a multicriteria decision analysis method expounded in the research conducted by Singh et al. (2018). Within this framework, the AHP-entropy technique harnesses data gathered from a questionnaire survey involving highly experienced specialist's adept at identifying flood susceptibility areas. Moreover, determining criterion weights involves normalizing matrix values and their division by multiple criteria, ensuring a statistically robust assessment of judgment accuracy (Dolui and Sarkar, 2023).

The foundational steps in executing the AHP approach, as outlined by Zahedi (1986), involve a comparative assessment of factors. Utilizing a scale comprising nine intensity levels, a pair-wise matrix is thoroughly constructed following the specifications outlined in the supplementary material (Table S1). Equation 1 is applied to derive the respective values within this comparison matrix, with C11 representing the values in the first row and first column of the matrix. This comprehensive and systematic methodology ensures a holistic evaluation of criteria and sub-criteria in delineating flood susceptibility areas within the study's scope.

$$Comparison\ matrix = \begin{bmatrix} C_{11} & C_{12} & C_{13} & \ddots & C_{1n} \\ C_{21} & C_{22} & C_{23} & \ddots & C_{2n} \\ C_{31} & C_{32} & C_{33} & \ddots & C_{3n} \\ \ddots & \ddots & \ddots & \ddots & \ddots \\ C_{n1} & C_{n2} & C_{n3} & \ddots & C_{nn} \end{bmatrix} \quad (1)$$

The complete matrix: Values within the matrix were summed individually for each column (Shunmugapriya et al., 2021). Furthermore, the column totals of the pair-wise matrices are computed using equation (2):

$$C_{ij} = \sum_{i=1}^{n} C_{ij} \quad (2)$$

Matrix normalization: The following equations can represent the normalization of each column value.

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} = \begin{bmatrix} X_{11} & X_{12} & X_{13} & \ddots & X_{1n} \\ X_{21} & X_{22} & X_{23} & \ddots & X_{2n} \\ X_{31} & X_{32} & X_{33} & \ddots & X_{3n} \\ \ddots & \ddots & \ddots & \ddots & \ddots \\ X_{n1} & X_{n2} & X_{n3} & \ddots & X_{nn} \end{bmatrix} \quad (3)$$

Weight calculation: Following the normalization process, the sum of each row in the normalization matrix was divided by the total number of criteria, as outlined by Majeed et al. (2023). The subsequent explanation elucidates the methodology used to compute the criteria weights for the priority vector.

$$W_{ij} = \frac{\sum_{i=1}^{n} X_{ij}}{n} = \begin{bmatrix} W_{11} \\ W_{12} \\ W_{13} \end{bmatrix} \quad (4)$$

Compute the consistency ratio (C.R.): The reliability of the judgment value is assessed solely through the consistency ratio (C.R.) value. Hence, if the C.R. value falls below 0.10 (10%), as specified by (Saaty, 1987), the comparison matrix is considered consistent.

Lambda (λ) max: The principal eigenvector (λmax) was determined by computing the average value of each consistency vector. The equation below illustrates the method employed to derive the principal eigenvalue (λmax).

$$\lambda_{max} = \sum_{i}^{n} XCV_{ij} \quad (5)$$

The consistency index (CI): Selected to gauge a matrix's deviation from consistency, the value of λmax was emphasized as crucial for calculating the consistency ratio. The computation of the consistency index (CI) was carried out in the following manner:

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (6)$$

where λmax is the maximum eigenvalue and n represents the number of criteria.

Random index (R.I.): The sole determinant influencing the random index was the number of elements being compared.

Consistency ratio (C.R.): The ultimate consistency ratio was established by comparing the CI with the random index (Saaty, 1987). To ensure the reliability of judgments, the next stage involves verifying consistency and drawing conclusions from the results. Since individual judgments may not perfectly align, the Consistency Ratio (CR) was employed to measure the degree of consistency achieved in the ratings. A CR less than or equal to 0.1 is considered acceptable, indicating reliable judgments. A ratio exceeding 0.1 suggests the need for matrix revision. Revision entails identifying inconsistent judgments regarding the importance of criteria and reassessing these judgments by reviewing pairs of criteria judged inconsistently (Yahaya et al., 2010).

The formula for Calculating Consistency Ratio (CR)

$$C.R = \frac{CR}{CR} \quad (7)$$

RI= Random Consistency Index

n= number of criteria.

λmax= priority vector multiplied by each column total.

where CI = Consistency Index and RI = Random Consistency Index, n = number of criteria, λmax = priority vector multiplied by each column total. Then, CR was computed using the formula (Saaty 1980).

Random consistency index

The number of criteria ranges from 1 to 15 i.e order of the matrix. The corresponding values for the Random Index (RI) are 0, 0, 0.58, 0.90, 1.12, 1.24, 1.32, 1.41, 1.45, 1.49, 1.51, 1.48, 1.56, 1.57, and 1.59 (Saaty, 1997).

This study exhibits a Consistency Ratio (C.R) of 0.05, which falls below the established threshold of 0.10. Should the computed C.R exceed this threshold, any inconsistencies within the pair-wise comparison matrix would necessitate a reassessment and repetition of the process (Dolui and Sarkar, 2023). This outcome suggests that the assigned weights were fittingly allocated (Table S 2). Moreover, the model aptly mirrors the conditions prevailing within this research area, showcasing the methodology's effectiveness in identifying and mapping flood risk areas. Fifteen (15) assumed flood causative factors used in this study area. The selection of these ten flood causative factors (Table S 3) is well-justified as they collectively offer a comprehensive and tailored approach to flood susceptibility assessment, considering both natural and human-related variables and the unique characteristics of the region. This approach ensures a thorough understanding of susceptibility, supporting effective flood management and resilience-building efforts. Table S4 presents normalized weighting of flood causative factors.

Table 2: Comparison Matrix

Sub Criteria	Rainfall	Elevation	Slope	DD	Dist from River	TWI	SPI	Flow Accumulation	Geology	LULC	Soil	NDVI	Flow Direction	Rainfall Erosivity	Dist. from Roads	Relative Weight	Geometric Weight
Rainfall	15.00	14.00	13.00	12.00	11.00	10.00	9.00	8.00	7.00	6.00	5.00	4.00	3.00	2.00	1.00	0.30	30.14
Elevation	7.50	7.00	6.50	6.00	5.50	5.00	4.50	4.00	3.50	3.00	2.50	2.00	1.50	1.00	0.50	0.15	15.07
Slope	5.00	4.67	4.33	4.00	3.67	3.33	3.00	2.67	2.33	2.00	1.67	1.33	1.00	0.67	0.33	0.10	10.05
Drainage density	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00	0.75	0.50	0.25	0.08	7.53
Distance from river	3.00	2.80	2.60	2.40	2.20	2.00	1.80	1.60	1.40	1.20	1.00	0.80	0.60	0.40	0.20	0.06	6.03
Topographic Wetness Index	2.50	2.33	2.17	2.00	1.83	1.67	1.50	1.33	1.17	1.00	0.83	0.67	0.50	0.33	0.17	0.05	5.02
Stream Power Index	2.14	2.00	1.86	1.71	1.57	1.43	1.29	1.14	1.00	0.86	0.71	0.57	0.43	0.29	0.14	0.04	4.31
Flow Accumulation	1.88	1.75	1.63	1.50	1.38	1.25	1.13	1.00	0.88	0.75	0.63	0.50	0.38	0.25	0.13	0.04	3.77
Geology	1.67	1.56	1.44	1.33	1.22	1.11	1.00	0.89	0.78	0.67	0.56	0.44	0.33	0.22	0.11	0.03	3.35
Land Use Land Cover	1.50	1.40	1.30	1.20	1.10	1.00	0.90	0.80	0.70	0.60	0.50	0.40	0.30	0.20	0.10	0.03	3.01
Soil	1.36	1.27	1.18	1.09	1.00	0.91	0.82	0.73	0.64	0.55	0.45	0.36	0.27	0.18	0.09	0.03	2.74
NDVI	1.25	1.17	1.08	1.00	0.92	0.83	0.75	0.67	0.58	0.50	0.42	0.33	0.25	0.17	0.08	0.03	2.51
Flow Direction	1.15	1.08	1.00	0.92	0.85	0.77	0.69	0.62	0.54	0.46	0.38	0.31	0.23	0.15	0.08	0.02	2.32
Rainfall Erosivity	1.07	1.00	0.93	0.86	0.79	0.71	0.64	0.57	0.50	0.43	0.36	0.29	0.21	0.14	0.07	0.02	2.15
Distance from Roads	1.00	0.93	0.87	0.80	0.73	0.67	0.60	0.53	0.47	0.40	0.33	0.27	0.20	0.13	0.07	0.02	2.01
	49.77															1.00	100.00

RESULTS AND DISCUSSION

Flood Causative Factors

Elevation

In the context of floods, elevation plays a crucial role, as areas at lower elevations are more prone to inundation and flood damage. On the other hand, higher elevations may provide some level of natural protection against flooding (Ntajal et al., 2017; Ghosh and Kar, 2018). Figure 3a provides evidence that the northeastern region of the Hadejia Basin is highly susceptible to flooding and erosion due to its lower elevation. The lower elevation in this area increases the likelihood of water accumulation during flood events, leading to a higher risk of inundation and the potential for erosion.

Slope

The slope, as depicted in Figure 3b, plays a crucial role in determining the vulnerability of this area to floods and erosion. The basin's topography exhibits a steeper slope, gradually descending from the center towards the northeastern part (Figure 3b). This gradual descent in slope plays a crucial role in the hydrological dynamics of the basin, influencing the flow patterns of rivers and streams, as well as the distribution of water during periods of heavy rainfall or flooding events. Steeper slopes are more prone to rapid surface runoff, leading to increased erosion and a higher risk of flash floods. On the other hand, areas with gentle slopes have a reduced risk of erosion and are more capable of retaining water, potentially leading to localized flooding or waterlogging (Ouma and Tateishi, 2014).

Rainfall Distribution

Rainfall is a fundamental factor contributing to flood occurrences (Leal et al., 2020; Dinis et al., 2021). Figure 3c depicts the rainfall patterns observed in the study area. Figure 3c illustrates that intense rainfall occurs in the basin's southern part, leading to water flow towards the northern region of the basin. Consequently, this water movement from the south to the north contributes to annual and severe flooding. The uneven distribution of rainfall and downstream flow intensifies the flood risk in the northern part of the basin. Intense or prolonged rainfall events can lead to increased volume of water entering rivers, streams, and drainage systems, exceeding their capacity and resulting in flooding (Douglas et al., 2008).

Drainage Density

Drainage density, shown in Figure 3d, measures stream network abundance and connectivity. It's total stream length per unit area. Higher density means a more developed network, impacting flood risk. Values ranged from 0.0 km/km² to 17.7 km/km². Higher density increases runoff and flood risk; lower reduces both. The map is categorized into five classes: very high, high, moderate, low, and very low. Flood susceptibility decreases with decreasing density: very high (14.2 - 17.7 km/km²) -> high (10.7 - 14.1 km/km²) -> moderate (7.08 - 10.6 km/km²) -> low (3.54 - 7.07 km/km²) -> very low (0 - 3.53 km/km²). High-density areas are more flood-prone due to runoff. Expanding drainage networks raises flood risk (Ogden et al., 2011; Mahmoud and Gan, 2018).

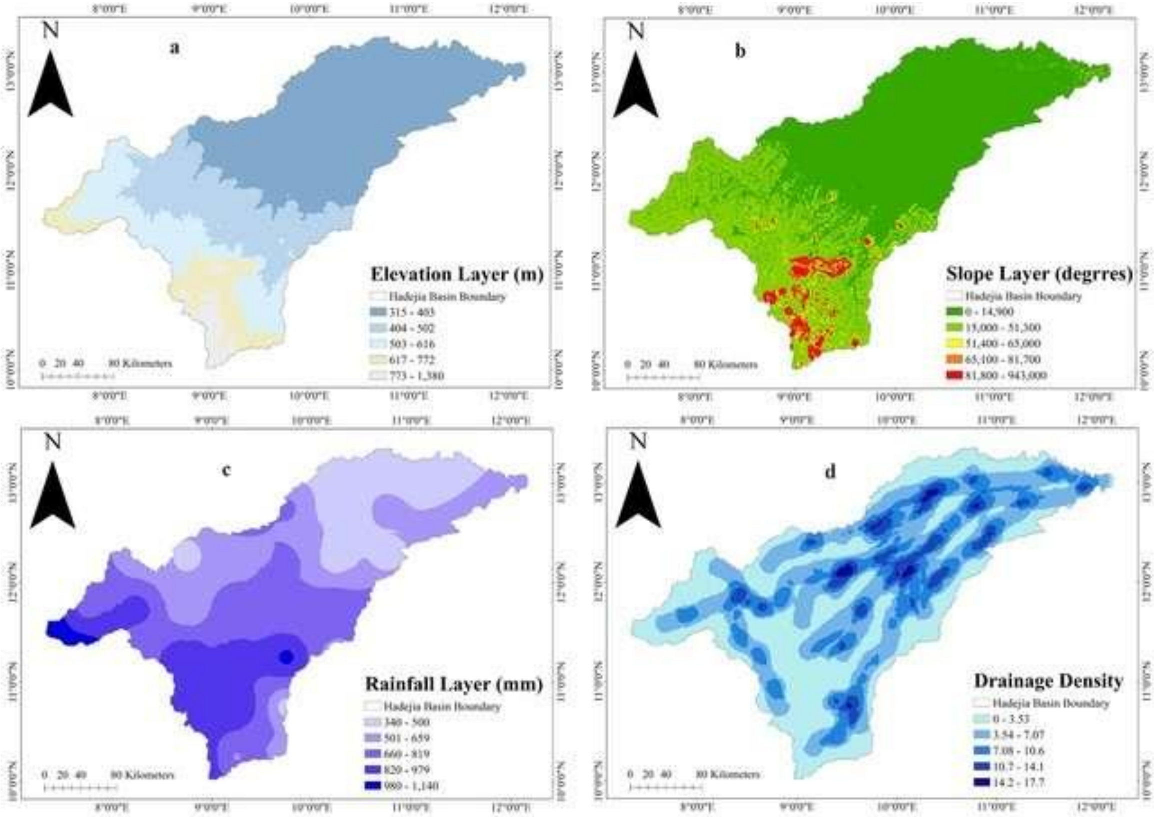

Figure 3: Flood Causative Factors: a. Elevation, b. Slope, c. Rainfall Distribution, d. Drainage Density

Distance from the River

Figure 4a represents the flood causative factor of "Distance from River." It depicts the spatial distribution of distances between locations within the study area and the nearest rivers. This factor is an important determinant of flood vulnerability, as it influences the proximity to potential water sources during flooding events. Figure 4a demonstrates that areas close to the river are more susceptible to flooding than those located farther away. The distance from the river affects flood risk due to factors such as the river's capacity, channel morphology, and floodplain characteristics. To assess the influence of distance from the river on various factors, sequential buffers were constructed along the Hadejia River Basin using drainage lines. These multi-ring radial buffers were created at fixed intervals of 1000m, 2000m, 3000m, 4000m, 5000m, and beyond (greater than 5000m or 5km). Each buffer ring was assigned a rank based on its distance from the river. Proximity to the Hadejia River significantly affects flood susceptibility, with the low-lying floodplains in the northwest and southwest regions of Jigawa state being particularly vulnerable to flooding (Figure 4a). Distances from 5km and above depict the least susceptibility and distances from 1000m depict a high susceptibility to flooding (Figure 4a).

Geology

Figure 4b details basin geology: rock types, layers, and formations. Geology influences flood risk; impermeable rocks increase runoff, flood risk, and porous rocks decrease it. Hadejia River basin's geology is categorized into Tertiary, Quaternary, Precambrian, Mesozoic igneous, and Cretaceous rocks. Cretaceous rocks have moderate flood risk, smallest area; Tertiary rocks have low risk, larger area due to high infiltration. Mesozoic igneous rocks have low porosity and high risk. Precambrian rocks are the second largest area, with high clay content, low permeability, and high flood risk. Quaternary rocks have the largest area and moderate risk due to medium permeability.

Topographic Wetness Index (TWI)

Figure 4c presents the Topographic Wetness Index (TWI), assessing landscape wetness. Derived from slope, elevation, and flow accumulation, it identifies waterlogged or runoff-prone areas. Higher TWI = more water saturation, higher flood risk. Hadejia basin TWI analysis shows varying wetness levels. High TWI = wetter areas, low TWI = drier. TWI influences water movement and flood likelihood. High TWI indicates low elevation, flat terrain, prone to inundation; low TWI = higher elevation, steeper slopes, less flood risk. TWI range: -15.8 to 12.7; high TWI (-0.366 – 12.7) = high flood susceptibility; very low TWI (-15.8 - -10.9) = low susceptibility.

Stream Power Index (SPI)

Figure 4d illustrates the Stream Power Index (SPI), representing stream erosive power. They were derived from slope, flow accumulation, channel characteristics, higher SPI = greater erosion potential, and intense river processes. SPI aids in identifying flood-prone areas where rivers contribute significantly to flooding and land erosion. It's a causative factor for flood susceptibility, indicating stream channel energy. Higher SPI values (1,070,000 – 3,190,000) suggest increased erosion potential, wider and deeper channels, and higher flood risk during high flow. High SPI streams are prone to channel instability, bank erosion, and sediment transport, increasing flood risk. Low SPI values (-1,770,000 - 5,590,000) are associated with low flood risk.

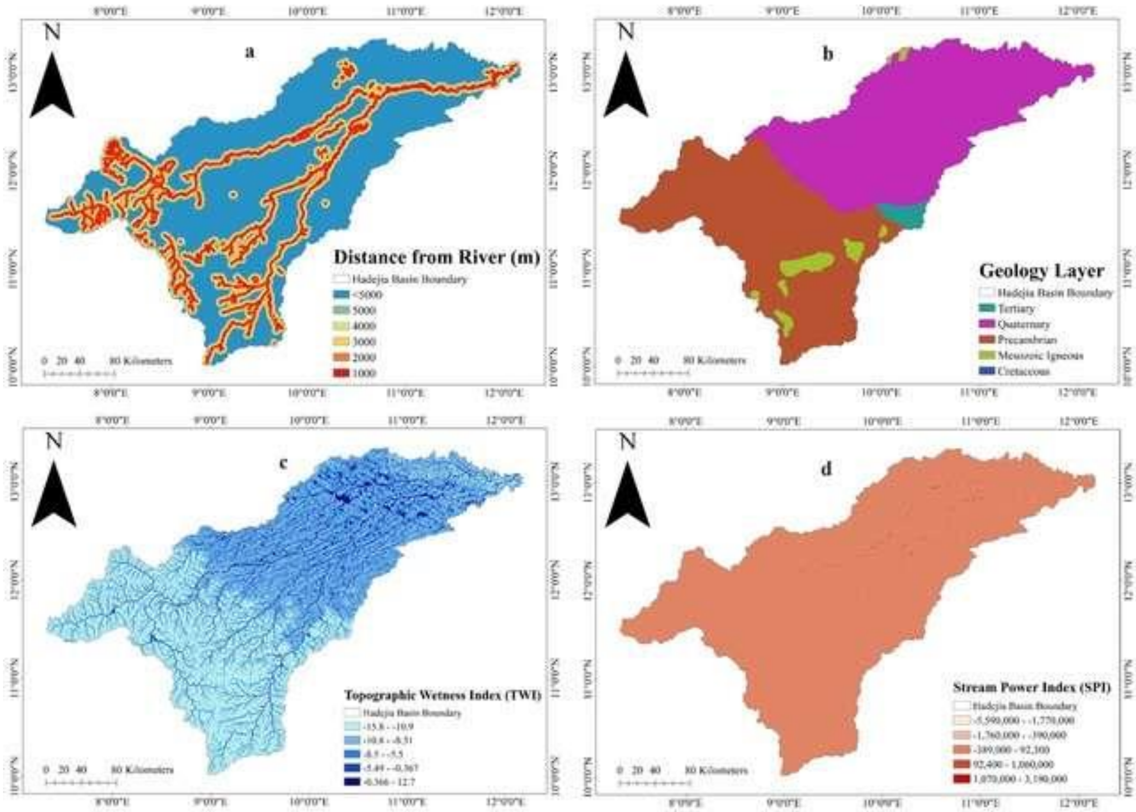

Figure 4: Flood Causative Factors: a. Distance from the River, b. Geology layer, c. Topographic Wetness Index (TWI), and d. Stream Power Index (SPI)

Soil Type

Figure 5a shows soil composition in the study area, influencing flood vulnerability. Soil permeability affects water retention and runoff. High permeability soils like sandy or loamy reduce runoff and lower flood risk. Low permeability soils like clay increase runoff, raising flood risk. Sandy soil types (Arenosols, Luvisols) in Jahun and Kiyawa LGAs have very low flood susceptibility due to high permeability. Lithosols with low clay content and high infiltration have low susceptibility. Regosols with rocky surfaces, coarse textures, and high infiltration have low susceptibility. Fluvisols with high clay content and low infiltration are highly susceptible to flooding. Birniwa, Auyo, Hadejia, and Miga LGAs have Fluvisols and high flood susceptibility.

Land Use Land Cover

Land Use Land Cover (LULC), shown in Figure 5b, provides information about the types and distribution of land uses and covers within the study area. Different land use types, such as urban areas, agricultural fields, forests, or wetlands, can influence flood vulnerability. Impermeable surfaces, such as concrete or asphalt in urban areas, can increase surface runoff and exacerbate flooding. Conversely, areas with natural vegetation or wetlands have a greater capacity to absorb water, reducing flood susceptibility. Maximum Likelihood "supervised classification using multiple ground control points collected from Google Earth images and a field survey, in 2021 Landsat image of 30 m spatial resolution was used to generate Land Use Land cover map of the study area". The land use map is categorized into seven classes: water body, dense vegetation, riparian vegetation, farmland, Built-Up area, bare land, and shrubland. Urban expansion generates more surface runoff than bare land and dense vegetation. Thus, built-up areas, water bodies, and riparian vegetation are given significant weight in the study.

Normalized Difference Vegetation Index

Figure 5c presents the Normalized Difference Vegetation Index (NDVI), assessing vegetation density and health in this basin. NDVI uses remote sensing data to evaluate vegetation vigor, impacting flood vulnerability. Vegetation absorbs rainfall, enhances infiltration, reduces runoff, mitigating floods. Higher NDVI values suggest denser vegetation and potentially lower flood risk. While NDVI isn't a direct flood causative factor, it influences flood susceptibility by affecting soil infiltration and surface runoff. High NDVI areas (0.336-0.629) have higher infiltration, reducing runoff and lowering flood risk. Vegetation also alters land surface roughness, slowing water flow during floods and mitigating flood susceptibility. NDVI range: -0.199 to 0.629.

$$NDVI = NIR - RED \div NIR + RED \quad (8)$$

Distance from Road

Figure 5d provides an insightful representation of vulnerability concerning distance from the road, categorized into distinct ranges. The delineation into specific distance intervals helps identify areas with varying degrees of vulnerability to potential flood impacts. The outlined intervals, ranging from 0 to 0.0327 meters, 0.0328 to 0.0655 meters, 0.0656 to 0.0982 meters, 0.0983 to 0.131 meters, and 0.132 to 0.164 meters, serve as a guide for assessing the vulnerability levels across different spatial extents. Areas falling within the lower end of these intervals (0 to 0.0327 meters) are likely to exhibit higher vulnerability, while those in the higher range (0.132 to 0.164 meters) may have relatively lower vulnerability. Analyzing these ranges facilitates a targeted understanding of potential flood vulnerabilities based on proximity to roads, aiding in formulating effective mitigation and preparedness strategies for specific regions.

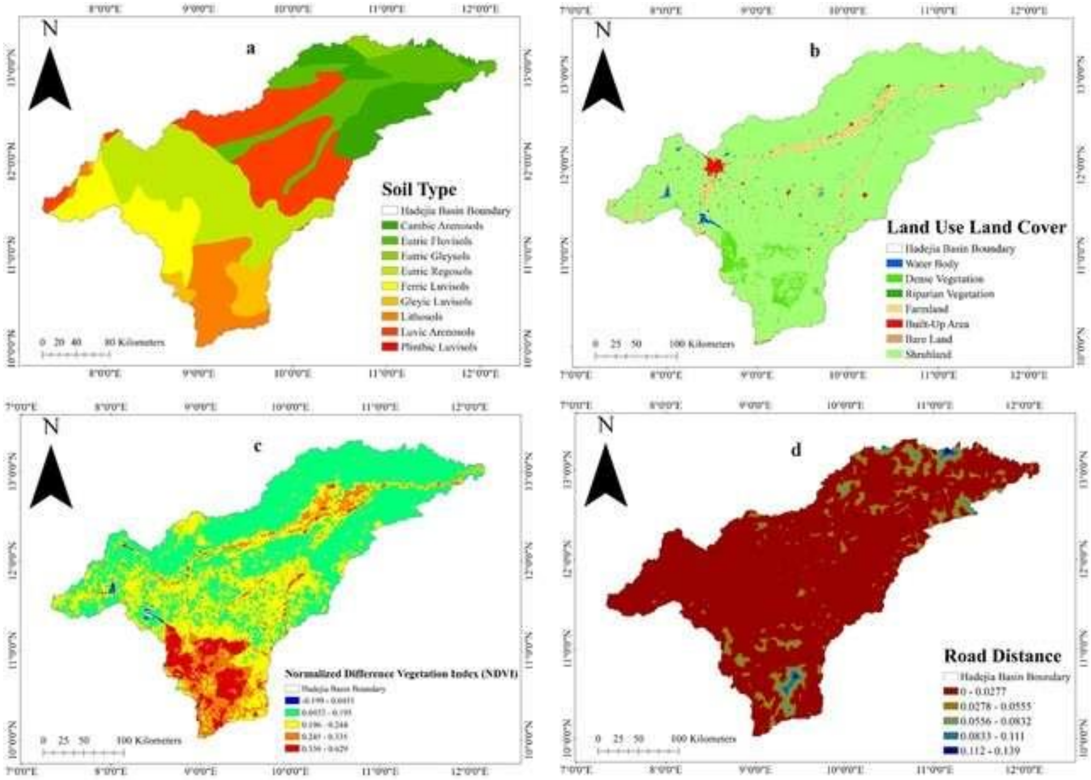

Figure 5: Flood Causative Factors: a. Soil Layer, b. Land use Land cover. c. Normalized Difference Vegetation Index d. Distance from ROAD

Flow Accumulation

The expert survey found flow accumulation to be one of the most important parameters, indicating the degree of surface flow concentration. The flow accumulation values increase downstream as concentration. The flow accumulation is considered among the most important factors in delineating flood hazard zones (Ntajal et al., 2017). Figure 6a presents a comprehensive depiction of vulnerability related to flow accumulation, organized into distinct pixel ranges. This classification identifies areas with varying susceptibility to flood hazards based on flow accumulation values. The specified pixel intervals, ranging from 0 to 2860 pixels, 2870 to 10800 pixels, 10900 to 20000 pixels, 20100 to 34600 pixels, and 34700 to 81000 pixels, serve as benchmarks for assessing the magnitude of flow accumulation and, consequently, the flood vulnerability in different regions. Areas falling within the lower pixel range (0 to 2860 pixels) are likely to have lower susceptibility, while those in the higher pixel range (34700 to 81000 pixels) may exhibit heightened vulnerability. High flow accumulation signifies high susceptibility to flooding and vice-versa (Mahmoud and Gan, 2018).

Flow Direction

Figure 6b provides valuable insights into flood vulnerability through the representation of flow direction, categorized into specific pixel ranges. Each interval, such as 1 to 2 pixels, 2.01 to 8 pixels, 8.01 to 23 pixels, 32.1 to 64 pixels, and 64.1 to 128 pixels, signifies different degrees of flow concentration. Lower pixel ranges suggest areas with a more dispersed flow direction, potentially indicating lower susceptibility to flooding. On the other hand, higher pixel ranges imply concentrated flow directions, pointing towards areas more prone to potential flood hazards. This pixel-based classification facilitates understanding how flow direction contributes to vulnerability, aiding in the targeted identification of regions with varying flood risk levels.

Rainfall Erosivity

Rainfall erosivity refers to the ability of rainfall to cause soil erosion, and it serves as an essential indicator in assessing the potential for floods in a given area. Rainfall erosivity refers to the ability of rainfall to cause soil erosion, and it serves as an essential indicator in assessing the potential for floods in a given area. Figure 6c presents the spatial distribution of rainfall erosivity, quantified in MJ mm/ha per year, with values categorized into distinct ranges. The intervals, namely 170 to 272 MJ mm/ha per year, 273 to 338 MJ mm/ha per year, 339 to 397 MJ mm/ha per year, 398 to 460 MJ mm/ha per year, and 461 to 569 MJ mm/ha per year, signify varying degrees of erosive potential associated with rainfall. Lower ranges indicate a moderate erosive effect, while higher ranges suggest a more pronounced impact on soil erosion. Therefore, our analysis shows that the central, south-south, and southwestern regions of the Hadejia Basin are particularly vulnerable to the erosive impact of rainfall (Figure 6c). This detailed categorization is instrumental for understanding the erosive forces driven by rainfall, contributing to soil erosion susceptibility and subsequent flood risk assessment.

Flood Susceptibility

Flood Susceptibility, as shown in Figure 6d, assesses the susceptibility of different areas within the study area to flooding. Figure 6d illustrates that the northeastern part of the basin poses a significant risk of flooding. The data and analysis in the figure indicate a higher likelihood of flood occurrences in this region than in other parts of the basin. Factors such as the slope, land use patterns, and proximity to water bodies contribute to the increased flood risk in the northeastern area. The Flood Vulnerability map helps identify areas that are more prone to flooding and have a higher risk of flood-related damage (Figure S1).

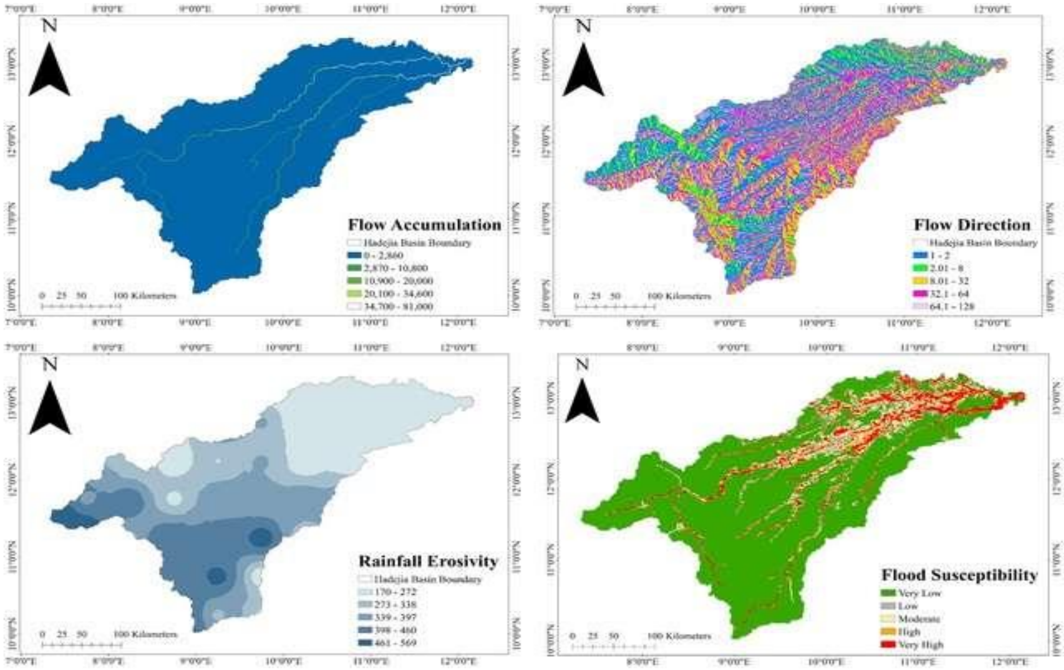

Figure 6: A. Flow Accumulation, B. Flow Direction, C. Rainfall Erosivity, D. Flood Susceptibility

Discussion

The results of this study provide valuable insights into the extensive challenges and consequences associated with flooding in Nigeria, with a specific focus on the flood-prone communities along the Hadejia River Basin. These findings are consistent with the research conducted by Shuaibu et al. (2022), which identified Auyo, Guri, Hadejia, Ringim, Kafin Hausa, and Jahun as areas characterized by a high susceptibility to floods. Flooding in the Hadejia basin is recurring due to several factors, including heavy rainfall, overflow of water bodies, encroachment onto floodplains, and inadequate drainage systems (Figure S2). The basin experiences periodic floods, especially during the rainy season, significantly damaging infrastructure, farmland, and communities in flood-prone areas (Shuaibu et al., 2022). The devastating effects of floods in these areas highlight the urgent need for proactive and sustainable measures to mitigate the hazards and reduce the vulnerability of the affected communities (Tudunwada and Abbas, 2022).

The survey results provide valuable insights into the causes and impacts of flooding as the respondents perceive. Notably, heavy rainfall and the encroachment of buildings onto flood plains were identified as the primary underlying causes of flooding in the study area (Figure S2). The findings of Umara et al. (2019) and Kazaure (2013) align with the findings of this study that heavy rainfall is one of the causative factors contributing to flooding in the Hadejia basin. This suggests that natural and human-induced factors play significant roles in the occurrence and severity of floods (Stefanidis and Stathis 2013; Lawal et al. 2014). Consequently, comprehensive flood management strategies should address both factors, including improved drainage systems, land-use planning, and policies to prevent encroachment onto flood-prone areas (Hansson et al. 2008; Djalante 2012; Birkholz et al. 2014).

This study also highlights the extensive damage caused by flooding in the study area. Building collapse, destruction of infrastructure, and the spread of diseases were among the general impacts reported by the respondents (Table S5). These damages have far-reaching consequences for the affected communities, including the disruption of essential services and the increased risk of health issues. The studies conducted by Paranjothy et al., (2011), and Abubakar (2020) consistently highlight the damaging impacts of flooding, particularly in relation to the disruption of essential services and the increased risk of health issues. Understanding the direct impacts on individuals, such as property damage and economic losses, emphasizes the need for effective flood prevention and mitigation measures to protect the well-being and livelihoods of the affected population (Olugunorisa 2009; Aitsi-Selmi et al. 2015; Abubakar, 2020; Shuaibu et al. 2022).

The coping strategies employed by the respondents provide insights into the immediate actions taken by individuals to deal with flooding (Table S6). The reliance on sandbags as a coping mechanism suggests the need for more effective and sustainable strategies for flood protection and property preservation. Additionally, the suggestions provided by the respondents for flood prevention measures highlight the importance of various interventions, including policy implementation, river dredging, infrastructure provision, early warning systems, and improved drainage systems (Table S6). These recommendations align with best practices in flood management and emphasize the need for multi-faceted approaches to reduce the occurrence and impact of floods (Demeritt and Nobert 2014; Chourushi et al. 2019).

One key aspect that emerges from this study is the gender imbalance among the respondents, with a significant majority of male participants compared to female participants (Table S7). This gender disparity is substantial in disaster response and resilience, as cultural expectations and societal norms often place men in leadership roles during crises. The findings of this study suggest that males exhibit greater activity and involvement in flood management than females. This gender disparity in flood management roles is consistent with the prevailing societal norms and gender dynamics within the Hadejia basin. In a study conducted by Gaisie et al. (2022), it was found that female-headed households face significant challenges in preparing for, coping with, and recovering from the impacts of flooding. These challenges arise from various factors, including gender roles, larger family sizes, care responsibilities, limited employment opportunities, and restricted resource access. This research highlights the reduced capacities of female-headed households in dealing with flood-related issues and emphasizes the need for gender-responsive approaches in flood management and mitigation strategies.

Another important finding is the predominance of informal education among the respondents, indicating a predominantly rural population. This highlights the need to tailor educational initiatives and awareness campaigns to the specific needs and characteristics of the target population. Dufty (2008) and Aslam (2018) highlight the importance of enhancing flood-related knowledge and awareness within communities to improve their preparedness and resilience in the face of future flood events. This study further emphasizes the prevalence of farming activities among the respondents, with a significant proportion engaged in agriculture as their primary occupation. This highlights the importance of considering the impacts of floods on agriculture and the livelihoods of farming communities. Developing strategies that integrate flood resilience with agricultural practices can help minimize the disruption caused by floods and support the long-term sustainability of agricultural activities in these areas.

CONCLUSION

Flooding in the Hadejia Basin is a significant concern with both environmental and socio-economic implications. The basin in northeastern Nigeria is prone to recurrent flooding due to several factors. The causes identified, such as heavy rainfall and encroachment onto flood plains, call for proactive measures to mitigate and prevent flooding. The damages caused by flooding, including building collapse, infrastructure destruction, and disease outbreaks, demonstrate the urgent need for effective flood response and recovery plans. The gender imbalance among the respondents emphasizes the importance of considering gender dynamics in disaster management. Women in flood-prone areas face unique challenges, and inclusive approaches should be developed to address their specific vulnerabilities and capacities. Education and awareness are crucial in empowering communities to take proactive measures. Providing targeted information on flood risks, mitigation strategies, and coping mechanisms can enhance community resilience and decision-making. The coping strategies employed by the respondents, particularly the use of sandbags, highlight the need for more sustainable flood protection measures. Exploring innovative approaches like nature-based solutions, such as green infrastructure and floodplain restoration, can enhance resilience and reduce reliance on temporary measures. This study provides valuable insights into the challenges and opportunities in flood management in the Hadejia basin and contributes to the existing knowledge on flooding in Nigeria. The findings emphasize the need for integrated approaches involving multiple stakeholders and sectors to effectively address the complex and dynamic nature of flooding and build resilient communities that can withstand and recover from flood events. Future research should continue exploring innovative strategies and approaches for flood mitigation, preparedness, and response, focusing on addressing the specific vulnerabilities and capacities of different population groups, including gender considerations, to foster sustainable and inclusive flood management practices.

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