KADUNA JOURNAL OF GEOGRAPHY
2026, VOL. 8, No. 1, 417-432
https://doi.org/10.47514/kjg.2026.08.01.043

Research Article

# Temporal Patterns of Flooding in The Midstream and Downstream Catchments of The River Kaduna Basin, Kaduna, Nigeria

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**ABSTRACT**

This study examines the temporal patterns of flooding in the midstream and downstream catchments of the River Kaduna Basin, with a view to improving flood risk assessment and management. A mixed-methods approach combined GIS-based multi-criteria analysis (MCA) with a household survey of 384 respondents within a 1 km river buffer. Physical factors (rainfall, slope, soil permeability, wetness, NDBI, NDVI, drainage) were weighted using the Analytic Hierarchy Process to generate flood occurrence frequencies and predictions via Monte Carlo simulation. Flooding was strongly clustered (Moran's I = 0.67, p<0.001). Chikun, Tudun Wada North, and Nassarawa wards constitute a persistent high-risk belt covering 32% of the study area. Time-series decomposition of flood vulnerability over an 18-year period revealed an upward trend, from 0.424115 in 2016 to 0.428838 in 2034. Vulnerability distribution is: Very High 11%, High 20%, Moderate 24%, Low 16%, Very Low 29%. Areas experiencing annual flooding grew from 28% (2016) to 37% (2024), and average flood duration increased from 3.2 to 4.8 days. The most pronounced increase occurred in the Very High vulnerability category, which expanded by 54.9 km2 (10.9%) over the study period. The study recommends risk-sensitive land-use planning, ecosystem-based measures, institutional coordination, and community resilience building.

**ARTICLE HISTORY**
Submitted 26 April 2025
Accepted 3 June 2026
Published 7 June 2026

**GUEST EDITOR**
A. M. Ahmed

**KEYWORDS**
Flooding, temporal analysis, midstream, downstream, vulnerability, Analytic Hierarchy Process, Multi-Criteria Analysis

## 1 Introduction

Rivers are vital for food, water, transport, electricity, biodiversity, and recreation (Postel & Richter, 2012). However, river corridors also pose flood hazards, causing loss of life and property and disrupting communities during severe floods. These natural hazards cause displacement and loss of farmland (Internal Displacement Monitoring Centre [IDMC], 2015). Monitoring is key to mitigation. Flooding, a common disaster affecting about 250 million people annually and causing US $40 billion in damages (OECD, 2016), results from rapid runoff or water overflow. Bangladesh, China, and Europe have experienced thousands of flood-related deaths over the past century.

In 2022, West and Central Africa faced one of the worst floods, affecting over 8.5 million people across 20 countries. Heavy rains caused extensive damage: 1,567 deaths, 4,401 injuries, 3.2 million displaced, and 517,000 houses destroyed in 18 countries. Nigeria, Chad, and the DR Congo were most affected, with Nigeria experiencing flooding in Abuja's Trademore Estate and other areas in 2023. Kaduna State often faces floods; in 2003, floods displaced over 5,000 people and submerged 30,000 houses. River basins, especially the River Kaduna Basin (about 8% of Nigeria), are crucial for flood modeling, as floods cause loss of life, displacement, crop damage, and property destruction (Khomsi et al., 2023).

GIS techniques are vital for integrating and analyzing data such as satellite imagery, digital elevation models, and hydrological data in flood modeling. They help create accurate flood maps, identify flood-prone areas, and assess the vulnerability of assets and communities. These tools support decision-making for flood management strategies like early warning systems, land-use planning, and infrastructure development. Jeb and Aggarwal (2008) analyzed satellite imagery, elevation data, rainfall patterns, and other geospatial datasets to produce hazard maps, identify vulnerable areas, and assess impacts on populations and infrastructure.

Flood risks are high in states bordering major rivers like Adamawa, Kano, Niger, Jigawa, Kaduna, Cross River, and Kebbi (Akintola, 1994; Iloeje, 2001). The 2006 flood in Kano caused casualties and property damage (Adebayo & Oruonye, 2013). In 2012, the Kaduna flooding affected over 400 people and damaged more than 538 farmlands (Ijigah & Akinyemi, 2015). Kaduna River often floods, damaging infrastructure, causing deaths, and disrupting livelihoods. Consequently, a lack of detailed flood knowledge hampers planning. Although flood modeling studies exist in Kaduna, key gaps remain.

The UN IOM's (2022) Displacement Tracking Matrix reported 14 flood-affected LGAs in Kaduna State, impacting 38,290 people and 7,548 households. Chikun

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LGA had the most affected (10,115), followed by Kaduna North (7,236). GIS and remote sensing could improve flood risk reduction in the River Kaduna Basin, but current studies mainly focus on Kaduna city and need broader hydrological modeling. Researchers such as Sule et al. (2016) and Muhammad and Iyortim (2013) emphasize the need for further analysis and improved flood management.

Addressing these issues is vital for improving flood risk assessment, early warning, and management for the River Kaduna floodplain. Remote sensing and GIS enable accurate flood modeling to support decision-making and reduce the impacts of flooding. Kaduna North, Kaduna South, and Chikun LGAs are especially vulnerable due to natural factors, human activities, poor urban planning, and weak disaster preparedness. Tackling these issues requires better land-use policies, improved drainage, flood forecasting, and community awareness. The midstream and downstream sections of the River Kaduna, where these LGAs are located, reveal a knowledge gap regarding the potential for flood damage. This study aims to fill that gap by analyzing flood temporal patterns and reviewing management strategies.

Therefore, the study aims to analyze the factors contributing to flooding in the study area; examine the temporal patterns of flooding in the midstream and downstream parts of the River Kaduna Basin, and determine the potential for flooding in the study area until 2034.

## 2 Theoretical Framework and Literature Review

### 2.1 Theoretical Framework

Flood vulnerability is the susceptibility of communities, ecosystems, or systems to flood damage, determined by exposure, sensitivity, and adaptive capacity. It encompasses physical, social, economic, and institutional factors. Understanding disaster vulnerability is fundamental to assessing urban disaster risk and developing effective mitigation strategies. The conceptual evolution of disaster vulnerability highlights key theoretical shifts that inform current assessment frameworks (Graveline & Germain, 2022; Sandoval et al., 2023). The study focuses on the Exposure, Sensitivity, and Adaptive Capacity (ESAC) Model and Cutter's (1996) Hazard of Place Model.

The ESAC framework assesses flood risk by evaluating vulnerability in terms of exposure, sensitivity, and adaptive capacity. Exposure involves the presence of people, property, and infrastructure in flood-prone areas, primarily determined by geography and land use, including proximity to rivers, lakes, floodplains, and coastal zones, as well as urban development near water. Climate change and the expansion of settlements into flood zones also increase exposure. Sensitivity indicates how likely exposed individuals are to be affected, considering infrastructure resilience and socio-economic factors such as population density, income, access to healthcare, demographic factors, and environmental degradation weakening natural defences. Adaptive capacity is the ability to respond and recover, involving early warning systems, monitoring, insurance, and social safety nets. Strong governance, local institutions, disaster risk planning, public awareness, community engagement, and access to emergency services are crucial. The ESAC Model helps planners assess flood risks and allocate resources efficiently. It emphasizes social, economic, and environmental resilience and promotes integrated strategies. By identifying gaps in vulnerability, decision-makers can focus on upgrading infrastructure, protecting communities, and improving early warning. Overall, the ESAC Model offers a holistic approach to understanding flood risks and developing tailored strategies to reduce vulnerability and support recovery (Fortini et al., 2017).

The Hazard of Place Model of Vulnerability, developed by Cutter (1996), advances understanding of how disasters impact different locations and populations. Unlike models that focus solely on environmental hazards or social factors, this model combines both to provide a comprehensive view of vulnerability. It suggests disaster risk depends on how a place's physical features interact with its social conditions. Biophysical risks such as earthquakes and floods are influenced by geography, climate, and hazard exposure, but their effects depend on social factors such as poverty, age, infrastructure, healthcare, language, and social networks. For example, two flood-prone cities may face similar risks, but the one with better response, infrastructure, and community support will likely suffer fewer consequences. Therefore, the Hazard of Place Model focuses on spatial analysis, using GIS to overlay hazard and social vulnerability maps, highlighting 'hotspots" where danger aligns with vulnerable communities. Vulnerability varies geographically, driven by environmental and social factors. It is also dynamic, changing with community growth, economic and demographic shifts, policy, technology, and environmental changes (Cutter, 1996).

### 2.2 Literature Review

The study identified and examined various works on the temporal analysis of the study area. Shen et al. (2017) highlight the importance of understanding flood seasonality for better flood management. They analyze changes in the timing of Annual Maximum Floods (AMFs) across more than 250 US catchments since 1980, finding that about one-third have experienced significant shifts. In the northeast, many catchments faced peak floods weeks earlier, while some in the west experienced delays. These changes are mainly linked to rising temperatures, causing earlier snowmelt and altered precipitation patterns. Statistical analyses show clear links between climate factors and variations in flood seasonality. Catchments with synchronized water and energy cycles tend to align their AMF with the Annual Maximum Rainfall (AMR), whereas less synchronized catchments exhibit greater variability due to high antecedent storage. Increased soil water storage has made flood seasonality more pronounced, but areas with higher pre-flood rainfall have become less predictable. In the east, rising rainfall intensity and reduced soil water storage have caused more erratic flood timing. These insights are vital for enhancing flood risk management and predicting future flood patterns.

Duran et al. (2025) found that floods have a significant impact on humans, causing economic losses, infrastructure damage, and fatalities. This study explores flood effects on Iowa transportation, focusing on bridge inundation, waterway crossings, and traffic disruptions during 50-, 100-, and 500-year floods. Southeastern Iowa, especially Marion, experiences significant bridge inundation during major floods. The study also considers bridge age condition, vulnerability, and how closures disrupt traffic and evacuations. Overall, the findings emphasize the complex relationship between flooding and transportation, highlighting bridge vulnerabilities and traffic impacts.

Ali et al. (2015) studied rainfall patterns in the Segamat District of Australia to support flood planning. They used the Average Variability Method to analyse 5-minute interval data from 2003 to 2012, obtained from four rainfall stations. The research identified temporal rainfall patterns across different intervals and found that 75% were classified as intermediate, 11% as advanced, and 14% as delayed. These findings are essential for predicting rainfall durations and assessing flood risks.

Wang (2020) highlights the role of temporal patterns in rainstorms, influencing runoff and flood models. A new dynamic time warping method analyzed these patterns, identifying five key ones from over 13,000 Chinese rainstorms. Most rainfall in storms under 24 hours occurs within 3 to 6 hours, impacting flood planning. While macroclimates affect rainfall, local conditions seem more influential on temporal patterns, warranting further local research.

Kakavand et al. (2025) found variability in annual precipitation across stations in Iran's Doab Veysiyan watershed. Station A's precipitation increased by 24 mm per decade ($Z = 2.15$, $p < 0.05$), while Station B's decreased by 17 mm ($Z = -1.82$, $p < 0.10$). Higher rainfall areas saw runoff coefficients rise from 0.42 to 0.56 during peak years. These changes reflect local flood risk variability linked to rainfall, land, and upstream precipitation correlations to river discharge. Using a weighted linear combination, rainfall and runoff were key for flood hazard zoning, underscoring the need for trend analysis and hydro-climatic data-based zoning for effective flood management.

Aliyu and Suleiman (2016) describe the flooding pattern in Kaduna, noting that floods occur during heavy rainstorms and at the height of the rainy season (August/September), with 48.4% and 42.5% of flooding occurring during these periods, respectively. They also report that it takes 3-5 days for floodwaters to recede, depending on rainfall intensity and amount, as reported by 37.9% and 58.5% of respondents, respectively.

John et al. (2023) reported that Kaduna Metropolis continues to face seasonal flooding on the Kaduna River, exacerbated by climate change and rapid urban development. Notably, despite higher rainfall in 2022 than in previous years, which saw severe flooding, no incidents were reported. This suggests a need to examine how rainfall patterns, flood management strategies, and urban settlement in vulnerable areas interact, particularly with respect to dredging as a potential means of mitigating flood risks.

## 3 Materials and Methods

### 3.1 Study Area

The study area is situated within a larger basin, extending from Latitude $10^0$ 1' 16''N to $10^0$ 49' 18''N of the Equator and Longitude $6^0$ 42' 35''E to $7^0$ 43' 46''E of the Greenwich meridian, covering a total landmass of 4,582.76 km$^2$. The specific section of the basin under study, which comprises the lower and midstream regions, extends over 106.6 km, bounded by Latitude $10^0$ 6' 58''N to $10^0$ 30' 21''N of the Equator and Longitude $6^0$ 52' 50''E to $7^0$ 26' 19''E of the Greenwich Meridian. Within this section, the elevation ranges from 370 metres to 698 metres above mean sea level (Nigeria Hydrological Services Agency (NIHSA), 2024).

The Kaduna River Basin (KRB) is a key basin in Nigeria and West Africa. It is estimated to cover about 8% of Nigeria's total land area and drains a substantial part of north-central Nigeria (Chinwendu et al., 2017). The 550 km-long River Kaduna is Nigeria's third-longest, after the Niger and Benue. It flows northwest through varied terrain to Kaduna city, then southwest through Mureji, joining the Niger at Nupeko. Most of its course passes through savanna woodland; its lower part cuts gorges into the Niger floodplains. The river originates from Sherri Hills (1280 m) in Plateau State. The KRB spans about 65,878 km$^2$ mainly in Niger and Kaduna States (Ologunorisa et al., 2021). Figure 1 shows Kaduna State's local government areas: Kaduna South, Kaduna North, and Chikun. Figure 2 illustrates the basin's upstream, midstream, and downstream sections.

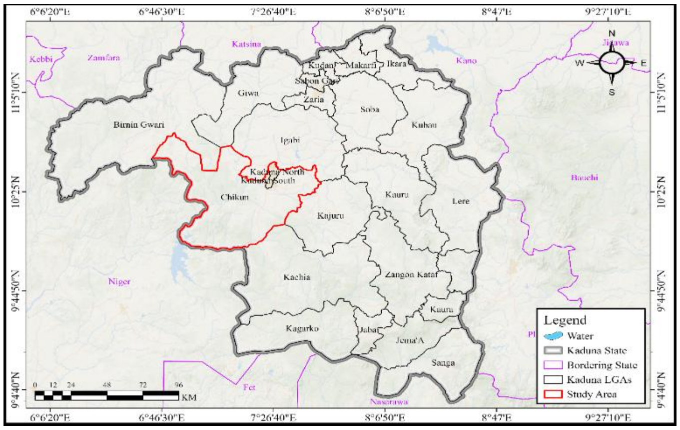

*Figure 1: Kaduna State Local Government Areas Indicating the Study Area*

*Source: Adapted from Federal Ministry of Lands and Survey (2024)*

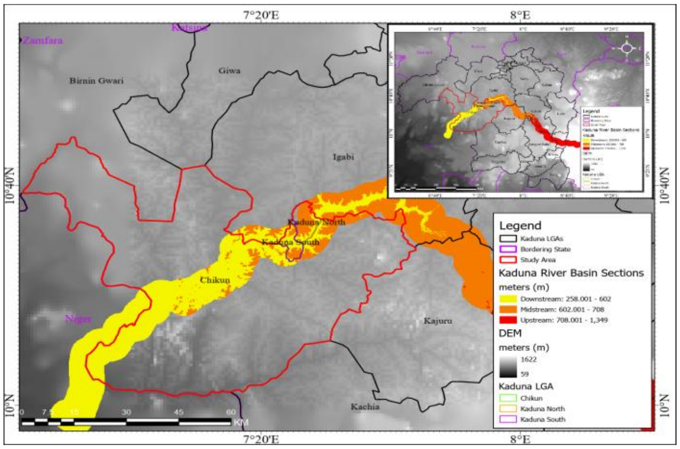

*Figure 2: Downstream and Midstream Sections of the River Kaduna Basin in the Study Area*

According to the Köppen classification, Kaduna has a tropical savanna climate (Aw) characterized by alternating wet and dry conditions (Abdussalam, 2020). The dry season runs from October to April of the following year, while the rainy season runs from April through mid-October, peaking in August (Abubakar et al., 2024; Abaje et al., 2016), with an annual average of 1323 mm (Baba et al., 2020). Temperatures are high throughout the year, with the highest average monthly value of about 28.9°C and the lowest of 22.9°C to 23.1°C (Abaje & Oladipo, 2019). The hottest months in this part of the country are March and April, with a mean monthly temperature of about 31°C, while the coolest months are December and January, with a mean monthly temperature of about 21°C (Murtala & Abaje, 2018).

Geologically, the Kaduna Basin is part of the more extensive West African Rift System. The basin has a complex geological history, shaped by a range of sedimentary and tectonic processes (Saadu et al., 2024). The Kaduna Basin primarily consists of pre-Cambrian Basement Complex rocks, comprising migmatites, gneisses, and biotite (Wali et al., 2021; Daramola et al., 2022). The primary rock type in the Kaduna Basin is a gneiss-migmatite complex beneath the Kaduna-Zaria region. Metasedimentary formations comprise undifferentiated rocks such as pegmatite, gneiss, quartzite, and schist (Wali et al., 2021). Across much of the central belt and metropolitan area, including Kaduna North, Kaduna South and parts of Chikun, the dominant soils are ferruginous tropical soils developed over crystalline basement rocks, typically with sandy-loam to loamy-sand surface horizons over more clayey subsoils (Sadiq et al., 2021; Saadu et al., 2024). As farming intensifies, the topsoil's water-holding capacity decreases, worsening flooding. The natural vegetation is characterized by the Northern Guinea Savannah, featuring dominant grasses and scattered trees that rarely exceed 15 feet in height (Iloeje, 2001).

The Kaduna floodplain has been transformed into urbanized land, leading to the conversion of viable agricultural land into built-up areas. Kaduna North LGA is mainly urban, with densely built areas such as Malali, Ungwan Rimi, and Kawo. Kaduna South LGA has both urban and semi-urban traits, with residential zones including a mix of planned and informal settlements, especially in Sabon Tasha and Ungwan Sanusi. Chikun LGA is mostly semi-urban and rural, with farmland used for growing crops such as maize and millet and for grazing livestock. Areas near the Kaduna River, especially in Kaduna South and parts of Chikun, are particularly susceptible to flooding (Umar & Abdullahi, 2024). The projected population for 2024 is 2,758,739 (National Population Commission, 2009).

### 3.2 Methodology

The research adopted a mixed-methods design, combining GIS-based spatial analysis with a questionnaire survey. Secondary data from satellite and climatic data were integrated through multi-criteria analysis to produce flood vulnerability maps, while primary survey data validated the spatial outputs and captured community-level flood experience. Primary data were collected directly by the researcher through field surveys tailored to this study's objectives, constituting a single, integrated source of firsthand insights into the socioeconomic and environmental factors affecting flood vulnerability. Secondary data obtained from existing records include rainfall data from 2016 to 2024 from the Nigeria Meteorological Agency (NiMET) and Sentinel-1A/B imagery, which provide C-band Synthetic Aperture Radar (SAR) data suitable for detecting water surfaces, soil moisture, and textural patterns associated with flooding. The Ground Range Detected (GRD) product in Interferometric Wide (IW) mode with VV polarization was utilized for each target year. All available images were composited using a mean reducer to generate an annual backscatter layer, from which a Wetness Index (WI) was derived to quantify radar signal responses related to surface moisture and potential inundation. Sentinel-2A/B multispectral imagery, which provided optical reflectance data across 13 spectral bands (visible to shortwave infrared), using Level-1C Top-of-Atmosphere (TOA) reflectance filtered for less than 10% cloud cover, composited annually using the mean reducer, from which the Normalized Difference Vegetation Index (NDVI) indicating vegetation vigour and green cover using NIR (B8) and Red (B4) bands and the Normalized Difference Built-up Index (NDBI) highlighting impervious and built-up surfaces using SWIR (B11) and NIR (B8) bands were derived. SRTM DEM at 30 m resolution, used for slope computation, flow direction, flow accumulation, and stream channel extraction; and soil permeability data from the Federal Department of Agricultural Land Resources (FDALR, 1990) supplemented by Nkwunonwo et al. (2015). Table 1 presents the metadata for all datasets used.

**Table 1: Metadata for Datasets Used for the Study**

| Source/Satellite | Spatial Resolution | Temporal Coverage | Collection ID | Provider |
|---|---|---|---|---|
| Sentinel-2A/2B (Copernicus) | 10m (B2, B3, B4 & B8)<br>20m (B5, B6, B7 B8A, B11 & B12)<br>60m (B1, B9 & B10) | 2016-01-01 to 2016-12-31<br>2018-01-01 to 2018-12-31<br>2020-01-01 to 2020-12-31<br>2022-01-01 to 2022-12-31<br>2024-01-01 to 2024-12-31 | COPERNICUS/S2_SR | European Space Agency (ESA) |
| Sentinel-1A/1B (Copernicus) | 10m | 2016-01-01 to 2016-12-31<br>2018-01-01 to 2018-12-31<br>2020-01-01 to 2020-12-31<br>2022-01-01 to 2022-12-31<br>2024-01-01 to 2024-12-31 | COPERNICUS/S1_GRD | ESA |
| Shuttle Radar Topography Mission (SRTM) | 30m | 2015 | USGS/SRTMGL1_003 | NASA/USGS |

The study employed a purposive sampling technique. A 1km buffer zone was delineated along the midstream and downstream stretches of the River Kaduna Basin to capture households in areas with greater hydrological relevance and a higher likelihood of flood interaction, based on proximity and past flood-event records. This purposive focus ensured that the sample was drawn only from communities most affected by flood dynamics.

The sample size was determined using Krejcie and Morgan's (1970) table, as shown in Table 2, which specifies a sample size of 384 respondents for populations above one million at a 95% confidence level and 5% margin of error. This figure was proportionally distributed across the three LGAs, Chikun, Kaduna North, and Kaduna South, based on their projected populations in 2025.

**Table 2: Population and Projected Growth of Study LGAs (2006–2025)**

| S/N | LGA | 2006 Census | 2025 Projection | Sample Size |
|---|---|---|---|---|
| 1 | Chikun | 372,272 | 656,000 | 125 |
| 2 | Kaduna North | 364,575 | 642,200 | 123 |
| 3 | Kaduna South | 402,731 | 710,900 | 136 |
| | Total | 1,139,578 | 2,009,100 | 384 |

*Source: National Population Commission (2009)*

Within each buffer zone, households, rather than physical houses, were used as the sampling unit. Since many buildings in the study area contain multiple tenants, only one household per building was purposively selected. To ensure reliability of responses and historical knowledge of flood events, the respondent chosen had to be a household head (or an adult representative) who had lived in the location for at least ten (10) years. Enumerators continued this purposive selection until the allocated sample size for each LGA was achieved. When multiple eligible households were present in a single building, one was selected using a simple random method (e.g., balloting). This approach ensured that only households with direct spatial and experiential relevance to flooding were included, and the sample remained proportionally distributed across the three LGAs.

### 3.3 Factors Contributing to Floods in the Study Area

To identify and quantify the relative importance of parameters influencing flooding in the study area, the Analytic Hierarchy Process (AHP) was employed. AHP was selected because it provides a transparent and reproducible framework for combining heterogeneous flood-conditioning factors that do not share the same measurement scale. In this study, the criteria comprised DEM, Rainfall, Soil Permeability, Slope, NDVI, Soil Wetness, and NDBI. These variables were selected based on their established hydrological relevance in flood-susceptibility studies and their demonstrated importance in the River Kaduna Basin context, where rainfall intensity, runoff concentration, terrain, soil conditions, land cover, and surface imperviousness jointly shape flood occurrence.

Each of the seven criteria was compared pairwise using Saaty's fundamental scale of relative importance (1–9), where 1 indicates equal importance, and 9 indicates extreme importance of one factor over another. The pairwise judgments were informed by hydrological reasoning, prior flood-vulnerability literature, and the physical characteristics of the study area. Rainfall received the highest priority because it constitutes the primary climatic trigger of flooding, directly controls stormwater input, and strongly influences the magnitude of runoff available for inundation. Slope received the next highest weight because it governs runoff velocity, concentration, and the likelihood of ponding in low-gradient terrain. Soil permeability and soil wetness were assigned relatively high weights because they determine how much rainfall infiltrates, how quickly the soil reaches saturation, and how readily excess water becomes surface flow. DEM was weighted slightly lower than rainfall and slope but remained important because elevation helps identify low-lying accumulation zones and floodplain settings where inundation is more persistent. NDBI was weighted above NDVI because built-up surfaces increase imperviousness and accelerate runoff generation more directly than vegetation reduction alone. NDVI received the lowest weight, not because it is unimportant, but because in the study area, its influence is more indirect, operating mainly through interception, surface protection, and evapotranspiration. The resulting comparison matrix was structured such that reciprocal values were placed symmetrically across the diagonal to preserve logical consistency.

Let $A = [a_{ij}]$ be a pairwise comparison matrix,

Where:

$a_{ij}$ represents the relative importance of the criterion $i$ over criterion $j$

$a_{ij} = a_{ij} = 1/a_{ji}$ $and$ $a_{ii} = 1$

To obtain the normalized principal eigenvector, each element of the matrix is divided by the sum of its column to normalize the matrix. Then, the average of each row in the normalized matrix gives the priority vector (weights) for each criterion.

$$w_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}$$

Where:

$w_i$ = weight of criterion $i$

$n$ = number of criteria

To ensure logical consistency in the pairwise comparisons, the Consistency Ratio (CR) was computed using the Consistency Index (CI) and a Random Index (RI) based on matrix size

$$CR = \frac{\lambda_{max} - n}{(n-1)\cdot R1}$$

Where:

$\lambda_{\max}$ = maximum eigenvalue of the matrix

n = number of criteria

RI = Random Index

Interpretation

If CR < 0.10 (10%), the judgments are consistent.

CR ≥ 0.10 indicates inconsistencies and requires matrix revision.

Additionally, questionnaire data collected from field surveys in Chikun, Kaduna North, and Kaduna South Local Government Areas were analyzed using the

Statistical Package for the Social Sciences (SPSS). Responses on flood causes were quantified and presented in frequencies and percentages to highlight community perceptions of key flood drivers.

### 3.4 *Temporal Pattern of Flooding in the Study Area and Model Validation*

The temporal pattern of flooding was mapped using the Inverse Distance Weighted (IDW) interpolation method to create a continuous surface of flood frequency from questionnaire-derived observations. IDW was considered appropriate because the available temporal information was point-based, derived from household responses, and required transformation into a spatially continuous surface that could reveal neighbourhood-scale recurrence patterns. The method assumes that locations closer to one another are more likely to share similar flood experience than locations farther apart, which is a reasonable assumption in riverine and urban floodplain environments where terrain, drainage pathways, and proximity to inundation corridors influence local recurrence. The same 1 km River Kaduna buffer used in the spatial analysis was retained as the processing extent to ensure methodological consistency between the spatial and temporal components of the study. The Flood Frequency IDW raster, with values ranging from 1 to 4, represents reported flood recurrence (1 = Rarely, 4 = Every year). This surface provided an interpretable representation of how recurrent flood experience varies across the study area and served as a descriptive basis for comparing observed temporal behaviour with modelled vulnerability trends. For visual interpretation, the Flood Frequency IDW raster was displayed using a red-to-blue colour ramp, where red represents areas with more frequent flooding and blue represents areas with relatively rare flooding. Questionnaire responses were collected from 384 respondents and analyzed in SPSS to calculate frequencies and percentages.

### 3.4.1 *Statistical Significance of Yearly Changes*

To assess whether the observed changes in flood vulnerability across years were statistically meaningful rather than random fluctuations, the Friedman test and the Wilcoxon Signed Rank Test were applied. These non-parametric procedures were appropriate because the yearly vulnerability outputs are related observations from the same study area across multiple time steps and do not require strict assumptions of normality.

#### *a. Friedman Test*

Used for comparing related samples across multiple years (non-parametric)

$$x^2 = \frac{12}{nk(k+1)} \Sigma R_j^2 - 3_n(k+1)$$

Where:

$n$ = number of observations (locations/pixels)

$k$ = number of time points (years)

$R_j$ = sum of ranks for year $j$

#### a. **Post-Hoc Wilcoxon Signed-Rank Test**

Pairwise comparisons between the years were conducted to locate specific significant differences. Bonferroni correction was applied to adjust for multiple comparisons

$$p_{adjusted} = \frac{p_{raw}}{number\ of\ camparisons}$$

Interpretation:

i. A significant Friedman Test result ($p < 0.05$) indicates flood patterns changed over the years.
ii. Wilcoxon tests pinpoint specific years with statistically significant shifts.
iii. This validates trends observed in the vulnerability maps and justifies predictive modeling.

### 3.4.2 *Model Sensitivity Analysis*

To assess the stability of model output to input variation, sensitivity analysis was performed using Standard Deviation ($\sigma$) and Coefficient of Variation (CV).

$$CV = \frac{\sigma}{\mu}$$

Where $\mu$ = mean vulnerability score.

Interpretation

Low CV (<0.2): Stable model; input variability has a limited effect.

High CV (>0.3): Model is highly sensitive to certain inputs, suggesting further refinement is needed, especially of AHP weights.

### 3.4.3 *Monte Carlo Simulation (Uncertainty Quantification)*

To quantify prediction uncertainty, a Monte Carlo simulation was performed (n = 1000 runs per year). For each year

$$CI = \mu \pm Z \times \frac{\sigma}{\sqrt{n}}$$

Where:

Z = 1.96 for 95% CI

n = 1000: number of simulations runs

**Interpretation**

Narrow CI: Reliable prediction with low uncertainty.

Wide CI: High model variability; revisit input assumptions or increase data quality.

Helps quantify risk margins for decision-makers.

### 3.4.4 *Time-Series Analysis and Trend Decomposition*

A trend analysis of the vulnerability scores over the years (2016–2034) was performed by fitting a linear regression model

$$V(t) = \alpha + \beta t + \epsilon$$

Where:
V(t) = vulnerability at time t
Β = trend slope
ϵ = error term

### *b. Interpretation*

A positive and significant β indicates increasing vulnerability over time, supports future scenario assessment, and strengthens the basis for preventive and adaptive interventions.

Future vulnerability surfaces for the years up to 2034 were generated using linear trend modelling because the available historical series (2016, 2018, 2020, 2022, and 2024) showed a gradual directional change rather than an abrupt oscillation. The linear regression framework was therefore adopted as a parsimonious forecasting approach that can extend recent vulnerability trajectories while preserving transparency and interpretability. This choice was also justified by the relatively short time series available, for which more complex forecasting models would introduce additional assumptions without necessarily improving explanatory value. The projection is therefore presented as a scenario-based estimate of likely future conditions under the continuation of observed land-surface and flood-vulnerability trends, not as a deterministic prediction of exact future flood events. Its reliability was further examined through correlation analysis, non-parametric significance testing, sensitivity analysis, and Monte Carlo uncertainty simulation.

## 4 Results

### 4.1 Analytical Hierarchy Process (AHP) of Flood Drivers

The Analytic Hierarchy Process (AHP) results in Table 3 show that rainfall (26.9%) and slope (20.0%) are the dominant flood-conditioning factors in the study area. This ranking is hydrologically plausible because intense rainfall supplies the primary water input, while slope governs the speed of runoff concentration, flow routing, and the likelihood of ponding in low-gradient terrain. Together, these two variables account for almost half of the total model weight, indicating that the temporal and spatial behaviour of flooding in the River Kaduna Basin is strongly controlled by rainfall delivery and topographic response.

The next tier of variables, soil permeability (11.5%), soil wetness (10.5%), and elevation/DEM (7.9%), captures the storage and retention conditions that either moderate or intensify flood formation. In practical terms, lower permeability and wetter antecedent conditions reduce infiltration and increase overland flow, while elevation influences the location of flood accumulation zones and floodplain exposure. NDBI (8.0%) and NDVI (5.4%) contributed less than rainfall and slope, but their combined effect remains important because built-up surfaces increase imperviousness and vegetation loss reduces interception and infiltration.

The Digital Elevation Model (DEM), with a weight of 7.9%, further underscores the role of elevation in determining flood-prone zones. This finding is comparable to Ahmad et al. (2025), whose Urban Flood Risk Index in Pakistan identified large areas of concentrated flood pressure. Soil wetness (10.5%) and the Normalized Difference Built-up Index (NDBI, 8.0%) also played important roles, reflecting how saturation conditions and urbanization patterns can intensify exposure to flood hazards. This is consistent with Gu et al. (2025), who showed that conversion of paddies to urban land reduces water retention and increases flood exposure.

Taken together, the AHP results indicate that flood vulnerability in the study area is not driven by a single variable but by the interaction of hydro-meteorological forcing, topographic controls, and land-surface characteristics. The hierarchy also supports the modeling framework used in this study, in which rainfall and slope explain where runoff pressure is generated, while permeability, wetness, elevation, vegetation, and built-up intensity explain how that pressure is either absorbed, transmitted, or amplified across the landscape.

**Table 3: Summary of Criterion Weights in the Seven-Factor AHP Model**

| Criterion | Normalised Weight | Percentage Contribution |
|---|---|---|
| Rainfall | 0.2685 | 26.85% |
| Slope | 0.2004 | 20.04% |
| Soil Permeability | 0.1145 | 11.45% |
| Soil Wetness | 0.1051 | 10.51% |
| DEM | 0.0790 | 7.90% |
| NDBI | 0.0804 | 8.04% |
| NDVI | 0.0539 | 5.39% |

Table 3 summarises the relative importance of the seven flood-conditioning factors, indicating that rainfall and slope exert the strongest influence on flood generation in the basin, while soil properties, elevation, and land-cover conditions shape how runoff is stored, retained, or amplified across different parts of the landscape.

The variable weights derived from the AHP are further visualized in Figure 3, which presents the percentage contribution of each factor in a clear, easy-to-understand format. The result confirms that Rainfall and Slope are the two most significant contributors to flooding, followed by Soil Permeability, DEM, and Soil Wetness, with NDBI and NDVI contributing the least. This hierarchy emphasizes the importance of enhancing rainfall management through improved stormwater infrastructure, rainwater harvesting, and policies that incorporate rainfall variability into spatial planning, including slope-sensitive urban planning, as well as strengthening land and water management practices, as recommended by Haruna et al. (2025) for climate-resilient agriculture and afforestation. It also emphasizes that, while vegetation cover provides some buffering capacity, its effect is less pronounced than broader hydrological and topographic controls, as indicated by Ke et al. (2025)'s thresholds for impervious surfaces below 0.2.

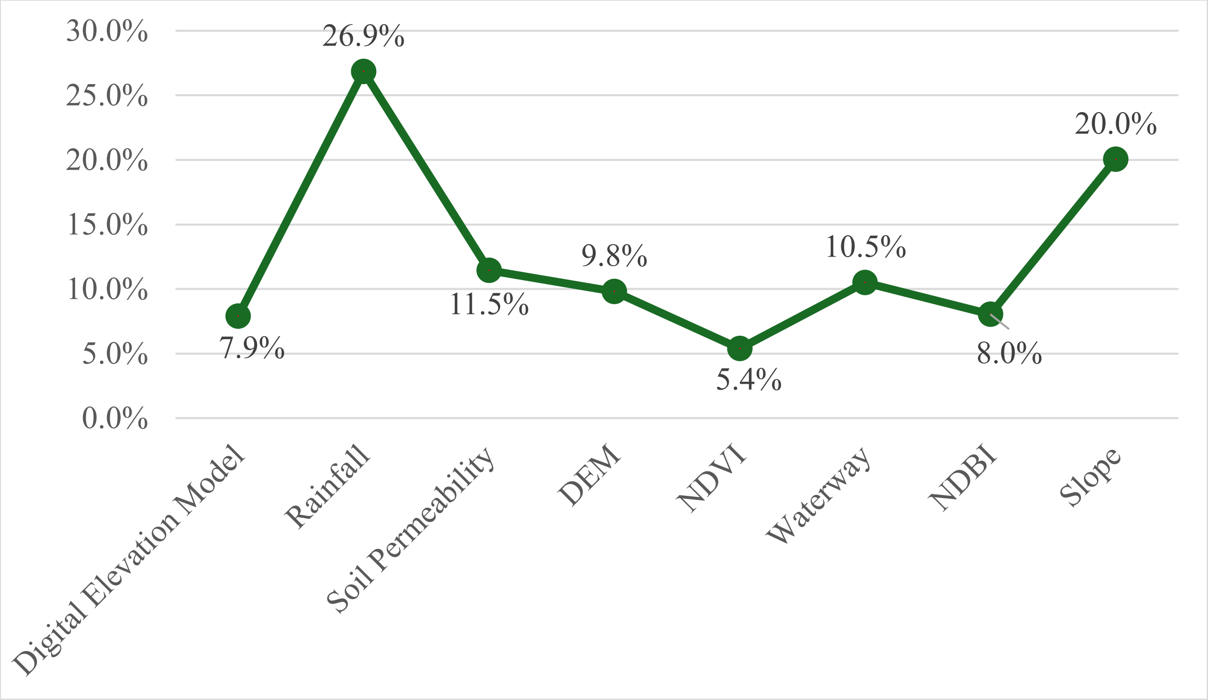

*Figure 3: Relative Contribution of Flood-Conditioning Factors in the Study Area*

### 4.2 Spatial and Temporal Recurrence of Flooding

The recurrence analysis reveals a clear spatial concentration of frequent flooding within the low-lying floodplain belt of Chikun and Kaduna South. Wards such as Narayi, Rido, Kakau, Goningora, and parts of Tudun Wada North and South show the highest recurrence, indicating that flooding in the basin is not randomly distributed but is repeatedly expressed in the same hydrologically constrained localities. This persistence is consistent with the strong influence of flat terrain, inadequate drainage, and proximity to floodplains observed elsewhere in the study.

The zones reporting floods every 2–3 years represent transitional environments between the most exposed riverine settlements and the more protected urban uplands. Their intermediate recurrence suggests that flood occurrence in these wards is highly sensitive to the intensity of wet season conditions and to the temporary effectiveness of local drainage infrastructure. In contrast, the less frequently flooded wards in Kaduna North and the more elevated parts of Chikun reflect the protective role of better topographic position and relatively improved runoff conveyance. The spatial distribution of flood recurrence in the study area is at Figure 4.

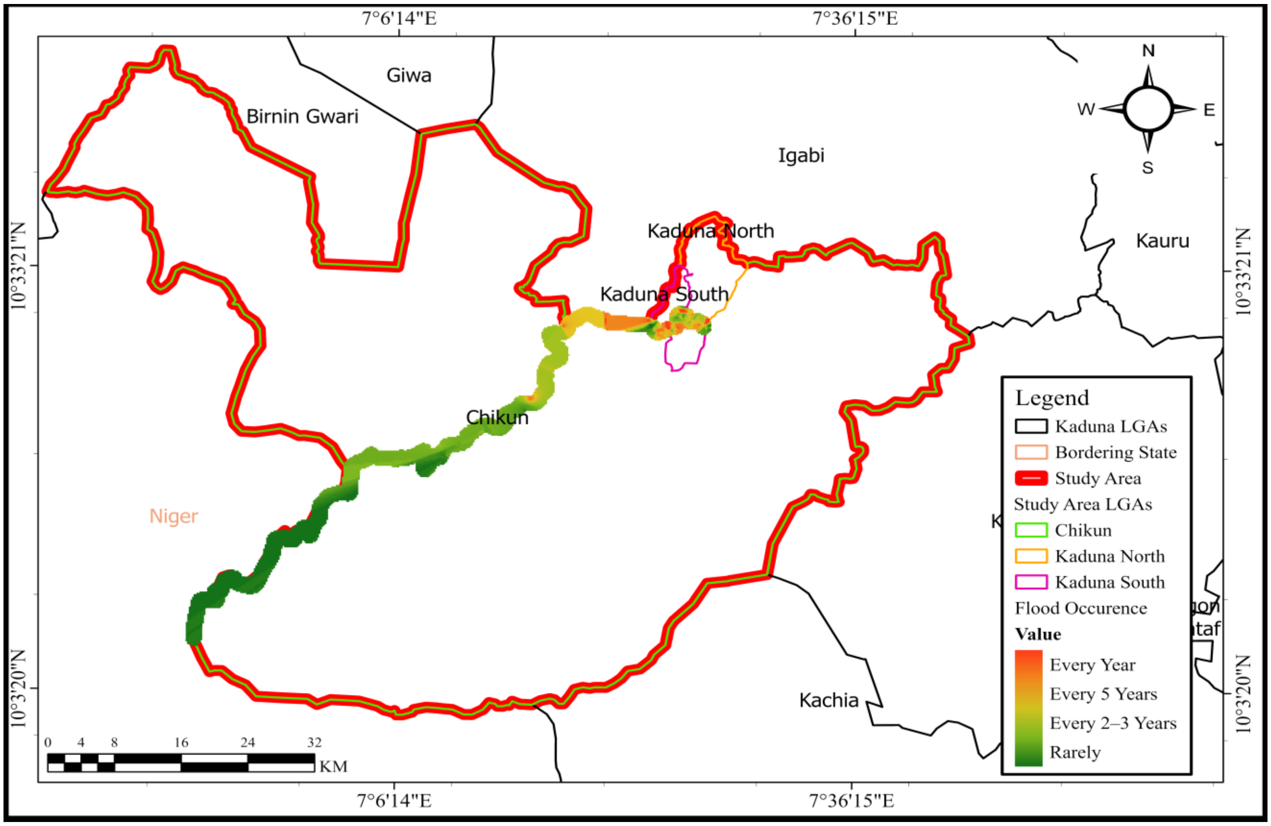

*Figure 4: Spatial Distribution of Flood Recurrence in the Study Area*

Wards where flooding is reported every 2–3 years are also widespread, spanning transitional zones between high- and low-risk areas, including Barnawa, Makera, Kabala, Nassarawa, Sabon Gari North, and Tudun Nupawa. These communities often experience flooding during particularly intense wet seasons but recover more quickly due to moderate elevation and partial drainage improvements. This pattern aligns with the findings of Yang et al. (2025), who demonstrated that reduced spatial heterogeneity in soil moisture corresponds to decreased heterogeneity in runoff generation, a dynamic likely present in these transitional zones, where more uniform drainage and moderate slopes promote faster recession of floodwaters after heavy rainfall.

Flooding every 5 years was more common in relatively better-drained or elevated wards, including Sabon Gari West, Sabon Gari Nassarawa, and parts of Kaduna North, where infrastructural drainage has been expanded in recent years. By contrast, wards with rare flooding were concentrated in the urban core and in elevated areas in Kaduna North and parts of Chikun, such as Rigasa, Dadi Riba, and Sardauna, where both improved infrastructure and elevated terrain provide natural protection against inundation. This aligns with Abu-hanifa et al. (2025)'s advocacy for integrating technology in southern Nigeria to shift from reactive to proactive flood forecasting.

The questionnaire results at Table 4, reinforce the mapped pattern of temporal flood recurrence. Nearly half of respondents (46.1%) reported recent flood experience, with the highest proportions in Chikun and Kaduna South, while Kaduna North recorded comparatively fewer recent events. The years 2022 and 2024 were most frequently identified as major flood years, and 37.2% of respondents reported flooding every year. This confirms that recurrent flooding is now an established feature of life in several parts of the basin rather than an occasional disturbance.

Flood events were most commonly reported in 2022 (25.4%) and 2024 (24.9%), corresponding to years of widespread inundation in the downstream portions of Kaduna, particularly within agricultural river corridors and low-lying urban settlements. This pattern indicates that flooding in the study area is both seasonally recurrent and spatially clustered in areas with inadequate stormwater management. The critical role of soil moisture spatial heterogeneity in governing high-resolution flood processes, as recently demonstrated by Yang et al. (2025), provides a vital framework for understanding this vulnerability, as their findings on soil moisture storage capacity as a key driver of runoff in semi-arid catchments are directly relevant to the River Kaduna Basin.

Regarding flood recurrence, the majority (37.2%) reported flooding every year, while another 29.7% reported flooding every 2–3 years. These frequent events are concentrated in Kaduna South and Chikun, consistent with their exposure to riverine overflow and urban runoff. Conversely, only 20.6% reported that flooding occurs rarely, mainly in Kaduna North, where improved drainage and elevated terrain mitigate impacts. This finding aligns with Abu-hanifa et al.'s (2025) observation of Nigeria's global shift towards data analytics for real-time flood prediction.

**Table 4: Household Responses on Flood Occurrence, Recurrence, and Local Prediction Systems**

| S/N | Indicator | Response Categories | Frequency | Percentage (%) |
|---|---|---|---|---|
| 1 | Occurrence of flood in recent years | Yes | 177 | 46.1 |
| | | No | 207 | 53.9 |
| | | Total | 384 | 100 |
| 2 | Years of experiencing flood | 2020 | 22 | 12.4 |
| | | 2021 | 33 | 18.6 |
| | | 2022 | 45 | 25.4 |
| | | 2023 | 33 | 18.6 |
| | | 2024 | 44 | 24.9 |
| | | Total | 177 | 100 |
| 3 | Frequency of Flood occurrence | Every year | 143 | 37.2 |
| | | Every 2–3 years | 114 | 29.7 |
| | | Every 5 years | 48 | 12.5 |
| | | Rarely | 79 | 20.6 |
| | | Total | 384 | 100 |
| 4 | Availability of Local flood prediction systems present | Yes | 114 | 29.7 |
| | | No | 270 | 70.3 |
| | | Total | 384 | 100 |
| 5 | Methods of local flood prediction | Observing River Water Levels | 57 | 50 |
| | | Weather Patterns (Clouds) | 33 | 28.9 |
| | | Oral Traditions/Elder Knowledge | 24 | 21.1 |
| | | Total | 114 | 100 |

The local prediction results further show that anticipatory flood management remains weak at the community level. Only 29.7% of respondents were aware of any local flood prediction system, and these were mainly based on river-level observation, weather cues, or oral knowledge rather than formal monitoring infrastructure. This suggests that although indigenous knowledge remains important, the basin lacks an operational forecasting framework capable of translating rainfall and river conditions into timely, standardized early-warning information.

### 4.3 Time-Series Decomposition Analysis

The time-series decomposition results show a gradual but persistent increase in flood vulnerability between 2016 and 2034. The observed values rise from 0.424115 in 2016 to 0.428838 in 2034, indicating that vulnerability is not static but slowly intensifying over time. This upward movement is modest in magnitude, yet analytically important because it points to cumulative change rather than year-to-year instability, as indicated in Table 5.

The trend component confirms that the dominant temporal signal is a slow, long-term increase in baseline vulnerability, while the seasonal component remains very small. This means that the principal explanation for changes in flood vulnerability in the study area is not short-term oscillations but the gradual accumulation of structural pressures, including the expansion of impervious surfaces, continued floodplain occupation, and uneven drainage improvements. The seasonal component shows minimal fluctuations, ranging from -0.00055 to 0.000526, indicating that seasonal variations, such as wet and dry cycles, continue to have a negligible impact on overall flood vulnerability patterns. This finding aligns with Garba and Abubakar (2023)'s documentation of non-significant rainfall-runoff trends ($p = 0.475$) in the River Kaduna Basin, suggesting that inter-annual climate variability exerts limited influence compared with long-term urban and environmental changes.

**Table 5: Time-Series Decomposition Components of Flood Vulnerability, 2016–2034**

| Year | Observed | Trend | Seasonal | Residual |
|---|---|---|---|---|
| 2016 | 0.424115 | NaN | -0.00055 | NaN |
| 2018 | 0.426885 | 0.426519 | 0.000022 | 0.000344 |
| 2020 | 0.428557 | 0.427119 | 0.000526 | 0.000912 |
| 2022 | 0.425915 | 0.426945 | -0.00055 | -0.00048 |
| 2024 | 0.426364 | 0.426569 | 0.000022 | -0.00023 |
| 2026 | 0.427426 | 0.42719 | 0.000526 | -0.00029 |
| 2028 | 0.427779 | 0.427779 | -0.00055 | 0.000547 |
| 2030 | 0.428132 | 0.428132 | 0.000022 | -2.2E-05 |
| 2032 | 0.428485 | 0.428485 | 0.000526 | -0.00053 |
| 2034 | 0.428838 | NaN | -0.00055 | NaN |

However, because the residual component is also small, most of the temporal variation is already explained by the fitted structure of the series. This strengthens confidence in the interpretation that vulnerability is increasing systematically (Figure 5). In practical terms, the decomposition suggests that existing flood-management efforts may be slowing change in some places, but they are not yet sufficient to reverse the longer-term vulnerability trend across the basin.

The progressive increase in vulnerability values from 2016 to 2034 suggests that existing flood management measures, while providing stability in the short term, may be insufficient to counterbalance the cumulative effects of urban development and environmental change over longer timeframes. This finding resonates with Widjonarko et al. (2025)'s observations in Semarang-Demak, where environmental degradation progressively amplified flood risks ($R^2$=0.74) despite localized interventions.

The decomposition analysis underscores the need for enhanced adaptive strategies to address the underlying drivers of this upward trend in vulnerability, particularly in the context of Kaduna's ongoing urban transformation.

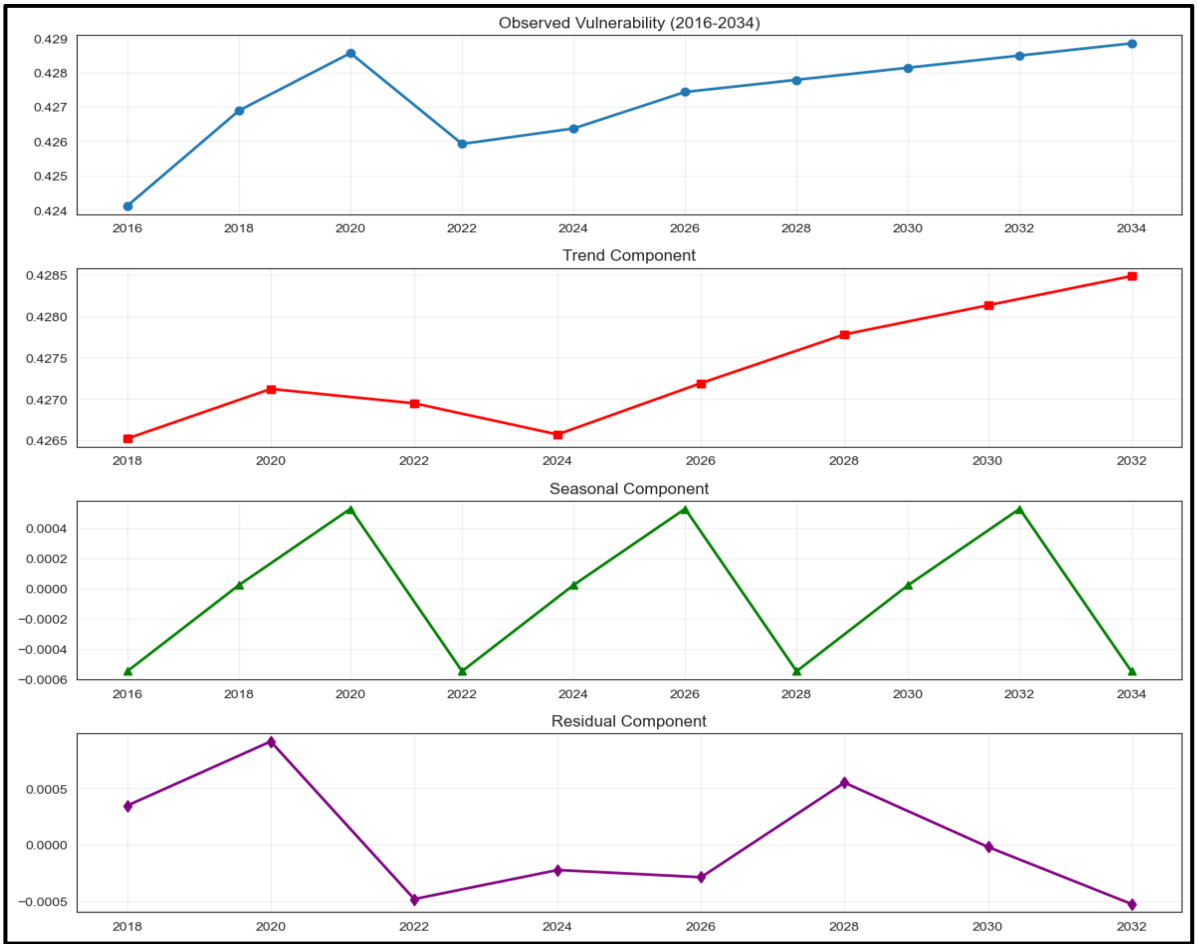

*Figure 5: Time-Series Trend in Flood Vulnerability, 2016–2034*

The Friedman test applied to the full time series yielded a chi-square value of 20190.069 with $p < 0.001$, confirming that observed changes in flood vulnerability over time are highly statistically significant and not attributable to random variation. Post hoc Wilcoxon signed-rank tests revealed significant differences in 44 of 45 possible year-to-year comparisons. This near-universal significance demonstrates that flood vulnerability in the River Kaduna Basin is fundamentally dynamic, aligning with the core tenets of Resilience Theory, which advocates adaptive, continuously learning management approaches rather than static, one-off interventions.

### 4.4 Time-Series Analysis of Vulnerability Levels

The time-series graph of flood-vulnerability areas in the study area (Figure 6) illustrates how the spatial extent of different risk levels has changed over the projected years. The most notable pattern is the growth of the Very High vulnerability category, which expanded by 54.9 km², representing a 10.9% increase over the study period. This category accelerated markedly in the later years, increasing from an annual rate of 0.57 km² during 2016–2024 to 5.5 km² annually during 2024–2034. This pattern suggests intensifying flood exposure in the most susceptible zones, potentially driven by increasing rainfall intensity and continued urban densification in floodplain areas, as also noted by Abubakar et al. (2025). At the same time, moderate-vulnerability areas recorded the greatest contraction, declining by 46.9 km² overall. Their trajectory shifted from positive growth in the earlier period to decline in the later period, suggesting that many transitional areas are increasingly shifting into either higher- or lower-risk classes.

The most remarkable transformation occurred in Low vulnerability areas, which showed a dramatic reversal of trend, increasing by 75.0 km² overall despite an initial decline. This category accelerated at an unprecedented 16.14 km² annually, achieving substantial growth of 9.69 km² per year in the recent period, indicating successful implementation of adaptive land-use practices and drainage infrastructure enhancements, as documented by Pérez-Molina et al. (2025). High-vulnerability areas maintained consistent pressure, with 21.4 km² of overall growth, accelerating from a slight decline to 2.5 km² of annual growth, highlighting persistent flood threats in built-up sectors subject to runoff concentration. Meanwhile, Very Low vulnerability zones remained relatively stable, with a minimal 7.9 km² increase, though showing recent deceleration, reflecting the persistent advantage of favourable topography and established drainage systems in these areas, per Liu et al. (2025). Collectively, these trends illustrate a risk polarisation phenomenon, with the study area increasingly divided between well-managed lower-risk zones and intensifying high-risk hotspots. The accelerated growth in the highest-risk categories suggests that current urban planning and climate adaptation measures require more aggressive, targeted interventions to counterbalance the compounding pressures of increased precipitation intensity and floodplain development, particularly in recurrent flood hotspots such as the Chikun, Tudun Wada North, Nassarawa, and Sardauna wards, where vulnerability remains persistently elevated.

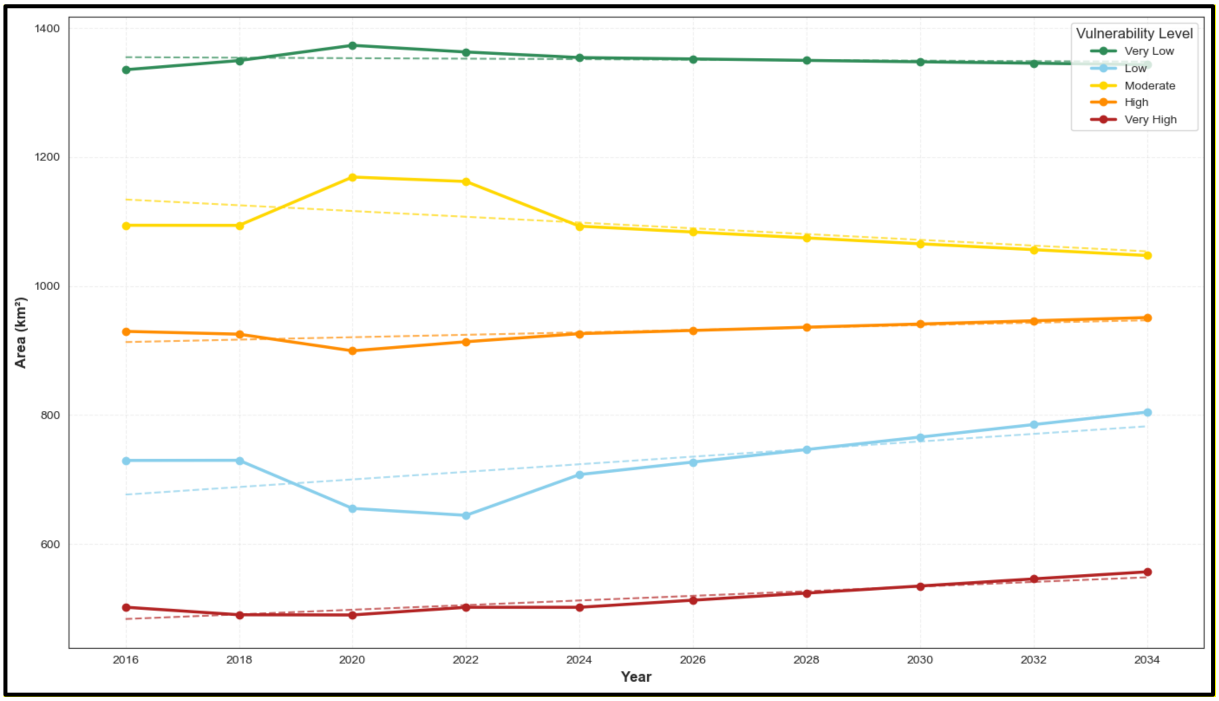

*Figure 6: Temporal Change in Flood-Vulnerability Levels, 2016–2034*

### 4.5 Synthesis: Theoretical Interpretation of Temporal Flood Patterns

The temporal patterns of flood recurrence and the state of prediction systems in the study area are comprehensively explained through the lens of Resilience Theory. The annual and bi-annual flooding in low-lying areas like Chikun and Kaduna South tests the absorption capacity of communities, constantly challenging their ability to withstand and recover from recurrent shocks. The gradient of flood frequency from annual events in floodplains to rare occurrences in elevated, well-drained wards maps directly onto the adaptive capacity inherent in the socio-ecological system, shaped by both natural topography and human infrastructure investments. Most critically, the overwhelming reliance on traditional prediction methods (observing river levels, weather patterns, and oral knowledge) and the lack of modern forecasting systems reveal a significant gap in the capacity to fundamentally change systems to reduce future vulnerability. This aligns with the theory's emphasis on learning and innovation as pathways to resilience. The findings underscore that building long-term resilience in the River Kaduna Basin requires not only improving physical defences but also fostering a transformative shift towards integrated, technology-augmented early warning systems that enhance anticipatory capacity.

## 5 Conclusion

This study focused on the spatiotemporal distribution of flooding and flood risk in the midstream and downstream catchments of the River Kaduna Basin, particularly in the Kaduna North, Kaduna South, and Chikun Local Government Areas. Using geospatial analyses (GEE, DEM/SRTM, Sentinel-1 and Sentinel-2 imagery), multi-criteria evaluation (AHP/MCA), socio-economic surveys via questionnaires, and statistical modeling, the research provides a detailed, location-specific understanding of how physical and human factors combine to influence flood vulnerability.

Temporal analysis for 2016–2034 shows a steady, deliberate rise in overall flood vulnerability at the basin level, with “High” and “Very High” risk zones increasing over time. Consistent year-on-year spatial correlations in vulnerability maps suggest that current exposure patterns, especially in low-lying wards, are likely to persist in the near future, even as long-term urban growth and potential adaptation measures may begin to alter risk in some areas.

Theoretically, the results are well explained by the Hazard of Place Model and the Exposure–Sensitivity Adaptive Capacity (ESAC) framework. Exposure is driven by biophysical characteristics (elevation, slope, drainage density, proximity to the river), sensitivity is mediated by settlement density, housing quality, assets, and livelihoods (urban versus peri-urban or agricultural), and adaptive capacity is shaped by planning quality, drainage provision, institutional responsiveness, and community preparedness. The study thus confirms that flooding in the midstream and downstream River Kaduna Basin is not merely a natural hazard but the outcome of a coupled human–environment system in which unplanned urbanization, weak enforcement of land-use regulations, and insufficient infrastructure play critical roles.

Building on empirical findings and theoretical insights, the following recommendations are proposed to improve flood management in the mid- and downstream catchments of the River Kaduna Basin.

i. There is a need for the government to enforce strict development controls in very high- and high-risk zones, especially along the River Kaduna floodplain in Chikun, Kaduna South, and parts of Kaduna North. Prohibit new residential construction in areas prone to recurrent flooding and, where feasible, relocate the most exposed, highly vulnerable households.

ii. Concerted efforts should be made to integrate flood-risk information into statutory planning instruments, including master plans, subdivision layouts, building permits, and environmental impact assessment procedures.

iii. The Kaduna State government should institutionalize the routine use of GEE, remote sensing, and GIS across Kaduna State agencies (e.g., KADSEMA, the Ministry of Environment, and Urban Planning Authorities) for seasonal monitoring of flood extent, land cover change, and encroachment. This should be achieved through targeted training in GIS, remote sensing, AHP/MCA, and statistical modeling for staff in Kaduna State agencies and LGAs, to ensure the sustainability of the advanced analytical approaches introduced in this study.

iv. Sustained community awareness and education programmes should be implemented on flood causes, warning signs, safe evacuation routes, and household-level preparedness measures such as elevated storage, sandbagging, and safe water storage. In addition, a basin-wide flood information platform or dashboard that integrates rainfall, river levels, flood maps, and incident reports would support more coordinated decision-making across relevant agencies.

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