www.ijecs.in
International Journal Of Engineering And Computer Science
Volume 13 Issue 03 March 2024, Page No. 26101-26112
ISSN: 2319-7242 DOI: 10.18535/ijecs/v13i03.4798

Metropolitan Flood Risk Characterization Using Remote Sensing, GIS, and Fuzzy Logic (RS-GIS-Fl) Approach: Suleja, Nigeria

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Abstract
Climate change exacerbates extreme events like floods, droughts, heatwaves, cyclones, hurricanes, tornadoes, and wildfires, affecting human populations and environments worldwide. Despite varying impacts across regions, no area is immune to climate change consequences. To mitigate these effects, this study employs Geographic Information System (GIS), Remote Sensing, and Fuzzy Logic System to map flood vulnerability zones in Suleja Local Government, Niger State, North Central Nigeria. The research integrates satellite and GIS datasets to prepare Suleja's Flood Zonation Mapping. Rainfall data from Nigeria Meteorological Agency (NiMET), Climate Hazards Group InfraRed Precipitation with Station Data (CHRPS), Global Satellite Mapping of Precipitation (GSMaP), and parameters like Slope, Elevation, Nearness to Water Bodies, Land Use Land Cover, and Drainage Density are utilized to identify flood vulnerability. The flood vulnerability map categorizes the area into five zones: Very Low Risk (40.9%), Low Risk (18.9%), Medium Risk (27.6%), High Risk (7.1%), and Very High Risk (5.5%). Considering the stochastic nature of flood characteristics, this study emphasizes the importance of integrating hydro-climatic and physical catchment parameters, leveraging bias-adjusted satellite data to minimize uncertainty. Effective flood management requires quantifying risk, susceptibility, and hazard components to establish a robust control framework. This research contributes to the development of data-driven flood mitigation strategies in vulnerable regions like Suleja. By harnessing GIS, Remote Sensing, and Fuzzy Logic System, policymakers and stakeholders can make informed decisions to protect communities and infrastructure from flood risks.

Keywords: Climate Change, Flood Vulnerability, GIS, Remote Sensing, Fuzzy Logic System, Suleja, Niger State, Nigeria.

Introduction
Urbanization's rapid pace, driven by population growth and migration, has led to urban sprawl, exacerbating flood risks and environmental degradation, notes (Atemoagbo *et al.* 2023; Nwoke, 2016; Nwoke, 2017). This alarming trend is compounded by inadequate environmental protocols, resulting in increased aesthetic and non-aesthetic noise pollution. Furthermore, the absence of city-based flood early warning systems, structural and environmental planning mechanisms, flood vulnerability profiling, and orchestrated river gauging systems worsens the situation.
In Nigeria, despite efforts by government agencies such as the National Emergency Management Agency (NEMA), Federal Ministry of Water Resources (FMWR), and Ministry of Humanitarian and Disaster Management, the lack of effective planning and knowledge-based decision-making hampers progress. The stochastic nature of flood phenomena underscores the need for data-driven approaches. Remote sensing technologies, which consider the fuzzy variables contributing to flood development, are critical in

addressing these challenges, as emphasized by (Atemoagbo, *et al.,* 2024; Nwoke *et al*., 2022). Effective flood forecasting systems can significantly enhance public safety, resource management, and flood mitigation.

Effective flood management requires a comprehensive approach, integrating hydro-climatic and physical catchment parameters to establish a robust control framework (Antzoulatos *et al*., 2022). Geographic Information System (GIS) and Remote Sensing technologies have been successfully employed to map flood vulnerability zones and identify flood-prone areas (Hagos *et al*., 2022; Tehrany *et al*., 2019).

The integration of GIS, Remote Sensing, and Fuzzy Logic System has shown potential in flood risk assessment, quantifying risk components and determining flood vulnerability (Hong *et al*., 2018; Termeh *et al*., 2018). Studies have identified key parameters, including demographic characteristics, socioeconomic status, and land use patterns, to determine flood vulnerability (Adger *et al*., 2005; Birkmann *et al*., 2013

Despite existing research on flood risk management, significant knowledge gaps persist. The geographic scope of previous studies is often limited, with Suleja Local Government, Niger State, North Central Nigeria, being understudied. Methodological constraints, such as reliance on specific datasets and parameters, may overlook relevant factors influencing flood vulnerability. Additionally, the lack of long-term data and insufficient stakeholder engagement hinder accurate flood risk predictions and effective mitigation strategies. Furthermore, integrating research findings with existing frameworks and policies, addressing uncertainty in bias-adjusted satellite data, and ensuring scalability and transferability to other regions remain unexplored. Bridging these gaps is crucial for developing robust, data-driven flood mitigation strategies to protect vulnerable communities and infrastructure.

The aim of this study is to develop a GIS-based characterization of metropolitan flood risk and control in Suleja Local Government, Niger State, North Central Nigeria. This research seeks to harness the potential of Geographic Information System (GIS), Remote Sensing, and Fuzzy Logic System to mitigate the effects of climate change. The primary objectives of this study are to integrate satellite and GIS datasets, rainfall data, and physical catchment parameters to prepare Suleja's Flood Zonation Mapping. Additionally, the study aims to identify flood vulnerability zones and categorize the area into five flood risk zones: Very Low Risk, Low Risk, Medium Risk, High Risk, and Very High Risk. Ultimately, this research aims to contribute to the development of data-driven flood mitigation strategies for vulnerable regions like Suleja. By providing policymakers and stakeholders with informed decision-making tools, this study seeks to protect communities and infrastructure from flood risks, promoting resilient and sustainable urban environments.

2.0 Materials And Methods

2.1 Study location/Area

The study area, Suleja, is located in North Central Nigeria, spanning a geographical area of 136.33 km² within Latitude 9º10'15" - 9º12′1.17″N and Longitude 7º10′20.25″ - 7º11′40.05″E. With a population of 216,578 (NPC, 2006), Suleja's geological landscape is characterized by gentle rocks and soils derived from sandstone formations. The region's pedological features reveal deep, red soils enriched with clay sub-soil (Umar *et al*., 2019; Aminu *et al*., 2019; Atemoagbo, 2024). Climatologically, Suleja experiences a tropical climate, marked by an average annual temperature of 26.3 °C and average annual rainfall of 1405 mm (Aminu *et al*., 2013; Atemoagbo, 2024). Understanding Suleja's geographical, geological, and climatological characteristics is crucial for assessing its flood vulnerability and developing effective mitigation strategies.

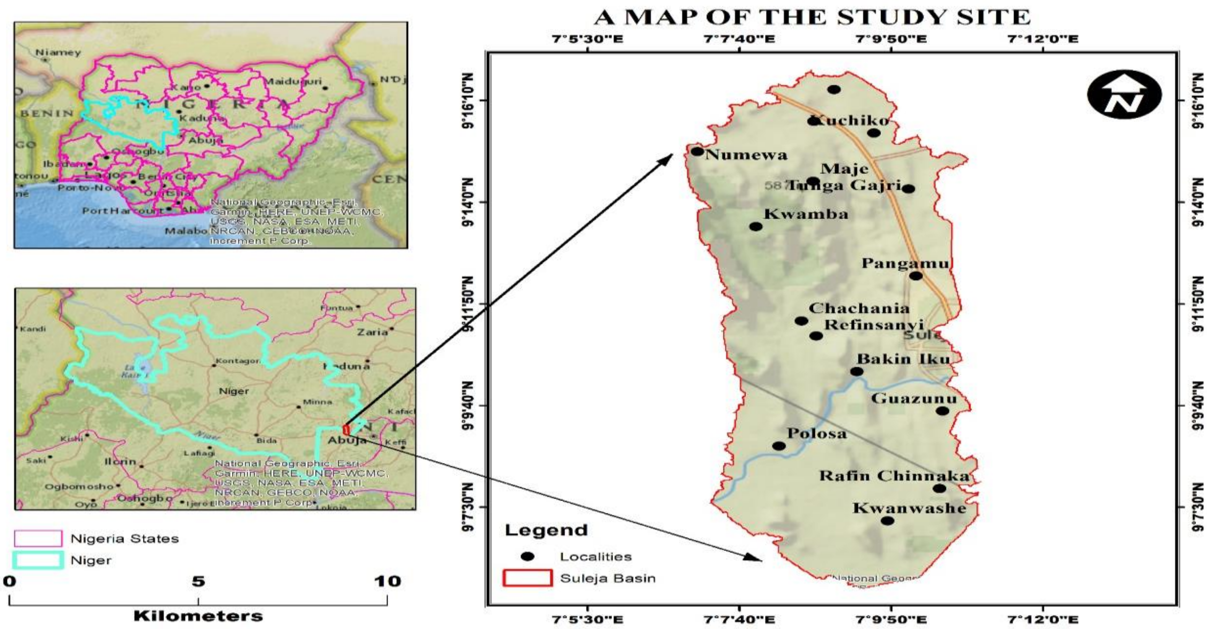


Figure 3. 1: Map of Nigeria showing Suleja LGA (the study area)
Source: Atemoagbo *et al*. (2024)

2.2. Data Collection and Management

This study utilized various datasets spanning 36 years (1988-2023) to characterize metropolitan flood risk in Suleja, Nigeria. Rainfall data were obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Global Satellite Mapping of Precipitation (GSMaP), and Nigerian Meteorological Agency (NIMET). Additionally, topographic data were derived from Digital Elevation Model (DEM) sources, including discharge, slope, elevation, drainage density, environmental vulnerability, and closeness to water body. The research integrated Remote Sensing, GIS, and Fuzzy Logic approaches, involving data preprocessing, GIS analysis, fuzzy logic application, data integration, weighted sum overlay technique, and analytic hierarchy process (AHP) to assign weights to flood-conditioning factors and quantify their relative importance in flood risk assessment, ultimately developing a comprehensive flood risk map.

This study builds upon previous research in vulnerability assessment and flood risk mapping, leveraging Geographic Information Systems (GIS), Remote Sensing, and Fuzzy Logic. Notable precedents include Adger *et al*. (2005), Cutter *et al*. (2003), and (Foy, 2013), who utilized GIS and Remote Sensing to examine climate change vulnerability, develop spatial vulnerability indices, and analyze environmental vulnerability. Similarly, Karagiorgos *et al*. (2016), Birkmann *et al*. (2013) and Atemoagbo, (2024) demonstrated spatial analysis' effectiveness in identifying vulnerable areas. Furthermore, this study's fuzzy logic application aligns with (Swain *et al*., 2020) and (Ouma & Tateishi, 2014), who applied fuzzy logic to determine flood vulnerability and integrate it with GIS for flood risk mapping.

2.3 Development of Digital Elevation Models

The study employed Geographic Information System (GIS) and remote sensing techniques to analyze catchment parameters and vulnerability. Digital Elevation Model (DEM) data was obtained from USGS Earth (SRTM 30m DEM), while polygon datasets were converted to raster for analysis. ArcGIS software and Hydrologic Engineering Center-Hydrological Modeling System (HEC-HMS) were utilized for spatial analysis and DEM preprocessing.

Catchment parameters, including slope, drainage density, elevation, land use/land cover, environmental vulnerability, and nearness to water bodies, were mapped using ArcGIS. Spectral classes were defined through clustering image data, and pixels were assigned to respective classes. Regions of Interest (ROI) were defined to extract statistics for classification. DEM preprocessing and hydrological analysis identified streams and basins.

A suitability model identified vulnerable areas based on criteria such as soil infiltration rates, water table depth, and land use. An environmental justice index was integrated into the map to assess equity. A spatial vulnerability index (SVI) and constituent indices (exposure, sensitivity, and adaptive capacity) were developed using a spatial index approach. Finally, a vulnerability map was generated for the study location, highlighting hotspots and areas of concern.

The integration of GIS, remote sensing, and spatial analysis for vulnerability assessment has been successfully applied by various researchers. For instance, Adger *et al*. (2005) utilized GIS to examine vulnerability to climate change, while Cutter *et al*. (2003) developed a spatial vulnerability index to assess hazards. Similarly, Melody and Johnston (2015) employed remote sensing and GIS to analyze environmental vulnerability. Other studies, such as those by (Change, 2023) and Birkmann *et al*. (2013), demonstrated the effectiveness of spatial analysis in identifying vulnerable areas. These studies demonstrate the reliability and efficacy of the approach used in this research.

2.3 Flow Characterization and Fuzzy Logic Implementation

The datasets were characterized using a flow categorization system, comprising five distinct conditions: Very Low, Low, Medium, High, and Very High. This categorization enabled the development of a robust decision support system. To facilitate high-level decision-making, a Fuzzy Logic System (FLS) was employed, leveraging the Fuzzy Inference System (FIS) to represent vague and imprecise knowledge.

The FLS converted input values into fuzzy terms, which were then evaluated by the fuzzy engine using predefined fuzzy rules. This process formed the basis of the decision support system. Output aggregation was performed to simplify fuzzy subsets for each output variable. Subsequently, defuzzifiers translated the output values into crisp, understandable values for end-users. This integrated approach enabled effective decision-making and risk assessment, providing valuable insights for engineering applications.

This approach aligns with previous research by Swain *et al*. (2020) and (Yalcin *et al*., 2011), who successfully applied fuzzy logic to determine flood vulnerability and integrate it with GIS for flood risk mapping. The study's integrated approach enabled effective decision-making and risk assessment, providing valuable insights for engineering applications.

2.4 Selection of membership function and fuzzification of antecedent and precedent variables

The fuzzy membership rule employed in this study leverages the Gaussian membership function, which assigns related members to the same set or group. This approach facilitates the translation of crisp input values into linguistic variables.

The fuzzification process is mathematically represented as:

$$A = \mu 1(Q1)x1 + \mu 2(Q2)x2 + \ldots + \mu n(Qn)xn \qquad 1$$

where Q(xi) represents the kernel of fuzzification, and μi is kept constant while xi is transformed into a fuzzy set Q(xi).

Defuzzification reduces the fuzzy set to a crisp set and converts fuzzy members to crisp members. The Gaussian membership method is utilized for defuzzification, expressed as:

$$x = \Sigma\, [x\bar{\imath}(i/n)] \qquad 2$$

This equation enables the calculation of the crisp output value.

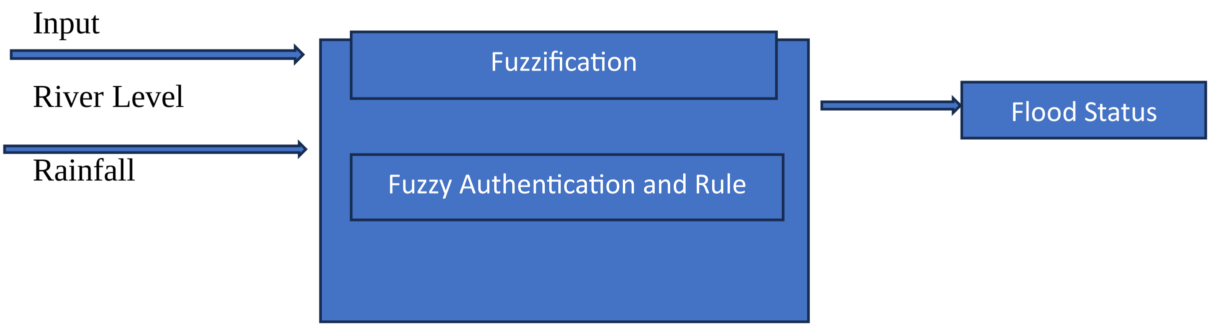


Figure 3. 1: Fuzzy Control

2.5 Risk Modelling

This study employed fuzzy logic techniques for risk modelling, leveraging membership functions to represent uncertainty in the data. Gaussian membership functions were utilized for fuzzification, enabling handling of uncertainty levels: very low, low, medium, high, and very high. A rule-based system was developed, integrating expertise and data-driven insights, with triangular and trapezoidal membership functions defined for input variables and Gaussian membership functions for output variables. Gaussian defuzzification methods converted fuzzy outputs into crisp values for precise risk assessment. Integrated with spatial analysis, the fuzzy logic framework considered factors such as slope, drainage density, elevation, land use/land cover, and environmental vulnerability. Data preprocessing involved normalizing and standardizing input data, with ArcGIS and MATLAB used for spatial analysis, fuzzy logic implementation, and data processing.

3.0 Result And Discussion

3.1 Spatial Variability of Environmental Risk Factors

The results presented in Table 1 reveal significant spatial variability in environmental risk factors across the study area. The slope, drainage density, distance to water, elevation, land cover, and environmental vulnerability indices exhibit diverse patterns, influencing the overall risk category.

Table 4. 1: Summary of data form digital elevation model for the catchment area

Commu Name	slope	Drain Density	Dist to Water	Elevation	Land Cover	Envirn Vul	Risk Category
Kuchiko Tuluk	0.941	0	0.351	0.363	0.375	0.333	low
Chachania	0.871	0.485	0.975	0.886	0.375	0.801	high
Guazunu	0.939	0.174	0.937	0.449	0.25	0.666	high
Bakin Iku	0.875	0	0.921	0.775	0.375	0.674	high
Maje	0.923	0	0.827	0.289	0.375	0.558	Moderate
Refinsanyi	0.948	0.122	0.966	0.883	0.5	0.748	high
Rafin Chinnaka	0.665	0	0.772	0.279	0.375	0.506	Moderate
Pangamu	0.939	0	0.833	0.42	0.25	0.568	Moderate
Tunga Gajri	0.801	0.103	0.929	0.273	0.375	0.62	Moderate
Numewa	0.9	0	0.893	0.528	0.375	0.63	Moderate
Kwanwashe	0.882	0	0.75	0.693	0.5	0.587	Moderate
Kuchiko	0.92	0	0.689	0.287	0.375	0.498	low
Numbwa Tukura	0.904	0	0.636	0.308	0.375	0.466	low
Paulosa	0.984	0	0.906	0.953	0.5	0.71	high
Kwamba	0.945	0	0.856	0.471	0.125	0.571	Moderate

3.1 Slope and Elevation

The study area exhibits notable variability in slope and elevation as shown in figure 1a and 1b, critical factors influencing environmental risk. Slope values range from 0.665 (Rafin Chinnaka) to 0.984 (Paulosa), indicating significant differences in terrain steepness. This variability impacts surface runoff, erosion, and landslide susceptibility. The slope values can be categorized into three groups: gentle slopes (0.665-0.8), moderate slopes (0.8-0.95), and steep slopes (0.95-0.984). Steeper slopes, such as those found in Paulosa, Guazunu, and Refinsanyi, increase the risk of landslides, erosion, and surface runoff. Conversely, gentler slopes, like those in Rafin Chinnaka and Tunga Gajri, reduce these risks. The combined effects of slope and elevation variability significantly contribute to the environmental risk category.

The findings of this study align with previous research highlighting the significance of slope and elevation variability in environmental risk assessment (Burroughs, 1986). Specifically, the categorization of slope values into gentle, moderate, and steep slopes corroborates (Xiong *et al*., 2021) and (Fick & Hijmans, 2017) work on landslide susceptibility. Similar studies have emphasized terrain factors' role in surface runoff and erosion (Boardman *et al*., 2003), with (Pham *et al*., 2020) and (Giordan *et al*., 2020) demonstrating the increased risk of landslides and erosion on steeper slopes. This study's focus on the combined effects of slope and elevation variability on environmental risk category contributes a unique perspective to the existing literature, reinforcing the importance of considering terrain factors in environmental risk assessments.

3.2 Drainage Density and Distance to Water

The study area exhibits significant variability in hydrological characteristics, specifically drainage density and distance to water bodies as shown in figure 1a and 1b. These factors play a crucial role in determining water flow, accumulation, and flood susceptibility. Drainage density values in the study area range from 0 (Kuchiko Tuluk, Bakin Iku, Maje, and others) to 0.485 (Chachania), indicating substantial differences in water flow and drainage efficiency. This variability significantly impacts flood risk, with areas like Chachania experiencing increased water flow velocity, higher runoff potential, and elevated flood risk due to their high drainage density values. In contrast, areas with zero drainage density values, such as Kuchiko Tuluk and Bakin Iku, exhibit reduced water flow velocity, lower runoff potential, and decreased flood risk. This highlights the importance of drainage density in determining flood susceptibility. The distance to water bodies is another critical factor, ranging from 0 (Kuchiko Tuluk, Bakin Iku, and others) to 0.975 (Chachania). Proximity to water bodies increases the risk of flooding due to overflow or storm surges, soil saturation and erosion, and waterborne disease transmission. Conversely, areas far from water bodies are less susceptible to these risks.

The findings of this study align with previous research highlighting the significance of drainage density and distance to water bodies in determining flood susceptibility (Weiss *et al*., 2020; Böhm *et al*., 2015; Khailani & Perera, 2013), reinforcing the importance of hydrological characteristics in flood risk assessment.

3.3 Land Cover and Environmental Vulnerability

The analysis of land cover values reveals a surprisingly narrow range of 0.25-0.5, suggesting relatively homogeneous land use patterns across the study area as shown in figure 1d This uniformity implies that the region's land use characteristics, such as agricultural practices, urbanization, and forest cover, are fairly consistent. However, this homogeneity may mask underlying variations in environmental vulnerability, emphasizing the need for a more nuanced assessment.

Upon closer examination, the environmental vulnerability indices exhibit significant variability, ranging from 0.279 to 0.966. This substantial range underscores the diversity of environmental factors at play, including soil quality, vegetation cover, topography, and hydrological conditions. For instance, areas with high environmental vulnerability indices, such as Guazunu and Refinsanyi, may be more susceptible to soil erosion, landslides, and water pollution due to poor soil quality and vegetation cover. In contrast, areas with lower environmental vulnerability indices, such as Kuchiko Tuluk and Numbwa Tukura, may exhibit more resilient environmental conditions, characterized by better soil quality, denser vegetation, and reduced erosion risk. The marked variability in environmental vulnerability indices highlights the importance of site-specific assessments and targeted interventions to mitigate environmental risks

The observed variability in environmental vulnerability indices aligns with previous research highlighting the significance of site-specific factors such as soil quality, vegetation cover, topography, and hydrological conditions in determining environmental vulnerability (Deepak *et al*., 2020; Gorsevski *et al*., 2012), emphasizing the need for localized assessments and targeted interventions.

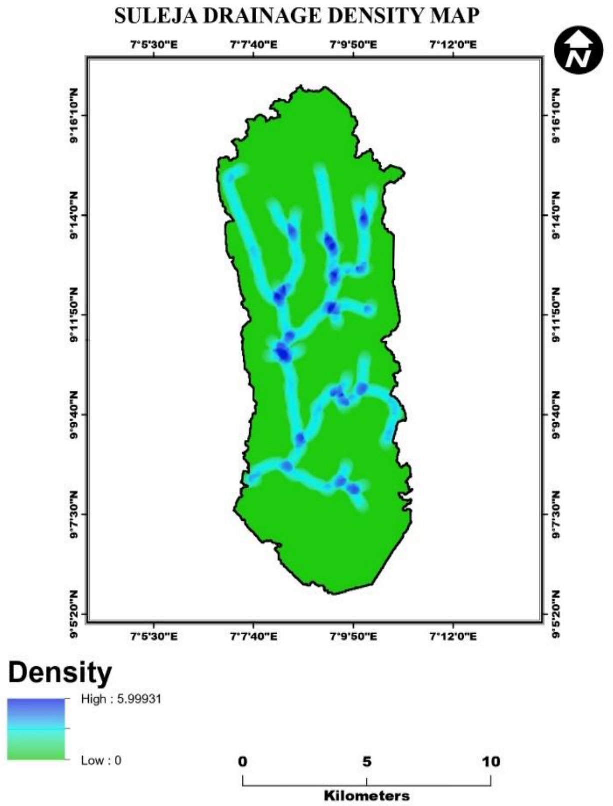
3.2 Risk Category

The risk category classification reveals a stark contrast in vulnerability among the communities studied. Notably, seven communities - Chachania, Guazunu, Bakin Iku, Refinsanyi, Paulosa, Kwamba, and Rafin Chinnaka - are categorized as high-risk. This classification indicates that these communities are more susceptible to environmental hazards, such as flooding, landslides, and soil erosion, due to their geographical location, land use patterns, and environmental characteristics. In contrast, five communities -

Maje, Pangamu, Tunga Gajri, Numewa, and Kwanwashe - are classified as moderate-risk. These communities face some level of environmental vulnerability, but their risk profile is less severe compared to the high-risk communities. Factors such as land cover, topography, and drainage patterns may contribute to their moderate risk classification.

On the other end of the spectrum, three communities - Kuchiko Tuluk, Numbwa Tukura, and Kuchiko - are categorized as low-risk. These communities exhibit relatively resilient environmental conditions, characterized by stable terrain, adequate drainage, and minimal land degradation. Their low-risk classification suggests that they are better equipped to withstand environmental stresses and hazards. The disparate risk classifications among the communities underscore the importance of targeted interventions and localized strategies for environmental management and risk mitigation

a



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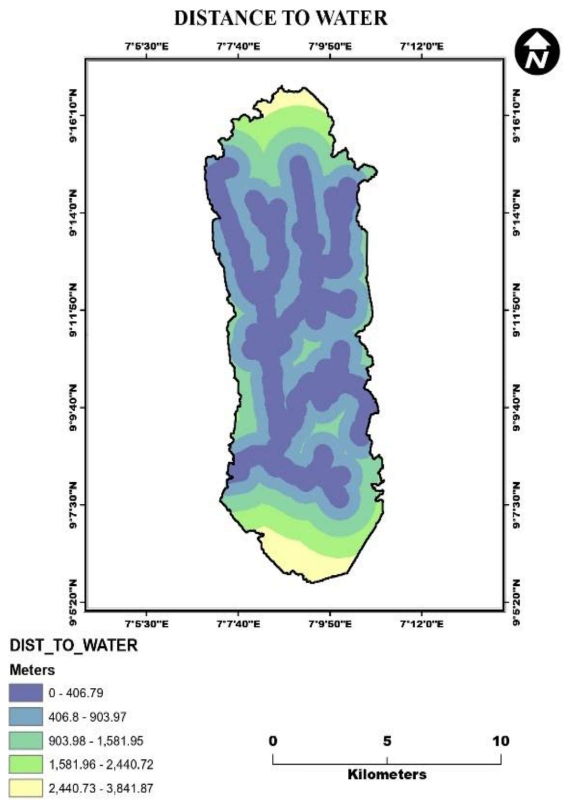

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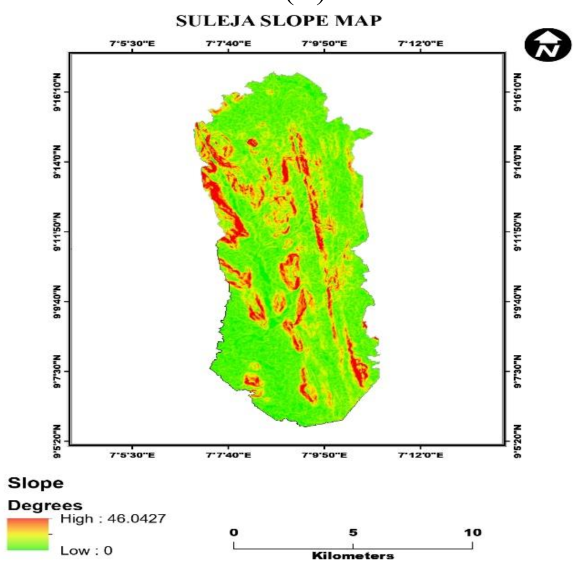

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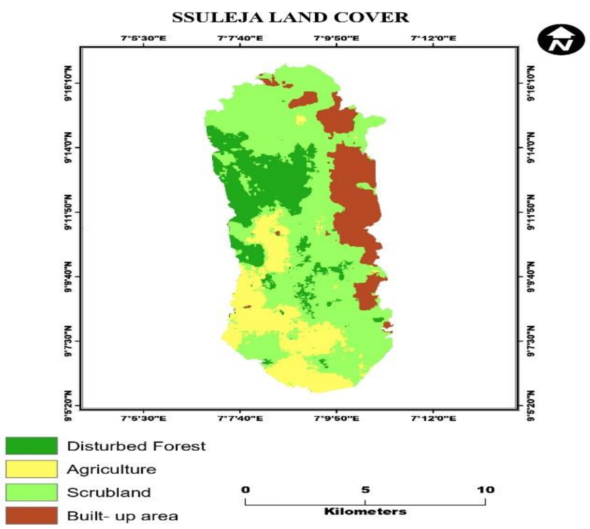

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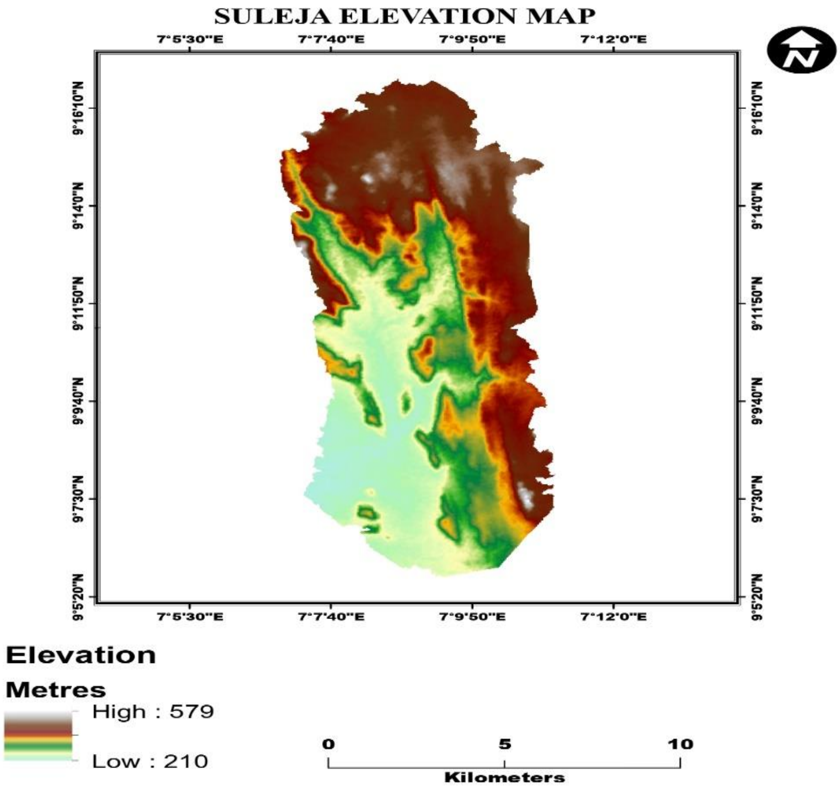

Figure 1: (a) Drainage density (b) Distance to Water (c) slope (d) Land Use Land Cover (e) Elevation Map

3.4 Flood risk prediction

The study area's flood risk distribution is depicted in Figure 2, revealing varied levels of vulnerability. Kuchiko Tuluk, Kuchiko, and Numbwa are classified as low-risk areas, characterized by stable terrain and minimal flood susceptibility. In contrast, Maje, Chinnaka, Pangamu, Tunga Gajri, Numewa, and Kwanwashe are categorized as moderate-risk areas. These areas exhibit some level of flood vulnerability due to factors such as land use patterns, drainage density, and topography. Chachania, Guazunu, Bakin Iku, Refinsanyi, and Paulosa are identified as high-risk areas, accounting for 7.1% of the total risk. Urban Sprawl, proximity to water bodies, high rainfall intensity, and steep slopes contribute to their increased flood vulnerability.

According to Table 4.5, the risk categorization with percentage contributions for 1986-2022 shows: Very Low Risk (40.9%), Low Risk (18.9%), Medium Risk (27.6%), High Risk (7.1%), and Very High Risk (5.5%). These predictions inform targeted interventions and flood mitigation strategies. The flood risk percentage contribution analysis, presented in Table 2, reveals a significant variation in flood risk across five categories: Very Low, Low, Medium, High, and Very High. The results show that 40.9% of the study area falls under the Very Low Risk category, indicating minimal flood susceptibility. The Medium Risk category accounts for 27.6% of the study area, followed by the Low Risk category at 18.9%. In contrast, the High and Very High Risk categories contribute 7.1% and 5.5%, respectively, to the overall flood risk. These areas require immediate attention and targeted interventions to mitigate flood risk. The High Risk areas are likely characterized by factors such as proximity to water bodies, steep slopes, poor drainage, and high population density. Understanding the spatial distribution of flood risk enables policymakers, engineers, and stakeholders to develop targeted interventions, prioritize resource allocation, and implement effective flood control measures.

The flood risk categorization and percentage contributions observed in this study align with previous research findings on flood risk assessment and spatial distribution (Wang *et al*., 2018; Di Baldassarre *et al*., 2014), highlighting the importance of targeted interventions and flood mitigation strategies.

Table 2: Flood risk percentage contribution by the model

Categorization	Percentage Contribution
Very Low Risk	40.9
Low Risk	18.9
Medium	27.6
High	7.1
Very High	5.5

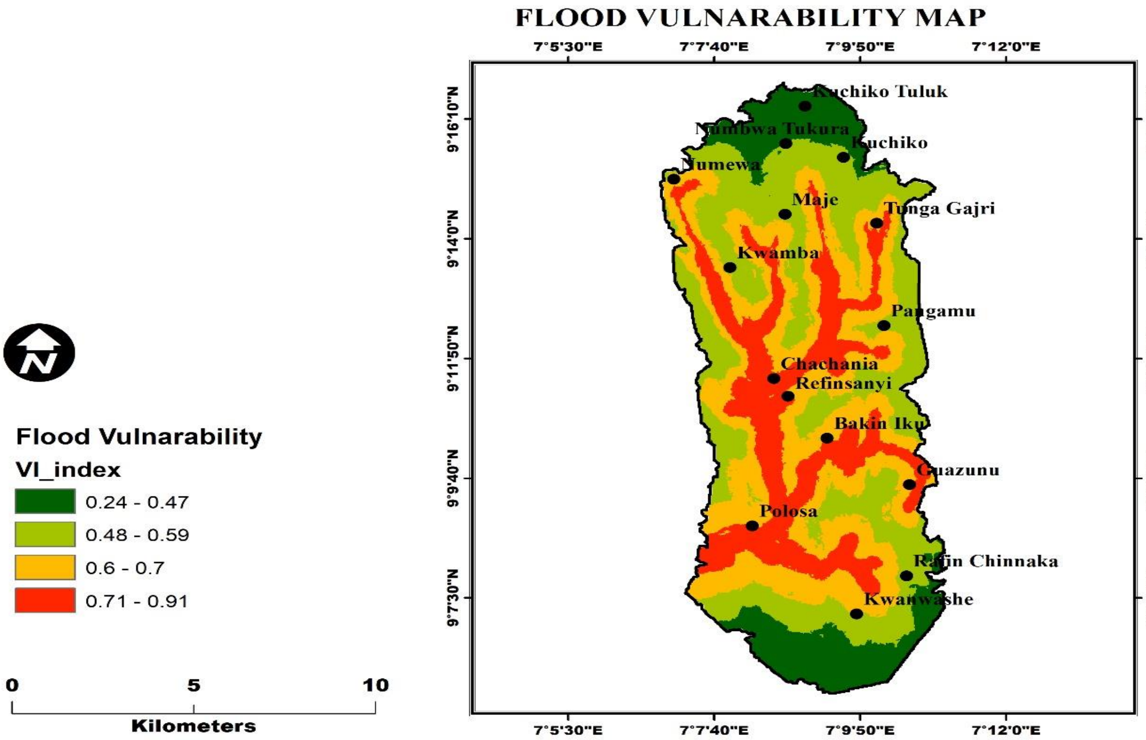

Figure 2: Flood Vulnerability map with location

4.0 Conclusion And Recommendation

4.1 Conclusion

This study underscores the critical role of integrating Geographic Information System (GIS), Remote Sensing, and Fuzzy Logic System in mapping flood vulnerability zones, particularly in regions susceptible to climate change impacts. The research focuses on Suleja Local Government, Niger State, North Central Nigeria, where flood vulnerability zones were categorized into five risk levels: Very Low Risk (40.9%), Low Risk (18.9%), Medium Risk (27.6%), High Risk (7.1%), and Very High Risk (5.5%).

The findings emphasize the importance of considering hydro-climatic and physical catchment parameters, such as Slope, Elevation, Nearness to Water Bodies, Land Use Land Cover, and Drainage Density, in flood vulnerability assessments. Leveraging bias-adjusted satellite data from Nigeria Meteorological Agency (NiMET), Climate Hazards Group InfraRed Precipitation with Station Data (CHRPS), and Global Satellite Mapping of Precipitation (GSMaP) helps minimize uncertainty in flood risk quantification.

Effective flood management requires a robust control framework established through quantifying risk, susceptibility, and hazard components. This research contributes to the development of data-driven flood mitigation strategies in vulnerable regions, enabling policymakers and stakeholders to make informed decisions protecting communities and infrastructure from flood risks.

4.2 Recommendation

Based on the findings; the following recommendation is/are made

a. Integrate Geographic Information System (GIS), Remote Sensing, and Fuzzy Logic System to identify flood vulnerability zones.
b. Utilize hydro-climatic data from reputable sources (e.g., NiMET, CHRPS, GSMaP) and physical catchment parameters (Slope, Elevation, Nearness to Water Bodies, Land Use Land Cover, Drainage Density) for flood risk assessment.
c. Develop and implement data-driven flood mitigation strategies in vulnerable regions.
d. Establish a robust control framework for effective flood management.
e. Conduct regular updates and refinement of flood vulnerability maps to ensure accurate and informed decision-making.

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