

Geospatial Assessment of Flood Susceptibility (Using Saaty AHP and Fuzzy-AHP Techniques) in Mokwa Area of Niger State, Nigeria

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Abstract: This study provides a comprehensive geospatial assessment of flood susceptibility using Analytical Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (F-AHP) techniques in Mokwa area of Niger State, Nigeria. Flooding has become a recurring environmental hazard in the area, resulting in significant socio-economic and infrastructural losses. To address this challenge, a multi-criteria decision-making approach integrated with Geographic Information Systems (GIS) and remote sensing data were used to carry out the research study. Nine flood conditioning factors were considered, including elevation, slope, rainfall, drainage density, land use/land cover, soil type, distance to river, TWI and sentinel 1 (Synthetic Aperture Radar). Spatial datasets were processed and standardized, and weights were assigned to each factor using both the Analytical Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (F-AHP) methods. The results reveal noticeable variations in the classification of susceptibility zones between the two models. Specifically, the area categorized under very low flood susceptibility is estimated at 17.1 km² for Analytical Hierarchy Process (AHP) and slightly higher at 17.4 km² for F-AHP. In contrast, the very high susceptibility zones show a more pronounced difference, with Analytical Hierarchy Process (AHP) identifying 310.4 km², while Fuzzy Analytical Hierarchy Process (F-AHP) delineates a significantly larger area of 380.1 km² (Table 4.11). Furthermore, the consistency ratio (CR) values obtained from both models demonstrate acceptable levels of judgment consistency, as they fall within the threshold of 10% acceptance level. The Analytical Hierarchy Process (AHP) model produced a CR of 5%, while the Fuzzy Analytical Hierarchy Process (F-AHP) model yielded a slightly lower CR of 4.3%.

Keywords: Flooding, Soil erosion, GIS and Remote sensing, Analytical Hierarchy Process, Pairwise matrix, Mokwa.

I. INTRODUCTION

Flooding is one of the most frequent and devastating natural disasters affecting human societies worldwide, causing significant loss of lives, livelihoods, infrastructure, and ecosystems. Globally, floods account for nearly 40% of all natural disasters, with their frequency and magnitude increasing due to climate change, rapid urbanization, and poor land management practices (Gupta & Nair, 2019). In developing nations, especially those in sub-Saharan Africa, floods are more catastrophic due to inadequate spatial planning, poor drainage infrastructure and limited disaster preparedness. Nigeria is particularly vulnerable to recurring flood events, which have intensified in recent years as a result of erratic rainfall patterns, river overflow, and unregulated land use (Adelekan, 2016). Nigeria is particularly vulnerable to recurring flood events,

which have intensified in recent years as a result of erratic rainfall patterns, river overflow and unregulated land use (NEMA, 2022).

Flood disasters in Nigeria have resulted in massive socio-economic losses, environmental degradation and displacement of communities, particularly in states along the Niger and Benue River basins. Niger State, located in north-central Nigeria, is one of the states most frequently affected by flood hazards due to its extensive river networks, including the River Niger and its tributaries (Ibrahim *et al.*, 2020). Mokwa Local Government Area, a prominent agrarian community within Niger State, lies along the floodplains of the River Niger and experiences annual flooding that disrupts agriculture, damages infrastructure and threatens human lives and properties. The area's low-lying floodplains, poor natural drainage systems, and gentle slopes

facilitate the accumulation of runoff water. In addition, the soil characteristics, particularly the presence of clayey and lateritic soils with low permeability, restrict water infiltration and enhance surface flow while dams such as Kainji and Jebba were constructed to provide hydropower and enhance water management; their operations have inadvertently contributed to seasonal flooding in Mokwa Local government area. This occurs primarily through excess water releases, altered flow regimes, and insufficient communication mechanisms.

Recent advancements in geospatial technologies such as remote sensing (RS) and geographic information systems (GIS) have revolutionized flood risk mapping and assessment. These technologies enable the integration of spatial and environmental variables such as elevation, slope, land use, soil type, drainage density, rainfall, and proximity to rivers to determine flood susceptibility zones (Kazakis *et al.*, 2015). Meanwhile, GIS-based flood susceptibility mapping allows researchers and decision-makers to visualize spatial variations in flood risk and make data-driven decisions for land-use planning and disaster management.

However, integrating and weighting these diverse flood conditioning factors requires a systematic multi-criteria decision-making (MCDM) approach. The Analytical Hierarchy Process (AHP), developed by Saaty (1980), provides a robust MCDM framework that allows the comparison and ranking of multiple factors according to their relative importance in contributing to flood occurrence the Analytical Hierarchy Process (AHP) uses a pairwise comparison matrix and consistency ratio to ensure logical and objective weighting of flood-influencing variables. When combined with GIS, the Analytical Hierarchy Process (AHP) enables the generation of spatially explicit flood susceptibility maps that delineate areas with varying degrees of flood risk (Nwilo *et al.*, 2021).

II. MATERIALS AND METHODS

2.1 Study Area

Mokwa Local Government Area (LGA) is one of the twenty-five administrative regions in Niger State, located in the North-central geopolitical zone of Nigeria. It lies approximately between latitudes 9°12' 23''N and 9°55'43''N and longitudes 4°30'12''E and 5°05'15''E. The area covers an estimated landmass of about 4,338 square kilometers, making it one of the largest local governments in the state in terms of spatial extent. However, Mokwa is home to 340,345 people with large population of women and children (NPC, 2006). Mokwa serves

as a significant agricultural and commercial hub, strategically positioned along the major Lokoja–Kaduna and Bida–New Bussa highways, which facilitate trade and communication within the region and beyond (Niger State Bureau of Statistics, 2021). Mokwa LGA shares boundaries with Lapai LGA to the east, Katcha LGA to the northeast, Lavun LGA to the north, and Mashegu LGA to the northwest.

2.2 Topography and Drainage

The topography of Mokwa LGA is generally undulating to gently sloping, with elevations ranging between 120 m and 260 m above sea level. The terrain slopes gradually toward the River Niger, forming extensive floodplains and alluvial valleys. These floodplains serve as fertile grounds for agriculture but also make the area highly susceptible to flooding during periods of intense rainfall or water release from upstream dams such as Kainji and Jebba. The drainage pattern is mainly dendritic, reflecting the natural flow of numerous streams and seasonal rivers that discharge into the River Niger (Ibrahim *et al.*, 2020).

Mokwa experiences a tropical continental climate, characterized by distinct wet and dry seasons. The wet season usually spans from May to October, while the dry season extends from November to April. Annual rainfall ranges between 1,100 mm and 1,400 mm, with August and September being the peak months (NIMET, 2022). The mean annual temperature varies between 26°C and 34°C, and relative humidity is typically higher during the wet season. The region occasionally experiences heavy downpours, which contribute to seasonal flooding, particularly in low-lying areas adjacent to the Niger River.

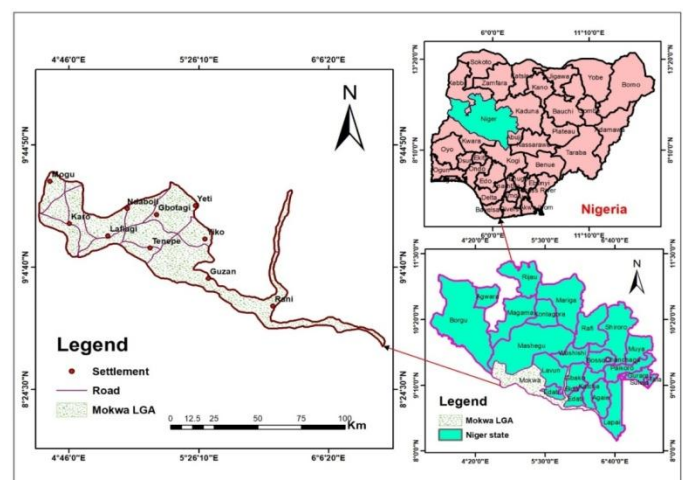


Figure 2.1: The study area map

2.3 Literature Review

Below is the review of existing studies on flood related mapping and susceptibility across the world. However, Flooding remains one of the most devastating natural hazards globally, particularly in developing countries where rapid urbanization and poor drainage systems increase vulnerability. Over the past two decades, researchers have increasingly employed geospatial technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) to map and assess flood susceptibility zones with improved accuracy and efficiency (Musa *et al.*, (2020)

Several studies have demonstrated the effectiveness of GIS-based multi-criteria analysis (MCA) and the Analytical Hierarchy Process (AHP) in flood risk assessment. For instance, Tehrani *et al.* (2014) used analytical hierarchy process (AHP) in GIS to assess flood susceptibility mapping in Malaysia and the study used slope, rainfall, land use, and proximity to rivers as critical factors influencing flood occurrence in the study area. However, the study did not consider historical flood data to validate the research work.

Similarly, Kazakis *et al.* (2015) conducted a study in Greece using weighted overlay analysis to identify flood-prone areas. The study showed a strong correlation between the predicted and actual flood zones after been validated with historical flood data. However, the study did not incorporate socio-economic factors that could influence flood vulnerability. Muhammad *et al.* (2015) conducted a flood hazard mapping study in Kencong District, Indonesia by integrating the Analytical Hierarchy Process (AHP) with Geographic Information Systems (GIS). The research categorized flood-prone zones into five classes: deficient (0.02%), low (4.26%), medium (37.11%), high (51.89%), and very high (6.72%). The findings revealed that the most influential factors contributing to flood susceptibility were proximity to rivers, slope gradient, and the topographic wetness index (TWI). Although the model achieved an 86% validation accuracy but the study did not incorporate socio-economic variables, which could have provided a more comprehensive understanding of flood vulnerability. Meanwhile, Basil *et al.* (2024) assessed flash flood hazard mapping using Analytical Hierarchy Process (AHP) and GIS Application in Barzan Area of Iraqi Kurdistan Region. The study used ten parameters such as Topographic Wetness Index (TWI), Elevation (E), Slope (S), Precipitation (P), Land Use Land Cover (LULC), Normalized Difference Vegetation Index

(NDVI), Distance from River (D1), Distance from Road (D2), Density of Drainage (D3), with type of Soil (S). The findings revealed that the very high and high flood susceptibility are predominantly located in the central, southeastern, and southwestern parts with a smaller area in the northwest. Nevertheless, the study did not any high-resolution imageries for the validation.

III. METHODOLOGY

3.1 Data Acquisition Procedure

The data procedure adopted for this study involved a systematic integration of remote sensing, geospatial, and multi-criteria analytical techniques to evaluate flood susceptibility mapping within Mokwa Local Government Area (LGA) of Niger State. The procedure was designed to ensure that all datasets were accurately acquired, processed, analysed and integrated to produce a reliable flood susceptibility map. However, Preprocessing was conducted to enhance data quality and ensure uniformity across all datasets. Satellite images were atmospherically corrected, subset to the study area boundary and resampled to a common spatial resolution of 30 meters. Cloud masking and noise reduction techniques were applied to remove atmospheric interference from optical images. The SRTM DEM was corrected for sinks and depressions to produce a hydrologically conditioned surface. Sentinel-1 SAR data were pre-processed using radiometric calibration, speckle filtering, terrain correction, and thresholding to delineate inundated areas accurately.

All spatial datasets were reprojected to a uniform coordinate reference system (WGS 84, UTM Zone 32N) to ensure spatial consistency during overlay analysis.

3.2 Data Sources

Flood susceptibility mapping relies heavily on the integration of diverse geospatial and environmental datasets to accurately identify areas prone to flooding. In a flood-prone region such as Mokwa in Niger State, Nigeria, the selection of appropriate data sources is crucial for producing reliable and scientifically sound susceptibility maps. These data sources are typically derived from remote sensing platforms, field observations, and existing geospatial databases, all of which contribute to understanding the physical and environmental factors influencing flood occurrence.

Table 3.1: Summary of Data Sources

S/N	Type	Sources	Resolutions
1	Landsat 9 (OLI-2) and land 7 (ETM+)	USGs	30m
2	SRTM(DEM)	USGs	30m
3	CHIRPS	CHC	0.05 degree
4	Sentinel 1(SAR)	(ESA)	5M
5	Soil data	FAO	-----
6	NIMET	NIMET Office	-----
7	Field Data (Interview)	Field	-----

(Source: Author's Compilation)

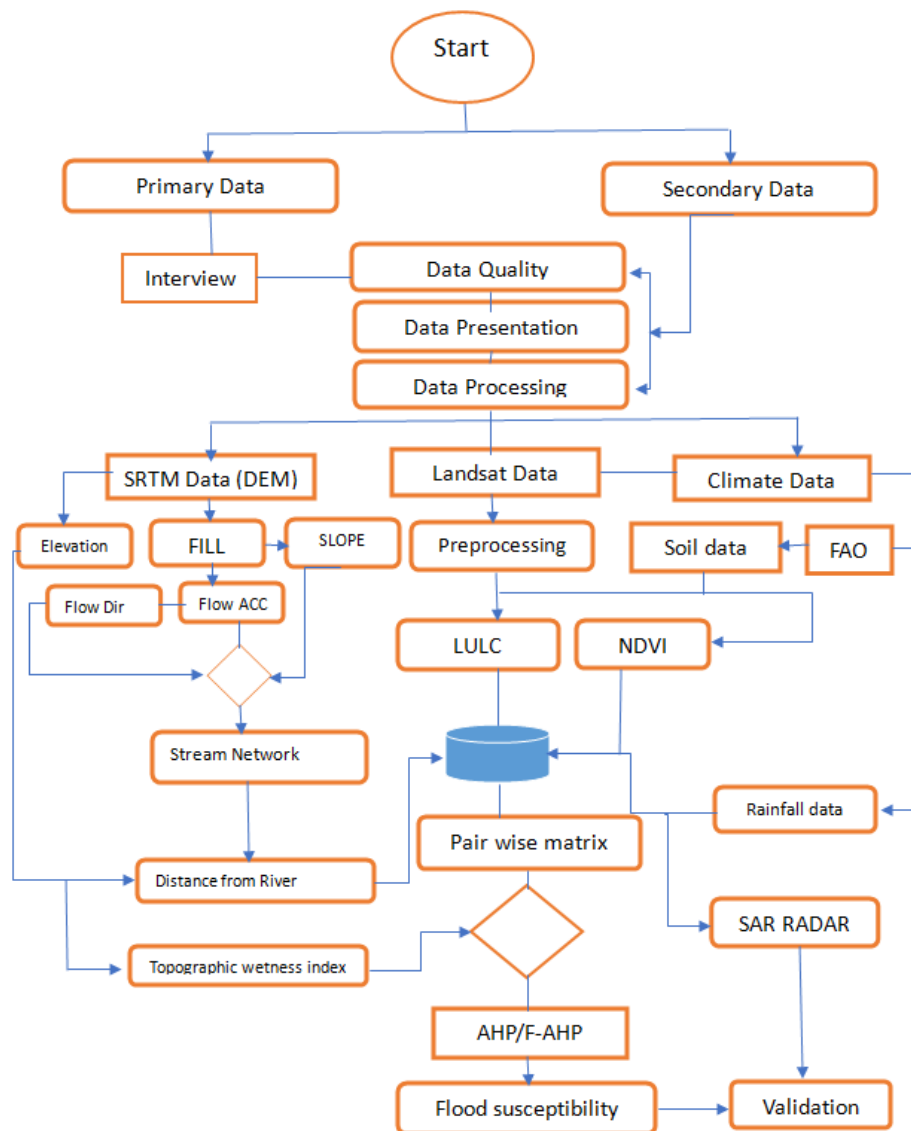


Figure 3.1: Methodology workflow

IV. RESULTS AND DISCUSSION

4.1 Flood Conditioning factors Influencing the Terrain within the study area

Flood conditioning factors for mapping flood susceptibility of the study area through a geospatial technique by Saaty Thomas L. (1980) and Chang 1996. Table 4.1 and Figure 4.1 showed the stream order by Strahler (1957) and their attributes. The River Niger has two hundred and eighty (280) tributaries ranging from order 1 to order 4, with order 1 covered a total area of 582.23 km², order 2 covered 221.48 km², order 3 covered 109.08 km² and order 4 covered 42.98 km² respectively.

Table 4.1: Stream Order and Length of River Tributaries in square kilometers of the study area

S/No	Stream order	River tributaries	Length (km ²)
1	Order 1	157	582.23
2	Order 2	75	221.48
3	Order 3	41	109.08
4	Order 4	7	42.98
Total		280	955.77

(Source: Author's Compilation)

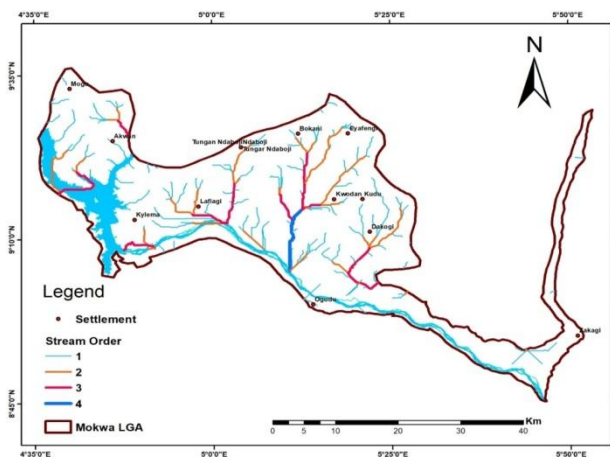


Figure 4.1: River Network and Stream Order Delineation Map of the study area using Strahler

(Source: Author's Compilation)

Figure 4.2 and Figure 4.3 showed bar chart of the stream order and fill elevation of the study area, highlighting the proportional dominance of lower-order streams and their contribution to surface runoff processes.

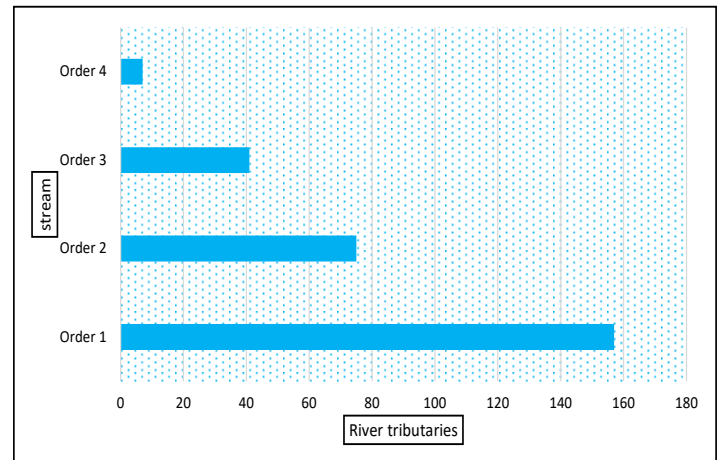


Figure 4.2: Bar chart of Stream Order Delineation of the study area using Strahler 1957

(Source: Author's Compilation)

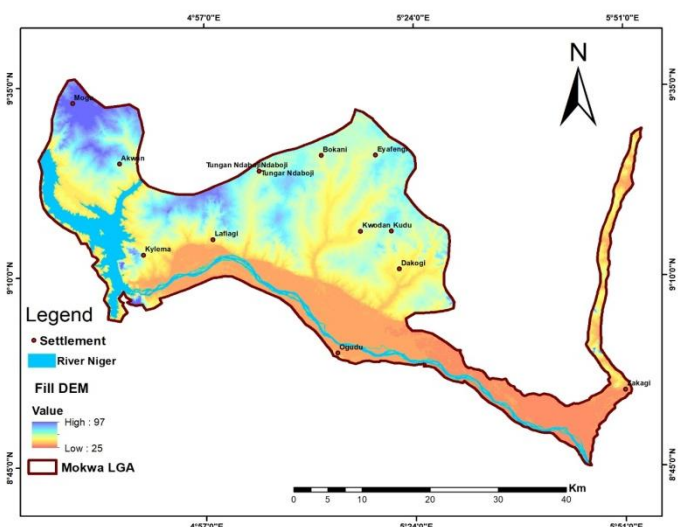


Figure 4.3: Fill Digital Elevation Model (DEM) Map of the Study Area

(Source: Author's Compilation)

Meanwhile Figure 4.4 and Figure 4.5 showed the 3D elevation and flow direction of the study area with a lowest elevation of 25m and highest elevation of 97m.

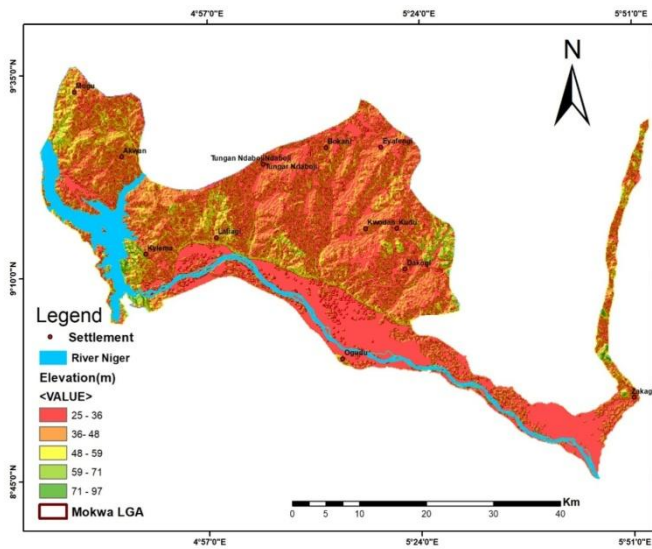


Figure 4.4: The Elevation Map of the Study Area using Three-Dimensional Model

(Source: Author's Compilation)

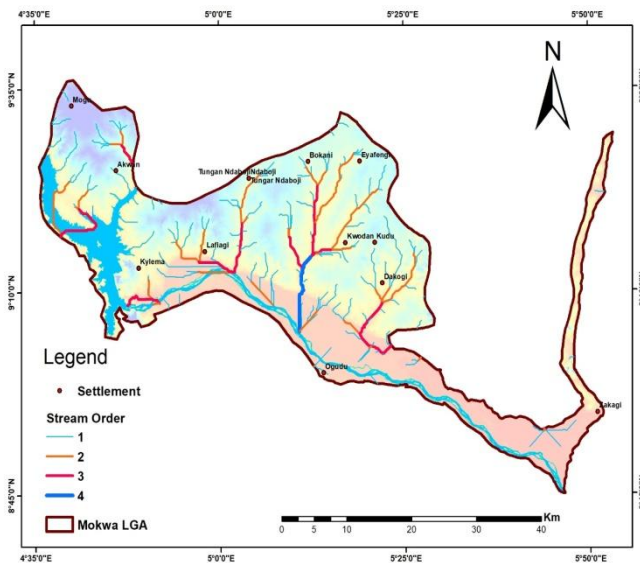


Figure 4.6: The Flow Accumulation Map of the Study Area

(Source: Author's Compilation)

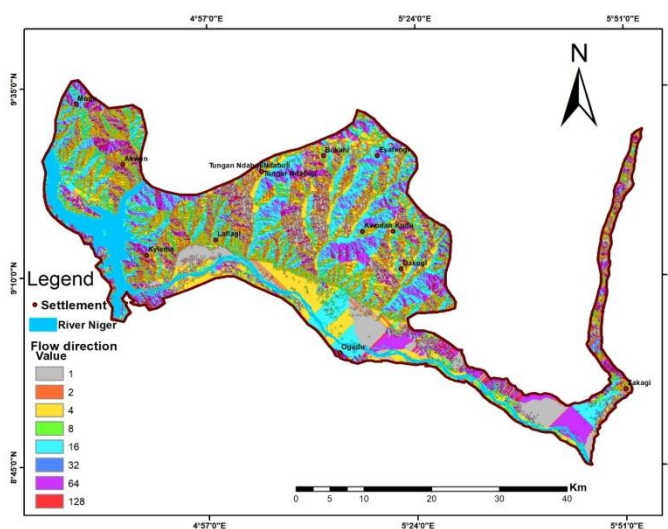


Figure 4.5: The Flow Direction Map of the Study Area using Three-Dimensional Model

(Source: Author's Compilation)

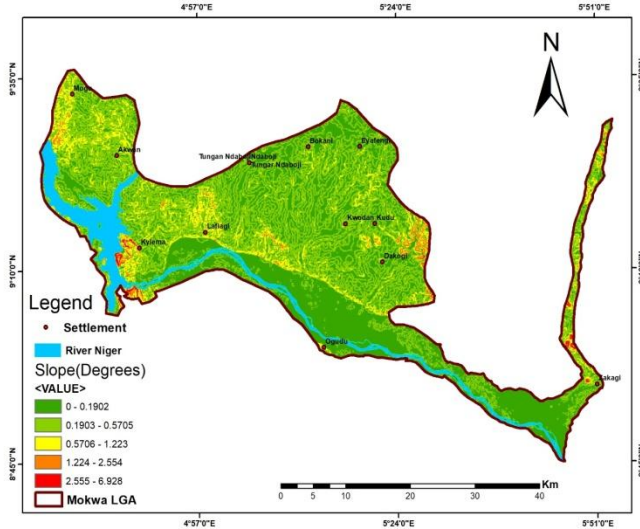


Figure 4.7: The Slope Map of the Study Area

(Source: Author's Compilation)

Also figure 4.6 and figure 4.7 showed hydrological behavior of the flow accumulation and the slope of the study area with steepness ranging from 0.12 to 6.7 degrees.

Figure 4.8 and Figure 4.9 showed the drainage density and topographic wetness index (TWI) across the study area. High drainage density signifies a well-developed channel network, which can either facilitate quick water evacuation or also indicate areas prone to rapid runoff generation depending on terrain and rainfall intensity.

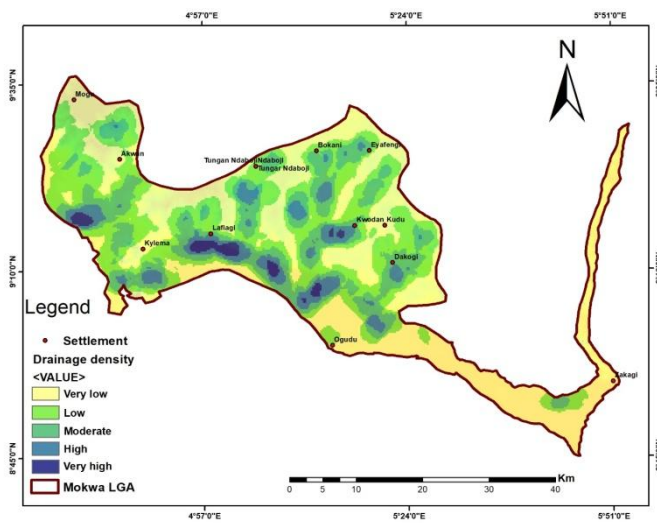


Figure 4.8: The Drainage Density Map of the Study Area using kernel Density

(Source: Author's Compilation)

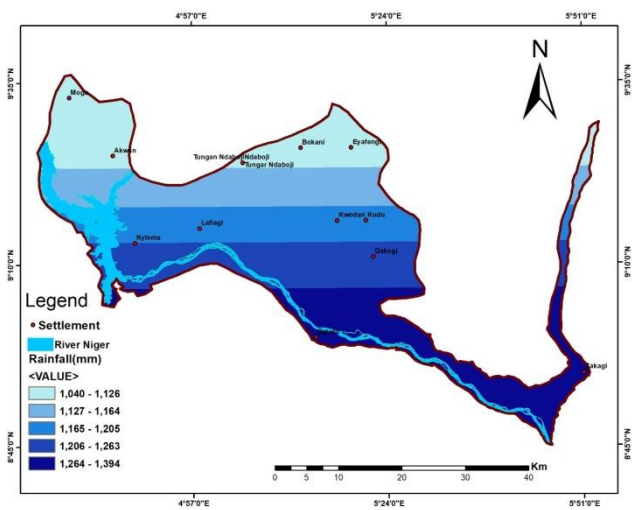


Figure 4.10: The Rainfall distribution Map of the Study Area Using CHIRP

(Source: Author's Compilation)

Figure 4.11 and Figure 4.12 displayed soil types and Distance from River within the study area.

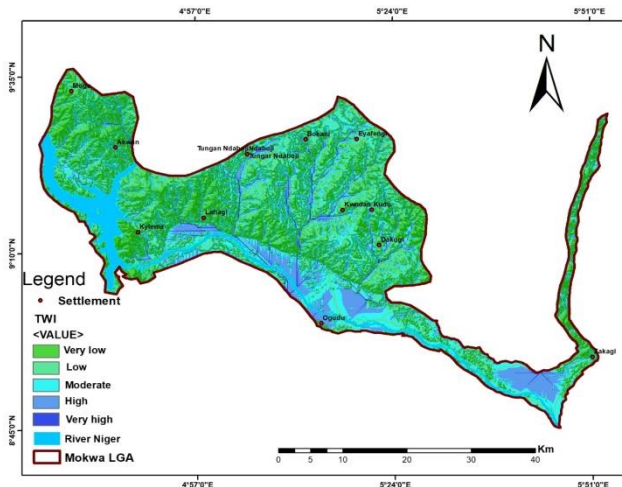


Figure 4.9: The Topographic Wetness Index (TWI) Map of the Study Area

(Source: Author's Compilation)

Figure 4.10 showed the distribution of annual rainfall across the study area, which ranging from 1040 mm to 1392 mm with the southern part of Mokwa local government area witness the highest rainfall of the year.

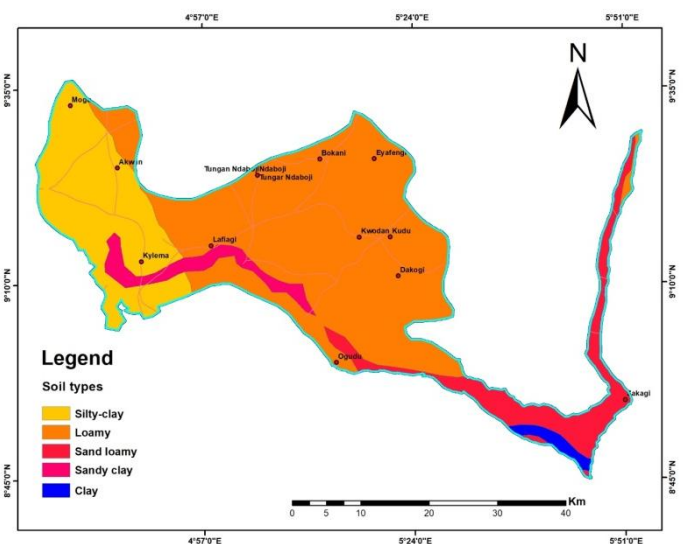


Figure 4.11: The Soil Types Map of the Study Area from Food and Agriculture Organization (FAO)

(Source: Author's Compilation)

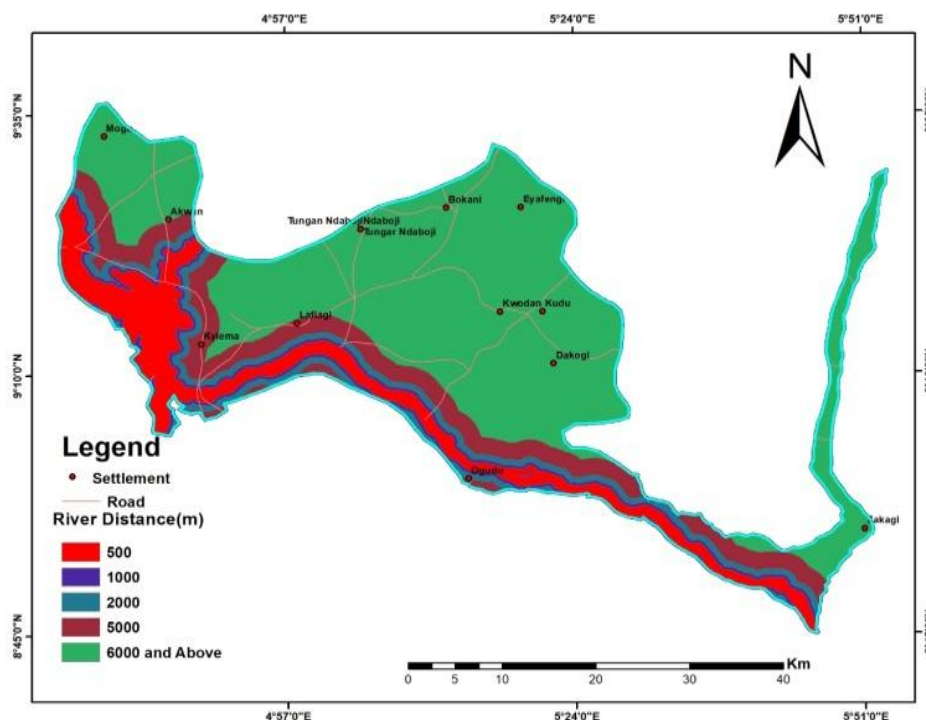


Figure 4.12: The Distance from River Map of the Study Area Using Proximity Analysis

(Source: Author's Compilation)

4.2 Evaluate and compare the performance of the two predictive models of Saaty Analytical Hierarchy Process (AHP) and Fuzzy- Analytical Hierarchy Process (F-AHP)

Table 4.2 and Table 4.3 showed Pairwise Comparison Matrix and Normalized Pairwise Comparison Matrix for Multi Criteria Decision Analysis. Individuals' weight was assigned to every flood conditioning factors.

Table 4.2: Pairwise Comparison Matrix (Saaty Thomas L., 1980)

Pair wise matrix	TWI	Rainfall	Elevation	Slope	LULC	River Distance	Soil types	Drainage density
TWI	1	1/5	1/5	3	1/3	1/5	1/3	1/3
Rainfall	5	1	1/5	5	3	1/3	1/3	3
Elevation	5	5	1	3	1/3	1/5	1/3	1/3
Slope	1/3	1/5	1/3	1	1/3	1/5	1/3	1/3
LULC	3	1/3	3	3	1	1/3	1	1/5
River Distance	5	3	5	5	3	1	3	1
Soil types	3	3	3	3	1	1/3	1	1/3
Drainage density	3	1/3	3	3	5	1	3	1
TOTAL	25.3	13	15.7	26	14	3.6	9.3	6.5

(Source: Author's compilation)

Table 4.3: Normalized Pairwise Comparison Matrix for Multi Criteria Decision Analysis (Saaty Thoams L, 1980)

Pair wise matrix	TWI	Rainfall	Elevation	Slope	LULC	River Distance	soil types	Drainage density	Weight	Percentage
TWI	0.039	0.015	0.013	0.115	0.024	0.056	0.036	0.051	0.044	4
Rainfall	0.197	0.077	0.013	0.192	0.214	0.093	0.036	0.459	0.160	16
Elevation	0.197	0.383	0.064	0.115	0.024	0.056	0.036	0.051	0.116	12
Slope	0.013	0.015	0.021	0.038	0.024	0.056	0.036	0.051	0.032	3
LULC	0.118	0.026	0.191	0.115	0.071	0.093	0.107	0.031	0.094	9
River Distance	0.197	0.230	0.318	0.192	0.214	0.278	0.321	0.153	0.238	24
Soil types	0.118	0.230	0.191	0.115	0.071	0.093	0.107	0.051	0.122	12
Drainage density	0.118	0.026	0.191	0.115	0.357	0.278	0.321	0.153	0.195	19
TOTAL	1	1	1	1	1	1	1	1	1	100

(Source: Author's Compilation)

Table 4.4 and Table 4.5 showed Consistency Ratio of Pairwise Comparison Matrix for Multi Criteria Decision Analysis and Weight Generated by Saaty 1980 and Chang 1996 comparison Matrix of the Study Area.

Table 4.4: Consistency Ratio of Pairwise Comparison Matrix for Multi Criteria Decision Analysis (Saaty Thomas L., 1980)

Pair wise matrix	TWI	Rainfall	Elevation	Slope	LULC	River Distance	soil types	Drainage density	Weight
TWI	0.044	0.009	0.009	0.009	0.131	0.009	0.015	0.015	0.030
Rainfall	0.800	0.160	0.160	0.032	0.800	0.053	0.053	0.480	0.318
Elevation	0.578	0.578	0.578	0.116	0.347	0.023	0.039	0.039	0.287
Slope	0.011	0.006	0.006	0.011	0.032	0.006	0.011	0.011	0.012
LULC	0.282	0.031	0.031	0.282	0.282	0.031	0.094	0.019	0.132
River Distance	1.190	0.714	0.714	1.190	1.190	0.238	0.714	0.238	0.773
soil types	0.366	0.366	0.366	0.366	0.366	0.041	0.122	0.041	0.254
Drainage density	0.585	0.065	0.065	0.585	0.585	0.195	0.585	0.195	0.357
C.R=5%									

Table 4.5: Weight Generated by Saaty 1980 and Chang 1996 Pairwise Comparison Matrix of the Study Area

Pair wise matrix	AHP Weight	FAHP Weight
TWI	0.04362	0.08362
Rainfall	0.16009	0.18321
Elevation	0.11563	0.10963
Slope	0.03178	0.02978
LULC	0.09397	0.10397
River Distance	0.23795	0.19795
soil types	0.12203	0.13203
Drainage density	0.19493	0.15117
TOTAL	1	1

(Source: Author's Compilation)

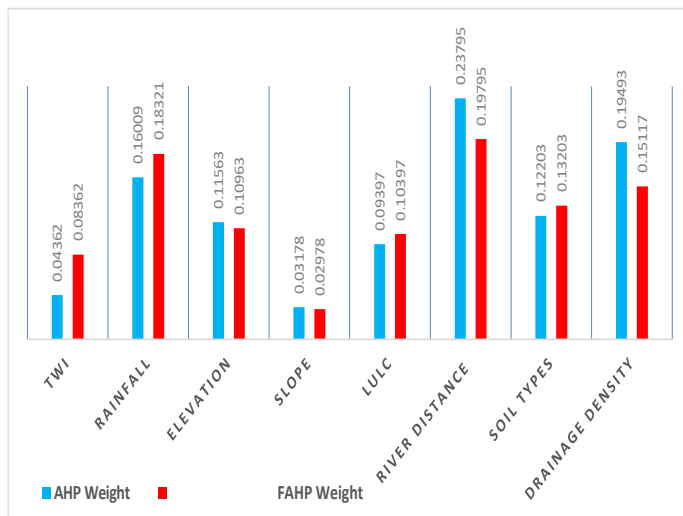


Figure 4.13: Chart of weight generated by Saaty Thomas L. 1980 and Chang 1996

(Source: Author's Compilation)

Figure 4.14 and Figure 4.15 shown the spatial distribution of flood susceptibility mapping across the study area by both Saaty Thomas L., 1980 and Chang 1996 which were classified into five classes ranging from very low susceptibility, low susceptibility, moderate susceptibility, high susceptibility and very high susceptibility.

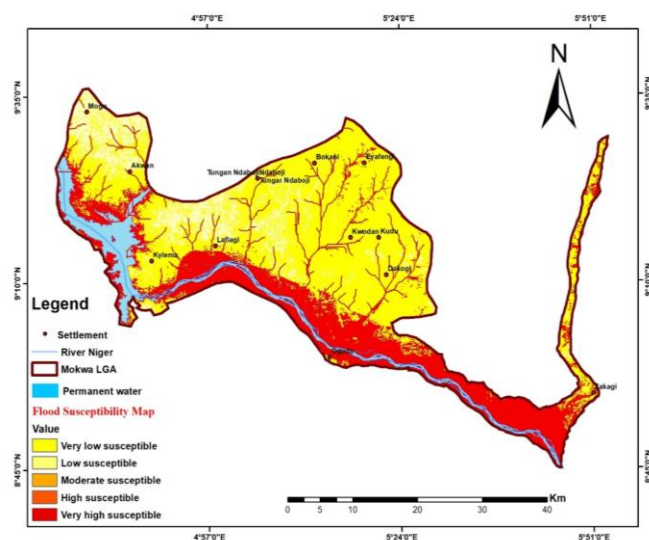


Figure 4.14: Flood Susceptibility Map of the Study Area Using Saaty Thomas L. 1980 Analytical Hierarchy Process (AHP)

(Source: Author's Compilation)

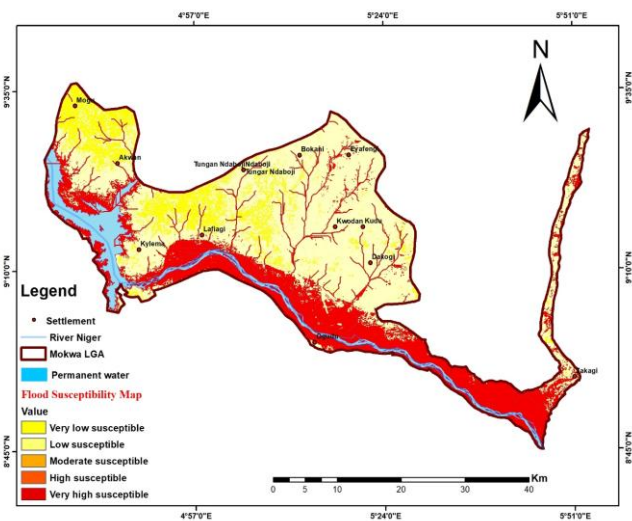


Figure 4.15: Flood Susceptibility Map of the Study Area Using Chang 1996 Fuzzy Analytical Hierarchy Process (FAHP)

(Source: Author's Compilation)

V. CONCLUSION

Figure 4.14 and Figure 4.15 shown the spatial distribution of flood susceptibility mapping across the study area by both Saaty Thomas L., 1980 and Chang 1996 which were divided into five categories: very low susceptibility, low susceptibility, moderate susceptibility, high susceptibility, and very high susceptibility. Nevertheless, Table 4.11 showed that the very low susceptibility covered a total area of 17.1km², low susceptibility covered 471.8km², moderate susceptibility covered 1287.7km², high susceptibility covered 1050.1km² and very high susceptibility covered 310.4km². Figure 4.19 and Figure 4.20 showed that majority of the areas susceptible to flooding in Mokwa local government area are low lying areas relatively close to the water bodies.

However, the results of both the Analytical Hierarchy Process (AHP) developed by Saaty Thomas L. (1980) and the Fuzzy Analytical Hierarchy Process (F-AHP) proposed by Chang (1996) were compared; there were noticeable variations in the classification of susceptibility zones between the two models. Specifically, the area categorized under very low flood susceptibility is estimated at 17.1 km² for Analytical Hierarchy Process (AHP) and slightly higher at 17.4 km² for F-AHP. In contrast, the very high susceptibility zones show a more pronounced difference, with Analytical Hierarchy Process (AHP) identifying 310.4 km², while Fuzzy Analytical Hierarchy Process (F-AHP) delineates a significantly larger area of 380.1 km². This

variation suggests that the Fuzzy Analytical Hierarchy Process (F-AHP) model is more sensitive in capturing high-risk flood zones, likely due to its ability to incorporate uncertainty and gradual transitions between classes. The expansion of high susceptibility areas in Fuzzy Analytical Hierarchy Process (F-AHP) may indicate a more precautionary and realistic representation of flood risk, especially in environments characterized by complex hydrological interactions. Furthermore, the consistency ratio (CR) values obtained from both models demonstrate acceptable levels of judgment consistency, as they fall within the threshold of 10%. The Analytical Hierarchy Process (AHP) model produced a CR of 5%, while the Fuzzy Analytical Hierarchy Process (F-AHP) model yielded a slightly lower CR of 4.3%. Although both models are considered reliable, the lower consistency ratio of the Fuzzy Analytical Hierarchy Process (F-AHP) suggests a marginally higher level of internal consistency in pairwise comparisons. This implies that the Fuzzy Analytical Hierarchy Process (F-AHP) model provides more stable and dependable weighting of criteria, thereby enhancing the overall accuracy of the analysis.

REFERENCES

- [1] Adelekan, I. O. (2016). Flood risk management in the coastal city of Lagos, Nigeria. *Journal of Flood Risk Management*, 9(3), 255–264.
- [2] Aderoju, O. M., Salami, A. W., & Jimoh, O. D. (2020). Flood vulnerability assessment in Lokoja, Nigeria using geospatial techniques. *Environmental Monitoring and Assessment*, 192(5), 1–14.
- [3] Abdullahi, K. L. (2025). Integrated geospatial and multi-criterion analysis of flood physical vulnerability in Mokwa LGA, Niger State, Nigeria. *Science World Journal*, 20(3), 928–940.
- [4] Abdullahi, A. (2025). Flood risk assessment and management strategies in Nigeria: A geospatial perspective. *Journal of Environmental Hazards*, 18(2), 45–60.
- [5] Adger, W. N. (2006). Vulnerability. *Global Environmental Change*, 16(3), 268–281.
- [6] Ayalew, L., & Yamagishi, H. (2005). The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda–Yahiko Mountains, central Japan. *Geomorphology*, 65(1–2), 15–31.
- [7] Basil, B. Y., Faisal, M. D., de Wilde, R., Ahmed, A. R., & Arbili, M. M. (2024). Flash flood hazard mapping using Analytical Hierarchy Process (AHP) and GIS application: In the Barzan area of Iraqi Kurdistan Region. *Zanco Journal of Pure and Applied Sciences*, 37(1), 12–45.
- [8] Baywood C.N, Babatunde A., Baywood P.D., & Ohamaigo D. (2024). Impact Assessment of Urban Heat Island on Land Use/Land Cover in Owerri Metropolis Using Geospatial Technique. *International Journal of Advances in Engineering and Management (IJAEM)*. 6(3) 45-34.
- [9] Birkmann, J. (Ed.). (2006). Measuring vulnerability to natural hazards: Towards disaster resilient societies. *United Nations University Press*, 3(23), 34–56.
- [10] Blakime, B. (2024). Flood vulnerability assessment using geospatial techniques in coastal settlements. *International Journal of Hydrology and Disaster Science*, 9(4), 112–128.
- [11] Chang, D.-Y. (1996). Applications of the extent analysis method on fuzzy analytic hierarchy process. *European Journal of Operational Research*, 95(3), 649–655.
- [12] Campbell, J. B., & Wynne, R. H. (2011). Introduction to remote sensing (5th ed.). *Guilford Press*. 6(3), 45–34.
- [13] Chorley, R. J., & Kennedy, B. A. (1971). Physical geography: A systems approach. *Prentice-Hall* 6(3), 45–34.
- [14] Charle K. D. (1958). The concentration and isotopic abundances of atmospheric carbon dioxide in rural areas. *Geochimica et Cosmochimica Acta*, 13(4), 322–334.
- [15] Dou, J., Yunus, A. P., Bui, D. T., Sahana, M., Chen, C. W., & Zhu, Z. (2019). A hybrid machine learning approach for flood susceptibility mapping using GEE and random forest. *Remote Sensing*, 11(4), -231-368.
- [16] Derber, D., & Wu, X. (1998). Flood hazard analysis and mitigation strategies in urban watersheds. *Journal of Hydrology*, 205(1–2), 78–92.
- [17] Elhadj, E., & Farouk, F. (2023). Flood risk assessment and management strategies in urban catchments. *International Journal of Water Resources and Flood Management*, 11(3), 77–92.
- [18] Elkhachy, I. (2015). Flash flood hazard mapping using satellite images and GIS tools: A case study of Najran City, Kingdom of Saudi Arabia (KSA). *The Egyptian Journal of Remote Sensing and Space Science*, 18(2), 261–278.
- [19] Eagleson, P. S. (1986). The emergence of global-scale hydrology. *Water Resources Research*, 22(9S), 6S–14S.
- [20] FAO (2012). FAO-UNESCO Soil Map of the World, Revised Legend. *Food and Agriculture Organization of the United Nations, Rome*. 6(7), 45–34.

- [21] Fuchs, S., Karagiorgos, K., Kitikidou, K., Maris, F., Paparrizos, S., & Thaler, T. (2017). Flood risk perception and adaptation capacity: A contribution to the socio-hydrology debate. *Hydrology and Earth System Sciences*, 21(6), 3183–3198.
- [22] Feizizadeh, B., & Blaschke, T. (2013). GIS-based ordered weighted averaging and Dempster–Shafer methods for landslide susceptibility mapping in the Urmia Lake Basin, Iran. *International Journal of Digital Earth*, 6(1), 66–93.
- [23] Gupta, A. K., & Nair, S. S. (2019). Flood risk and context of land-uses: Chennai city case. *African Journal of Geography and Regional Planning*, 6(4), 001–008.
- [24] Gregory, K. J., & Walling, D. E. (1973). Drainage basin form and process: A geomorphological approach. *Edward Arnold*. 8(7), 45-56.

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