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GIS-Based Multi-Criteria Analysis for Mapping Flood-Prone Areas in Oguta L.G.A, Imo State, Nigeria.

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ABSTRACT
This study utilizes an integrated approach combining Remote Sensing and GIS techniques to effectively manage floods. Its primary goal is to identify flood-prone areas within Oguta LGA, Imo state, enhancing our ability to mitigate flood hazards. As long as physical development continues to extend and spring up in urban centers, flooding is one of the natural occurrence hazards that cannot be completely eradicated. Flooding emerges as a highly impactful natural disaster, inflicting substantial socioeconomic losses on a wide scale. This present project, flood-prone zone mapping was carried out using Landsat ETM+ of 2023, Digital Elevation Model (DEM) Shuttle Radar Topographic Mission (SRTM), geological data, and meteorological data obtained from the USGS Earth Explorer website, and Tropical Rainfall Measuring Mission satellite respectively. The data were used to map out identified factors contributing to flood occurrence in the study area, mainly slope, elevation, rainfall, drainage density, Distance from River, LULC, rainfall, and lithology. Each of the factors was reclassified using ArcGIS 10.5. Using remote sensing, GIS and AHP techniques, each factor was evaluated, weight and Pairwise Comparison method adopted were validated and observed to have a consistency ratio. Then, applying a weighted overlay tool of ArcGIS 10.5 software to develop flood-prone maps. Five qualitative-based flood prone areas were identified and classified as Very low, low, moderate, high, and Very high. The result revealed that the highest percentage share was recorded in the high class, occupying about 10.40% of the total area which is very negligible. The moderate class accounts for 45.47% of the core area, while the very high class covers about 0.37%. These (High, Very High, and Moderate) equate to a total land area of 49.29km2, 1.75km2, and 215.58km2 respectively. While some part of the study belongs to the low-risk and very low-risk classes. The result proved that multispectral imagery and conventional data along with GIS tools are essential in determining areas prone to flooding. Therefore, geospatial and AHP techniques have emerged as formidable tools for addressing multiple facets of flood management, spanning prevention, warning systems, preparedness, and relief efforts. Their integration represents a significant advancement over traditional methodologies, offering enhanced precision and effectiveness in mitigating the impacts of flood disasters.

KEYWORDS: flood-prone, geospatial technology, multi-criteria analysis, AHP, Climate change.

I. INTRODUCTION

One of the natural disasters that cannot be completely eradicated but mitigate is flooding (Aydin and Birincioğlu, 2022). Flooding is widely recognized as one of the most pervasive natural disasters, posing significant threats to the environment and human life(Balogun et al.,2020). It is also the world's most destructive and pervasive natural disaster, posing serious risks to infrastructure, human lives, and livelihoods is flooding (Masoud et al., 2020; Nouri et al., 2008). Their frequency and intensity are projected to increase due to climate change and anthropogenic activities, exacerbating existing vulnerabilities (Mondal et al., 2015;Al-Quraishi & Babel, 2021). Effective flood risk management strategies require a detailed spatial understanding of flood-prone areas, empowering communities and policymakers to implement targeted mitigation and preparedness measures.Traditional flood hazard mapping approaches, predominantly reliant on deterministic methods, often face limitations due to data scarcity and inadequate representation of complex interactions between flood-influencing factors (Nasiri et al., 2021).Adjei-Mantey et al. (2023) propose a strategic approach for mitigating urban floods in Accra, Ghana, focusing on the potential of nature-based solutions (NBS). Utilizing Spatial Multi-Criteria Analysis (MCA) within a GIS framework, their study aims to identify suitable locations for implementing NBS and contribute to effective flood risk management.Baba et al.(2017) delve into flood hazard mapping for Fufore Local Government Area in Northeastern Nigeria. Recognizing the region's vulnerability due to low-lying areas, inadequate drainage, and proximity to the Lagdo River, they leverage a multi-criteria approach within a GIS framework.The GIS-based Multi-Criteria Decision Analysis (MCDA) approach was used to map flood susceptibility across the Lower Benue River Basin, Nigeria.The study identified eight key flood-influencing factors: rainfall, elevation, slope, drainage density, land use, soil type, distance to river, and stream power index (Ajayi et al., 2023)Multi-criteria decision analysis (MCDA) emerges as a promising alternative, offering a robust framework for integrating diverse spatial data and expert knowledge into flood susceptibility assessments (Nouri et al., 2008; Al-Quraishi & Babel, 2021).This study aims to employ geographic information systems (GIS)based multi-criteria decision analysis (MCDA) to map flood-prone zones with increased accuracy.In recent years, Multi-Criteria Decision Analysis (MCDA) has emerged as a promising approach for flood hazard mapping, particularly in data-scarce regions (Al-Quraishi & Babel, 2021). MCDA incorporates various flood-related factors, such as topography, rainfall, soil characteristics, and land cover, into a GIS-based framework (Nasiri et al., 2021). (Wang et al. 2017) applied MCA to assess factors such as topography, land use, and rainfall intensity, demonstrating its capability to produce accurate flood susceptibility maps. Similarly, Smith et al. (2019) utilized GIS-MCA to analyze terrain parameters and land cover, offering valuable insights for flood risk assessment.Traditional flood mapping methods, often reliant on physical surveys and historical data, are time-consuming, expensive, and often inaccurate. GIS, with its ability to integrate and analyze spatial data, offers a promising alternative. MCA, a decision-making framework that evaluates multiple criteria simultaneously, can effectively prioritize flood-prone areas based on their susceptibility.The integration of GIS and MCAfor flood mapping has gained significant traction in recent years. Studies like (A.K. Al-Sharif et al. 2020) successfully employed MCA in conjunction with GIS to identify flood-prone areas in Jordan, demonstrating its effectiveness in complex terrains. Similarly, M.P. Begum et al. (2015) utilized GIS-based MCA to map flood susceptibility in Bangladesh, highlighting its potential for data-scarce regions.Mapping of flood-prone areas using GIS-based Multi-Criteria Analysis (MCA) is a methodological approach that combines Geographic Information Systems (GIS) technology with multiple criteria, such as topography, land use, and proximity to water bodies. This integrated analysis assesses and prioritizes various factors contributing to flood vulnerability, resulting in a spatially explicit map. The approach aids in identifying high-risk areas, facilitating informed decision-making for disaster management, urban planning, and risk mitigation. By comprehensively evaluating multiple criteria, GIS-based MCA provides a detailed understanding of flood-prone landscapes, supporting proactive measures to address the increasing challenges posed by climate-induced flooding.Oguta L.G.A., Imo State, suffers recurrent floods that devastate lives, livelihoods, and infrastructure. Traditional flood control methods, often reliant on limited data and historical knowledge, prove inadequate. This study addresses this problem by developing a GIS-based multi-criteria analysis (MCA) framework to map flood-prone areas with comprehensive, data-driven accuracy. By analyzing critical factors like topography, soil properties, land use, and historical floods, this project aims to provide Oguta local government area, with precise flood vulnerability maps, empowering proactive risk management strategies for a safer and more resilient future.

II. MATERIALS AND METHODS

2.1 STUDY OF AREA.

Figure 1 shows the map of Oguta LGA, in Imo State, Nigeria, sits within the vast Niger Delta Basin. Its geographical heart lies at approximately 6°40'N 7°04'E, placing it slightly north of the equator and a touch east of Greenwich. Envision a verdant tapestry woven with rolling hills, shimmering Oguta Lake, and a network of meandering rivers – that's Oguta LGA. The area spans roughly 506 square kilometers, offering a diverse landscape ripe for exploration.

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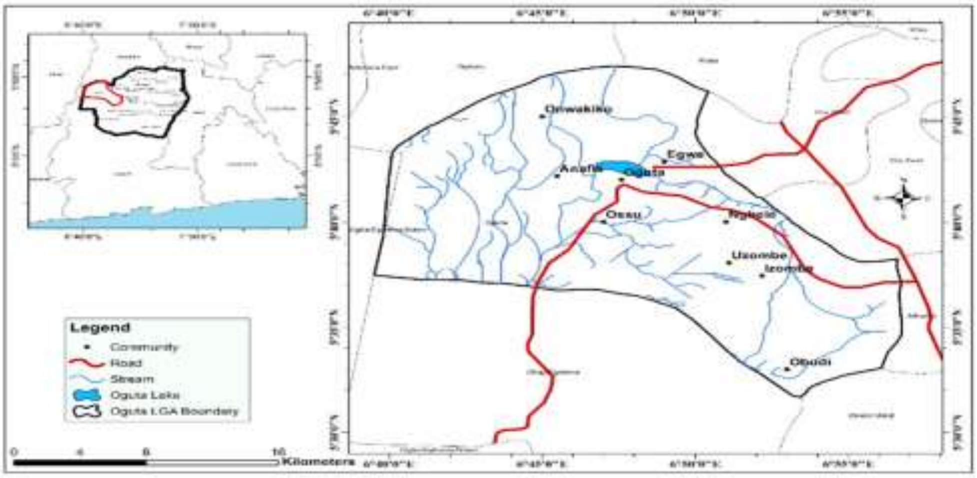

Figure 1. Map of Oguta L.G.A.

2.2 MATERIALS

Table 1showsthedifferentdatasetsusedforthis study and their sources

S/N	DATA	Acquisition Date	Spatial Resolution(m)	Source
1	Landsat 8 ETM+	2024	30	U.S. Geological Survey(USGS)
2	Rainfall	2024	0.05km	CHIRPS
3	Lithological data			NGSA
4	Administrative Map of Nigeria			OSGOF
5	SRTM (DEM)	2010	30	U.S. Geological Survey(USGS)

2.3 METHOD

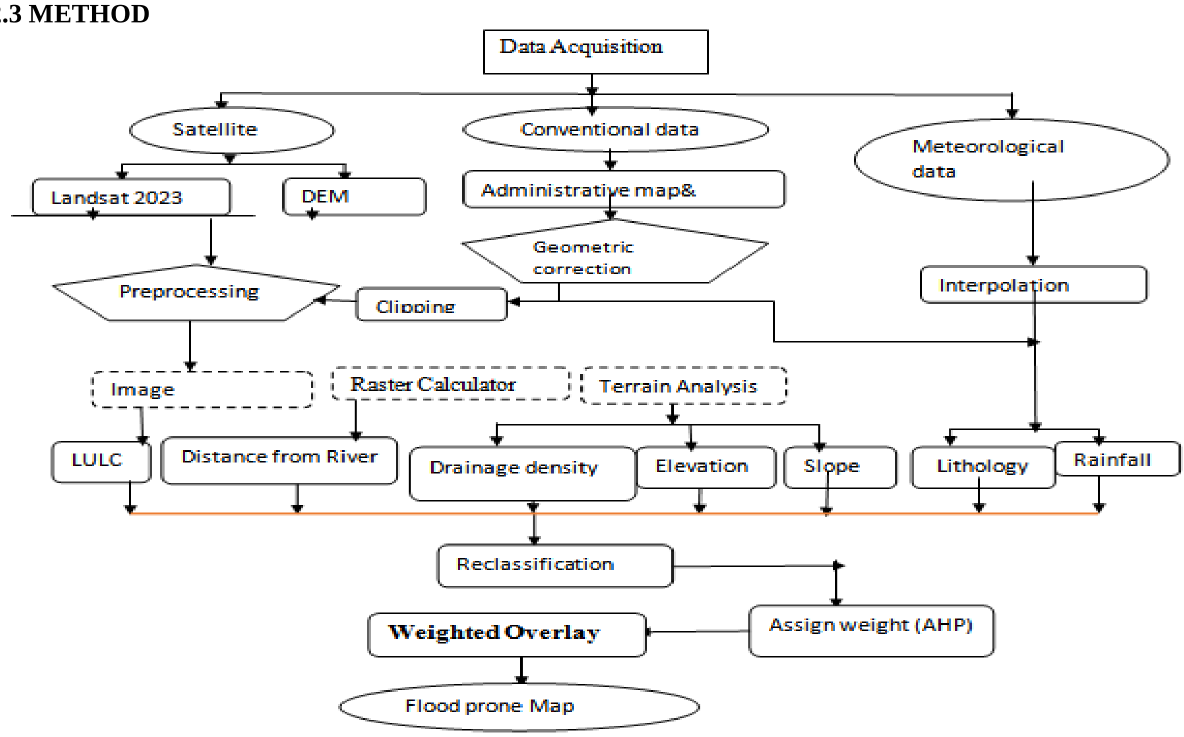

Figure 3: Methodology flow chart.

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2.3.1 DATA AND SOFTWARE REQUIREMENTS

The data used for this work is illustrated in table 1 above. The software utilized to achieve the goal of this work were ArcGIS 10.5, Idrisi Selva, and Microsoft Excel.

2.3.2 DATA PROCESSING

2.3.2.1 PRE-PROCESSING

Although all the data used for the analysis was ensured that it was cloud free, preprocessing was performed to further ensure some level of accuracy and precision. Geometric correction and radiometric correction were carried out (Shrinivas Khandare and Urmila Shrawankar, 2016, Baywood et.al.,2024). Each of the Imagery was clipped using ESRI software to extract the area of interest using the Nigeria shapefile. Also, to ensure that the data generated from the SRTM contains the correct values, errors must be fixed. The fill sink and the vegetation height or tree offset removal are notable errors. Sinks, or cells that are lower than all surrounding cells, was typically present in DEMs. While some sinks was as a result of DEM errors, others are natural features of the landscape (ponds). All sinks in the DEM need to be filled in order to model flow. This correction was carried out using the hydrological menu's fill sink menu.

2.3.2.2 SPATIAL ANALYSIS

This is a type of geographical analysis which explore to explain patterns of terrain behavior and its spatial expression in terms of mathematics and geometry. Spatial analysis can help in measuring distances and shapes, between objects, events, and places via referring their locations to geographical positions. Spatial analysis tools was use to carry out terrain analysis of my study area through the help of hydrology tools to derive different terrain characteristics such as contour, slope, flow direction, flow accumulation, stream order, and drainage.

2.3.2.3 FLOW ACCUMULATION

Creates a raster of accumulated flow into each cell. A weight factor can optionally be applied. The result of Flow Accumulation is a raster of accumulated flow to each cell, as determined by accumulating the weight for all cells that flow into each downslope cell. Builds and executes a single Map Algebra expression using Python syntax in a calculator-like interface. The Raster Calculator tool allows you to create and execute a Map Algebra expression that will output a raster.

2.3.3.4 SLOPE

Identifies the slope (gradient, or rate of maximum change in z-value) from each cell of a raster surface. is the rate of maximum change in z-value from each cell. The use of a z-factor is essential for correct slope calculations when the surface z units are expressed in units different from the ground x, and y units.This can be mathematically expressed as

$$\text{Tan } \square = \sqrt{\left(\frac{d_2}{dx}\right)^2 + \left(\frac{dZ}{dy}\right)^2} \quad \ldots\ldots \text{ equation 1}$$

2.4 RECLASSIFICATION.

This entails the systematic reassignment of values or categories to various geographical elements or parameters associated with flood risk. This process encompasses the reclassification of factors such as elevation, slope, land use/land cover, proximity to water bodies, and other influential variables that affect flood susceptibility before each of the parameters were weighted. The sole purpose of this was to achieve uniqueness for the parameters.

2.5 ANALYTICAL HIERARCHICAL PROCESS (AHP)

This is a structured decision-making method used to prioritize and assign weights to criteria based on their relative importance in a hierarchical structure. The weights of the themes were assigned on a scale of 1 to 5, based on their influence on flood occurrences. The features of each theme were assigned weights on a scale of 1 to 9 according to their relative influence on flood occurrences as shown in Table 2;

Table 2: Normalized Weight Assessment and preference

S/n	Factors	Values	preference	% Influence	Flood prone classes
1	ELEVATION	14 - 25	5	16.22	Very High
		26 - 44	4		High
		45 - 63	3		Moderate
		64 - 71	2		Low

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		72 - 96	1		Very Low
2	SLOPE	0 - 18	5	9.66	Very High
		18 - 36	4		High
		37 - 54	3		Moderate
		55- 71	2		Low
		72 -89	1		Very Low
3	Rainfall	590 - 610	1	29.14	Very Low
		620 - 620	2		Low
		630 - 640	3		Moderate
		650 - 660	4		High
		670 - 680	5		Very High
4	LAND USE/LAND COVER	Built_up	3	2.93	Moderate
		Vegetation	2		Low
		Bare Soil	4		High
		Forest	1		Very low
		Waterbody	5		Very High
5	Distance from River	100	5	23.75	Very High
		200	4		High
		300	3		Moderate
		400	2		Low
		3000	1		Very Low
6	DRAINAGE DENSITY	0 – 24	1	13.59	Very Low
		25 – 63	2		Low

		64 – 110	3		Moderate
		120 – 160	4		High
		170 – 320	5		Very High
7	Lithology	AL	4	4.70	Very High
		CPS	1		Low
		SDP	3		High
		LST	2		Moderate

Note: Al=River alluvium,CPS=sands and clay, SDP=Clays_Sandstones_Lignite_and_Shales , LST=Sands_Clays_and_Mangrove_Swamp

2.5.1 PAIRWISE COMPARISON

Table 3 and table 4 shows the results of the pairwise comparison and the interpretation of symbols (Normalized principal Eigenvector) used in depicting the different criteria. This can be achieved using the matrix to derive the relationship between the pairwise comparison values of two reciprocal criteria(Aydin and Birincioğlu, 2022). Equation 2, $x_{21}=1/x_{12}$

$$A=\begin{bmatrix} x11 & x1n \\ xn1 & xnn \end{bmatrix}=\begin{bmatrix} x11 & x1n \\ 1/x1n & xnn \end{bmatrix} \ldots \text{Eqn 2}$$

The matrix above must have acceptable consistency which can be determined using the consistency ratio (CR).

$$CR= CR/RI \quad \ldots\text{Eqn 3}$$

$$CI=\frac{(\gamma \max - n)}{(n-1)} \quad \ldots \text{Eqn 4}$$

If the Consistency Ratio (CR) is below 0.10,the comparison matrix is considered acceptably consistent. If it exceeds this threshold, the decision-making process should be repeated until consistency is improved. A CR of 0.00 represents the optimal value for consistency.(Saaty 1990; Subramanian and Ramanathan 2012,Aydin and Birincioğlu, 2022).

Table 3: The pair-wise comparison matrix table of the different factors used to determine flood prone area.

Matrices	Ra	DR	SL	EL	LULC	DD	Li
Rainfall	1	2	3	2	5	3	7
Distance from River	1/2	1	3	2	7	3	5
Slope	1/3	1/3	1	1/3	5	1	3
Elevation	1/2	1/2	3	1	5	1/2	7
LULC	1/5	1/7	1/5		1	1/3	1/5
Drainage density	1/3	1/3	1	2	3	1	5
Lithology	1/7	1/5	1/3	1/7	5	1/5	1

Ra= Rainfall, DR= Distance from River, SL= Slope, EL= Elevation , LULC=Land use/Land cover, DD= Drainage density, Li=Lithology.

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Table 4: Interpretation of criteria symbols (Normalized principal Eigenvector)

Factor No	factors	Weight (%)
1	Lithology	4.70
2	Distance to River	23.75
3	Elevation	16.22
4	LULC	2.93
5	Drainage density	13.59
6	Rainfall	29.14
7	Slope	9.66

2.6 FLOOD PRONE MAPPING

After the weighting calculation of all conditioning factors, the final flood prone map was produced using the AHP technique and the weighted overlay tool in ArcGIS 10.5 was explored to generate the flood model of the area. The flood level was delineated into five classes using the natural break method: very low, low, moderate, high, and very high.

III. RESULTS AND DISCUSSION

3.1 IDENTIFIED THE FLOOD PRONE CRITERIA OF THE STUDY AREA

Different factors were identified to be the major causes of flooding in the study area, and each of the factors was assessed and mapped using conventional and satellite data. The criteria identified are seven (7) considered as the main factors necessary for assessing flood risk and measuring its hazard for the study. The factors include; Lithology, elevation, distance from river, drainage density, rainfall, slope, and land cover and land use.

3.2. MAPPING OF FLOOD PRONE CONDITIONING FACTORS IN THE AREA

3.2.1 ELEVATION and SLOPE

The elevation is one of the topographical factors that influence the occurrences of a flood event. Elevation of the study area is categorized into five classes as 14 – 25m, 26 – 44m, 45 – 63m, 64 – 71m, and 72 – 96m (Figure 2). The elevation map (Figure 2) indicates that the most extensive portion of the study area belongs to the low elevation class (14 – 25m). Therefore,areas with low elevation are usually at higher risk of flooding compared to areas with higher elevation. Accordingly, the low elevation class implies very high flood vulnerability since they are more likely to be inundated by floodwaters than areas at higher elevations.

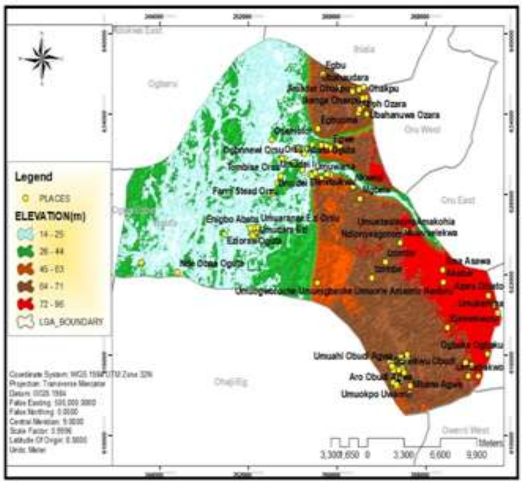

Fig2: Elevation map of the study area.

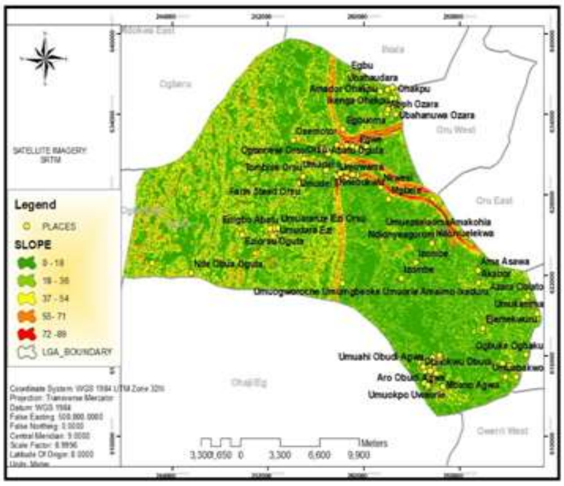

Fig 3: Slope map of the study area.

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Table 5: Slope classification and Unified preference value in the study area.

S/N	Slope(degree)	Terminology	Preference value	Flood prone class
1	0 – 18	Near flat	5	Very high
2	18– 36	Very gentle slope	4	High
3	37 – 54	Gentle slope	3	Moderate
4	55 – 71	Moderate slope	2	Low
5	72 – 89	Steep slope	1	Very low

Table 6: Statistical analysis of Land use/land cover of the study area for 2023

Land cover / Land use Class of the study area.

S/N	**Class Name**	**Area(km2)**	**Area (%)**
1	Settlement	49.6449	10.378187
2	Vegetation	159.5214	33.347695
3	Forest	155.799	32.569533
4	Waterbody	3.3858	0.707796
5	Bare soil	110.007	22.996788

3.2.3 LULC AND DRAINAGE DENSITY

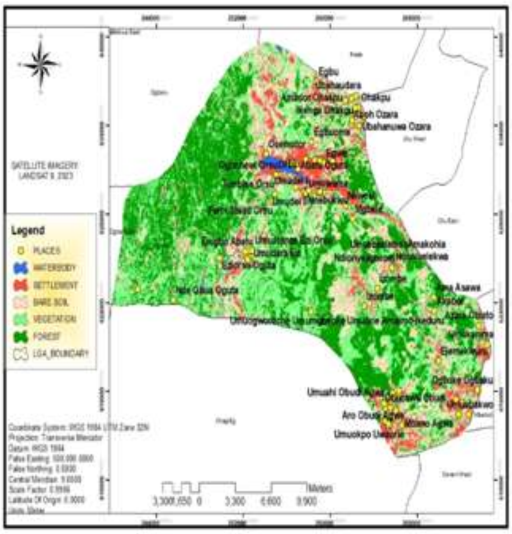

Fig 4: Land use/land cover map of the study area.

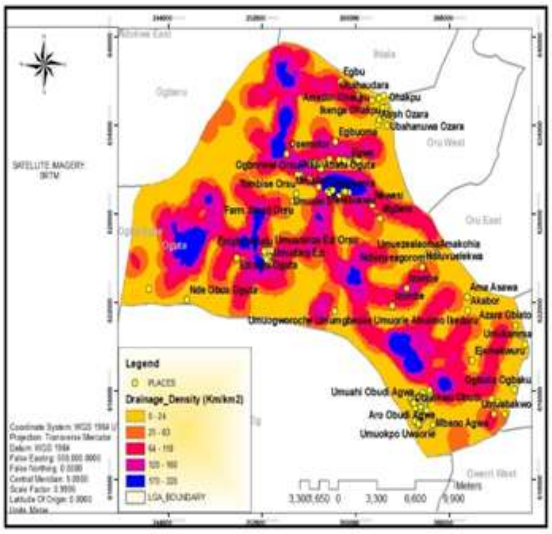

Fig. 5: Drainage density map of the study area.

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3.2.4 RAINFALL AND DISTANCE FROM RIVER

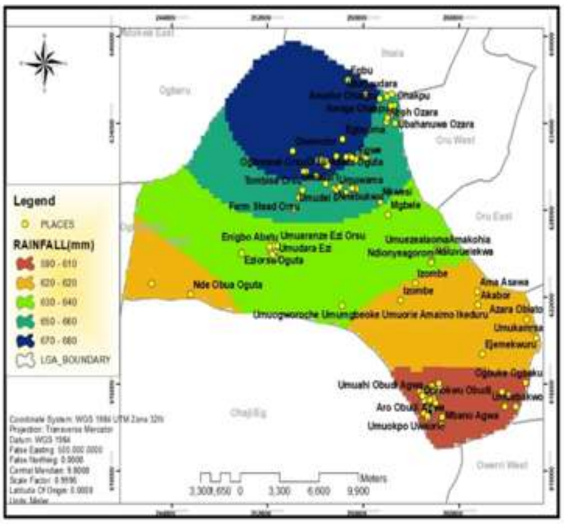

Fig. 6: Rainfall map of the study area.

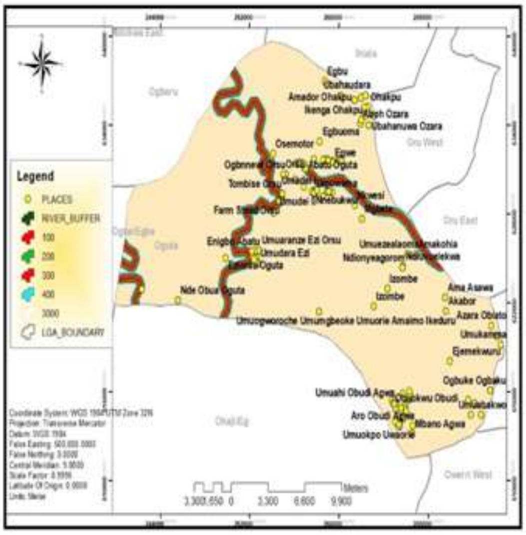

Fig. 7: Distance from River map of the study area.

3.2.5 LITHOLOGY

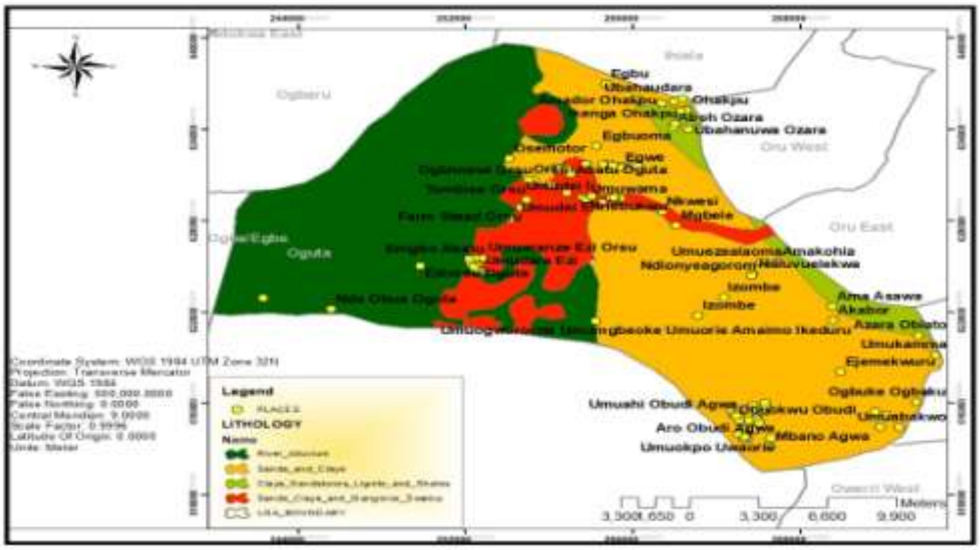

Fig. 8: Lithology map of the study area.

DISCUSSION

Elevation is a key factor in flood risk, with the study area categorized into five elevation classes: 14–25m, 26–44m, 45–63m, 64–71m, and 72–96m (Figure 2). The largest portion of the area falls within the lowest elevation class (14–25m), which faces a very high flood vulnerability due to increased likelihood of inundation, whereas higher elevations have a lower flood risk. The land slope significantly affects flood susceptibility, as it influences the speed of surface water flow. A slope map derived from the SRTM DEM in ArcGIS (Figure 3) and analyzed in Table 2 shows that areas with lower slopes (0-18 degrees) have a high flood risk due to slower water runoff, while steeper slopes (72-89 degrees) have lower flood risk, with water moving quickly downslope during rainfall events.

Table 6 and Figure 4 analyze land use categories within the study area, detailing their spatial distributions. A 2023 classified Landsat image (Figure 4), processed with ArcGIS 10.5 using supervised classification, reveals four land

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classes: settlement (red), vegetation (light green), agricultural land (deep green), and water bodies (blue). Settlement spans 49.6 km² (10.38%), forest covers 155.8 km² (32.57%), vegetation occupies 159.5 km² (33.35%), while water bodies and bare soil cover 3.39 km² (0.71%) and 110 km² (23%), respectively. Vegetation and agricultural lands enhance infiltration and reduce flood risks. Among flood-inducing factors, water bodies have the highest flood risk, whereas forests are low-risk.Figure 5 above reveals the drainage density map of the study area which ranges. Drainage density is included as part of the thematic layers used to determine areas probable to flooding because of its ability to describe the nature of the soil and its geotechnical properties such as permeability and infiltration capacity (Das, 2019). High drainage density contributes to greater surface runoff and thus increases flood vulnerability (Otokiti et al., 2019). The map revealed that the drainage density of the study area is between 16.2km to 49.4km (Figure 5).The rainfall was reclassified based on the ranges. The preference value was ranked based on the increase of precipitation values. Places with high rainfall are more prone to flood while areas with a low amount of rainfall. The rainfall distribution map of the study area figure 6 showed that rainfall intensity was high in northern part of the study area compared to the south-east part that has moderate to low rainfall intensity. Figure 6above shown the rainfall spatial distribution of the study area ranges from 590-680m.In the study, water features were mapped and analyzed using ArcGIS to identify flood-prone zones near streams, rivers, and lakes (Fig. 7). A 100-meter buffer zone around these water bodies marks areas most vulnerable to flooding. Findings show that locations within 400 to 3000 meters from rivers are free from flooding incidents.

Lithology can have a notable influent on flooding due to its impact and also its influence on groundwater flow, infiltration rates, and surface runoff characteristics. The lithology of the area was classified into four major geological units which include River alluvium, sands and clay, Clays_Sandstones_Lignite_and_Shales and Sands_Clays_and_Mangrove_Swamp. The lithology was extracted from the Nigeria Geological & Mineral Explorations survey map . Highly permeable lithologies such as sand and gravel allow water to infiltrate more easily, reducing surface runoff and potentially lowering flood risk (Nickolas et al.,2017). In contrast, impermeable lithologies like clay or bedrock can lead to rapid surface runoff, increasing flood susceptibility.

3.3 DEVELOPMENT OF FLOOD PRONE MAP

The thematic layers of lithology, elevation, drainage density, Land use/land cover, slope, rainfall and distance to the river were used to develop and determine the flood-prone area. The flood prone areas were obtained by aggregating a broad set of flood-inducing factors aforementioned. The output is shown in Figure 9, and the calculated area of flood prone zones and percentage share are presented in Table 7. Findings revealed that the highest percentage share was recorded in the high class, occupying about 10.40% of the total area which is very negligible. The moderate class accounts for 45.47% of the core area, while the very high class covers about 0.37%. These (High, Very High, and Moderate) equate to a total land area of 49.29km2, 1.75km2, and 215.58km2 respectively. While some part of the study belongs to the low-risk and very low-risk classes. The flood vulnerability map shows that Oguta is a highly developed low-lying part of Imo state, Nigeria is acutely vulnerable to flood threats. Human lives, ecosystem services, economic activities, housing, public facilities, and infrastructure are particularly at risk in this context. This could be attributed to the presence of rivers in the study area. Other contributing factors are changing climate, frenetic urbanization, dwindled proportion of undisturbed forest cover, and topographic features such as gentle slope and low elevation. These characteristics have been identified by Komolafe et al. (2020), who revealed that the proximity to water bodies, deforestation, and urbanization are intimately linked with an increase in vulnerability to severe flooding in Eti-Osa and Lagos Island, which are situated in the Lagos core. This study further confirms the reliability of MCDA in flood vulnerability mapping. However, it is essential to note that MCDA based on expert opinion and weighted overlay approach may be subjected to the researchers' bias, especially with respect to selecting and assigning weights to the flood-inducing factors. Hence, special attention should be given to selecting the best-fitting criteria for MCDA and the weighted overlay method.

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Table 7: Flood prone area

Flood prone classes	Area(km^2)	%
Very low	10.52	2.2
Low	196.96	41.54
Moderate	215.58	45.47
High	49.29	10.40
Very High	1.75	0.37

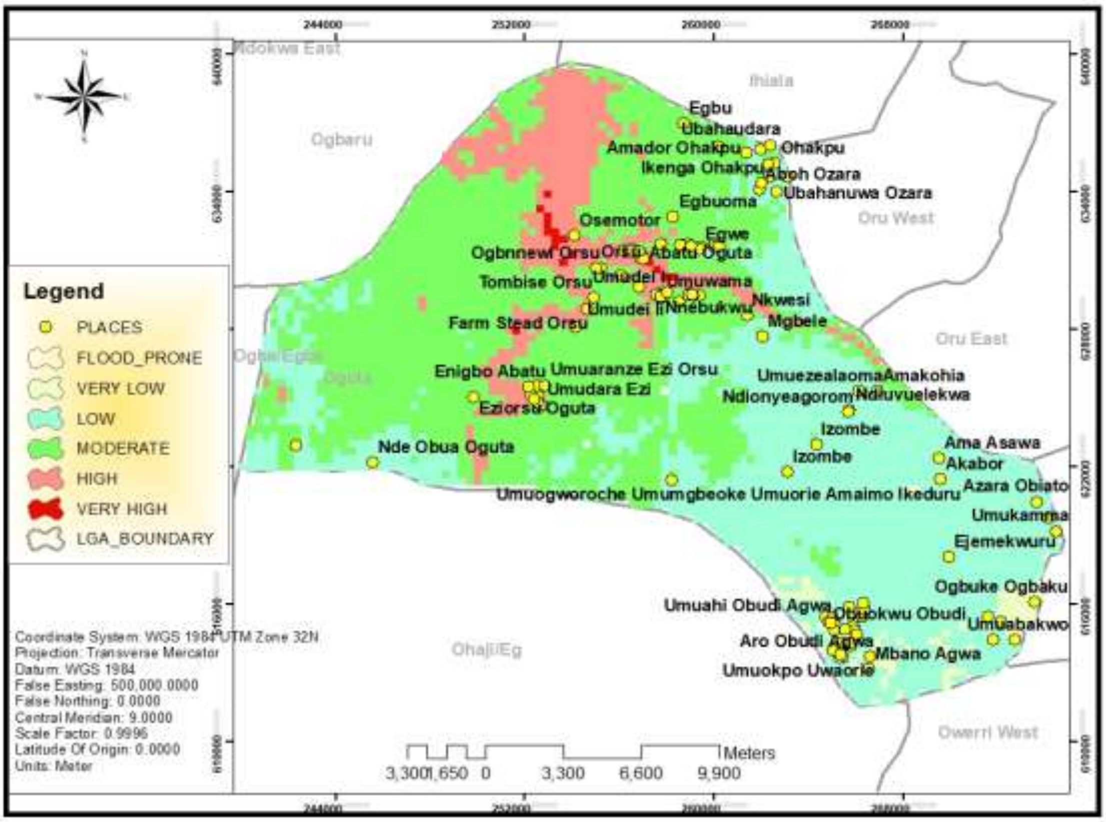

Fig.9: Flood Prone Area map of the study area.

IV. CONCLUSION

Flood is considered as one of the most damaging natural disasters throughout the world and researchers are trying to develop accurate and optimized methods for modeling floods for minimizing its damages. To estimate the discharge resulting in floods in the basins with no prior statistics, experimental models such as regional analysis of flood is utilized. But, as each basin is of its particular properties, it is necessary to make use of methods capable of simulating the flood discharge as per the characteristics of that basin. Flood prone zone delineation is a basic foundation to the success of flood response operations that emergency managers need for flood emergencies. Based on the results of this case study, the aim of the project has been achieved by integrated different flood causative factors derived using satellite imagery and meteorological data to producing the flood prone area maps of Oguta LGA, Imo state. The final output showing areas prone to flood, which can help both decision-makers and inhabitants of the areas that fall under very high, high prone, and moderate areas within the study area and also for humanitarian purposes. As long as physical development continues to extend and spring up in urban centers, flooding is may continue to be one of the major challenges if care is not taken, but, damages from severe flooding can be reduced if not eradicated. The result revealed that the highest percentage share was recorded in the high class, occupying about 10.40% of the total area which is very negligible. The moderate class accounts for 45.47% of the core area, while the very high class covers about 0.37%. These (High, Very High, and Moderate) equate to a total land area of 49.29km2, 1.75km2, and 215.58km2 respectively. While some part of the study belongs to the low-risk and very low-risk classes.The result also proved that multispectral imagery and conventional data along with GIS tools are very essential in determining areas prone to flooding. Therefore, It is noted that remote sensing and GIS applications haven't been fully utilized for flood risk reduction in certain regions, integrating them into environmental planning could substantially decrease post-disaster expenses. Consequently, geospatial and Analytic Hierarchy Process (AHP) techniques have emerged as formidable tools for various facets of flood management, including prevention, warning systems, preparedness, and relief management. These methods represent a significant improvement over traditional approaches.

REFERENCES

[1]. Ahmed, S. (2021). Integrating machine learning and remote sensing for flood vulnerability assessment. Journal of Hydrology, 589.

[2]. Akande, T. O., & Adesina, M. A. (2019). Integrating Socio-Economic Factors into GIS-Based Multi-Criteria Analysis for Flood Risk Assessment: A Case Study of Oguta, Imo State, Nigeria. Journal of Environmental Management, 241, 489–498.

[3]. adjei-Mantey, K., Mensah, P. L., & Amoako, E. E. (2023). Spatial Multi-Criteria Analysis for Discovering Nature-Based Solutions Location for Urban Flood Mitigation in Accra. Environmental Management, 92(6), 954–970.

[4]. Ajayi, O., Adeyemi, J. J., Oloke, L. S., & Akinsanmi, J. A. (2023). A GIS and Multi-Criteria Decision Analysis Approach for Flood Susceptibility Mapping in the Lower Benue River Basin, Nigeria. Nigeria. ISPRS - International Journal of Photogrammetry and Remote Sensing, 207, 284–298.

[5]. Al-Quraishi, A. M., & Babel, M. S. (2021). Flood hazard mapping in Iraq using multi-criteria decision analysis and machine learning techniques. The Egyptian Journal of Remote Sensing and Space Science, 24(2), 339–353.

[6]. Amoako, E. E., Acheampong, E. Y., Odoom, S. K., & Mensah, D. A. (190 C.E.). Integrating multi-criteria analysis and geospatial applications for mapping flood hazards in Sekondi-Takoradi Metropolis, Ghana. Journal of African Earth Sciences.

[7]. Akinola, M. O. (2020). Enhancing GIS-based Multi-Criteria Analysis for Flood Susceptibility Mapping: A Case Study of Oguta, Imo State, Nigeria. Nigeria. Water, 12(12).

[8]. Akpabio, U. (2018). Flood Risk Assessment in Oguta. In Using GIS and Remote Sensing Techniques.

[9]. Al-Sharif, Gaber, A. K., & El-Baz, A. S. (2020). Flood susceptibility mapping and risk assessment using multi-criteria analysis and machine learning (case study: Wadi Araba). Natural Hazards, 101(3), 877–900.

[10]. yahaya S, Ahmad N, Abdalla RF. 2010. Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are River basin, Nigeria. Eur J Sci Res. 42(1):71–83

[11]. Anueyiagu, V. O., & Anyanw, J. C. (2021). FLOOD HAZARD AND RISK ASSESSMENT IN IMO STATE USING GEOGRAPHIC Information System. Global Scientific Journal, 9(7), 146–157.

[12]. Aitkenhead, M. J., Aspinall, R., Graham, S., & Freeman, T. P. (2014). Flood risk in a high-resolution DEM: How does spatial resolution influence surface water connectivity? Journal of Hydrology, 518, 322–334.

[13]. Al-Najjar, Pradhan, H. A., & Ahmad, B. (2023). Integrated landslide susceptibility and flood hazard mapping using multi-criteria decision analysis and geospatial techniques in Northern Peninsular Malaysia. Geomatics, Natural Hazards and Risk, 14(1), 307–334.

[14]. AydinM.C. & Birincioğlu E.S (2022).Flood risk analysis using GIS‑based analytical hierarchy process: a case study of Bitlis Province.Applied Water Science 12:122 https://doi.org/10.1007/s13201-022-01655-x

[15]. Blaschke, T., Dymond, J. R., & Harrison, P. A. (2022). Citizen science in the context of participatory GIS and volunteered geographic information: a conceptual framework. International Journal of Geographical Information Science, 36(1), 3–22.

[16]. Baba, A. I., Ogunwumi, T. S., Waziri, E. S., & Udoh, J. C. (2017). Geospatial mapping of flood hazard using multi-criteria approach in Fufore local government area, northeastern Nigeria. International Journal of Disaster Risk Reduction, 23, 50–58.

[17]. 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).Volume 6, Issue 09 Sep. 2024, pp: 462-473

[18]. Begum, M. P., Swarnakar, L., & Khan, A. N. (2015). Flood susceptibility mapping using geospatial data and multi-criteria analysis: a case study of Brahmaputra floodplain in Assam, India. India. Geocarto International, 30(8), 688–703.

[19]. Ikechukwu, C. I., Osuji, L. C., & Ekwueme, O. C. (2022). Flood hazard assessment and map production using geo-information system and multi-criteria analysis in Owerri, Imo State, Nigeria. Water Resources and Management, 8(6), 1–18.

[20]. Jones, A., & Brown, C. (2019). Geographic Information Systems and Remote Sensing for Coastal Disaster Management: A Review. Natural Hazards, 99(2), 1035–1056.

[21]. Khandaker, A., Hossain, S., Dye, J., & Grumbine, R. E. (2020). Mapping flood-prone areas in coastal Bangladesh using a geospatial modelling approach. Natural Hazards, 101(3), 849–872.

[22]. Lawal, A. O. (2020). GIS-Based Multi-Criteria Decision Analysis for Flood Vulnerability Mapping in Zaria City.

[23]. Li, X., & Wu, J. (2018). GIS-based multi-criteria decision analysis for flood risk assessment in Dongguan, China. China. International Journal of Disaster Risk Reduction, 28, 142–150.

[24]. Liang, X. (2020). Challenges and Opportunities of Multi-Criteria Decision Analysis in GIS-Based Urban Flood Risk Assessment: A. Review. Water, 12(4).

[25]. Longley, P. A. (2015). Multi-Criteria Decision Analysis for Flood Risk Mapping.

[26]. Manson, S. M., Burrough, P. A., & McDonnell, R. A. (1999). Principles of geographical information systems: Spatial information systems and geostatistics. Economic Geography, 75(4), 422. https://doi.org/10.2307/144481

[27]. Masoud, M., Amini, M. H., Maghsoudi, S. F., & Alipour, S. (2020). Spatial multi-criteria decision analysis for flood susceptibility mapping in Talesh Coastal Plain, Iran. Iran. International Journal of Environmental Research, 14(2), 193–208.

[28]. Mondal, S., Sharma, M. C., Saxena, R., & Jai, S. (2017). Assessment of flood susceptibility using GIS and remote sensing data: a case study from Mahi River basin, India. India. Remote Sensing Applications: Earth Sciences, 7, 85–93.

[29]. Nasiri, S., Sharifi, E., Kiafar, M., & Maghsoudi, S. (2021). Flood susceptibility mapping using a novel data-driven ensemble model: a case study in the Dez River basin, Iran. Iran. Natural Hazards, 109(2), 605–632.

[30]. Nouri, H., Aybar, C., & Ozden, O. (2010). Multi-criteria analysis for flood vulnerable areas in Hadejia-Jama'are River basin, Nigeria. Nigeria. European Journal of Scientific Research, 43(3), 494–503.

[31]. Okafor, C. E. (2018). GIS-Based Multi-Criteria Decision Analysis for Flood Susceptibility Mapping: A Case Study of Oguta, Imo State, Nigeria. Geocarto International, 33(10), 1131–1146.

[32]. Okorie, C. C. (2022). Participatory GIS-Based Multi-Criteria Decision Analysis for Flood Risk Assessment in Oguta, Imo State, Nigeria. Nigeria. Sustainability, 14(1).

[33]. Ogallo, P., Ouma, G., & Titus, G. (2020). Flood susceptibility mapping using GIS and multi-criteria analysis in Kiambu County, Kenya. Kenya. International Journal of Remote Sensing Applications, 11(3), 196–208.

[34]. Oyedele, O. S., Adeyemi, I. O., Oloke, L. S., & Akinsanmi, J. A. (2023). Urban flood susceptibility mapping in Ilorin, Nigeria, using GIS and multi-criteria

decision analysis. Journal of Spatial Science, 147(1), 33–46.

[35]. Smith, A. J. (2019). Flood risk assessment using GIS and multicriteria decision analysis: A case study of Ciliwung River, Jakarta, Indonesia. Jakarta, Indonesia. Journal of Flood Risk Management, 12(S2).

[36]. Smith, J. (2018). Advances in Flood Risk Assessment Using GIS-Based Multi-Criteria Analysis. Journal of Environmental Management, 210, 133–143.

[37]. Wang, S. (2017). Flood susceptibility mapping using GIS-based multicriteria decision analysis: A case study of Dongguan, China. China. Geocarto International, 32(9), 1016–1035.

[38]. Abdullahi, S., Pradhan, B., Mansor, S., & Alamri, R. (2022). Flood susceptibility mapping using cloud-based geospatial technologies in the Wadi Bani Harthi catchment, Oman. Earth Environment, 26.

[39]. Hegde, S., Patil, J., & Badiger, S. (2015). Assessing the impact of spatial resolution on flood inundation mapping using LiDAR DEM. International Journal of Applied Geoinformatics, 7(2), 37–44.

[40]. Jusuf, S. K., Sahari, B., & Abdullah, R. (2020). Geometric and radiometric corrections of Landsat-8 image using QGIS and Erdas Imagine for land cover classification. IOP Conference Series: Earth and Environmental Science, 464.

[41]. Yahaya S, Ahmad N, Abdalla RF. 2010. Multicriteria analysis for flood vulnerable areas in Hadejia

[42]. Yoel, K., Khandidi, M. D., & Sulistya, B. W. (2023). The influence of spatial resolution on the accuracy of flood inundation modeling using LISFLOOD-FP model. IOP Conference Series: Earth and Environmental Science.

[43].