Spatial evaluation of flood risk using Geospatial and Multi-Criteria Decision Analysis (MCDA): A case study in Obio-Akpor, Rivers State, Nigeria.

Abstract

This study assesses flood risk in Obio-Akpor, Rivers State, Nigeria, using a Geospatial and Multi-Criteria Decision Analysis (MCDA) approach, incorporating Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP). The research aims to evaluate flood risk by analyzing critical environmental factors, including Digital Elevation Model (DEM), Land Use/Land Cover (LULC), slope, drainage density, flow accumulation, rainfall, geological type, Normalized Difference Water Index (NDWI), and curvature. This study addresses the need for a reliable flood risk assessment tool to aid urban planning and disaster management in flood-prone areas. The methodology involved processing spatial data with MCDA and AHP, analyzed using ArcGIS 10.6. Data were sourced from the United States Geological Survey (SRTM), European Space Agency (Sentinel-2 imagery), Nigeria Geological Survey Agency (geological map), and Nigerian Meteorological Agency (rainfall data). AHP was used to assign weights to flood risk factors based on expert judgment, and the reclassified data generated a flood risk map. The results indicate that 33% of the area is at low risk, 37% at moderate risk, 20% at high risk, and 10% at very high risk. The study concludes that DEM, LULC, and slope are the most significant factors influencing flood risk, while rainfall, geology, NDWI, and curvature have a lesser impact. These findings highlight the importance of elevation and land use in flood risk assessment and identify areas vulnerable to flooding. This research provides valuable insights for urban planners and policymakers, offering a robust tool for managing flood risks and enhancing resilience in vulnerable regions.

Keyword: Flood Risk Assessment, Geospatial Analysis, MCDA, Analytic Hierarchy Process (AHP), ArcGIS, Urban Flood

1. INTRODUCTION

Flood disasters have emerged as a significant global challenge, inflicting substantial economic losses, environmental degradation, and human suffering [1-3]. Developing countries, particularly those with rapid urbanization and inadequate infrastructure, are disproportionately vulnerable to these hydro-meteorological hazards [4,5]. Nigeria, with its burgeoning population and rapid urbanization, is no exception. The Niger Delta region, including Port Harcourt, the state capital of Rivers State, has the city has experienced rapid urbanization and population growth, which have exacerbated flood risks due to the alteration of natural drainage systems and the encroachment upon floodplains. This phenomenon has led to increased vulnerability of urban properties and infrastructure, necessitating effective flood risk assessment and management strategies [6]. To mitigate the adverse impacts of flooding, effective flood risk assessment is crucial. This involves identifying areas prone to flooding, evaluating potential consequences, and developing appropriate response strategies [7]. Traditional methods for flood risk assessment often rely on historical data and hydrological models, which may be limited in their ability to capture the complexities of urban environments [8]. Recent studies underscore the critical need for a spatial assessment of flood risk using advanced methodologies, such as Geospatial and Multi-Criteria Decision Analysis (MCDA), to inform decision-making and enhance disaster preparedness in flood-prone areas. Flood risk assessment involves evaluating both the likelihood of flooding and the potential consequences on human life, property, and the environment. It is essential to understand that flood risk is a function of hazard exposure, vulnerability, and adaptive capacity. The integration of geospatial data with MCDA provides a robust framework for analyzing complex flood risk scenarios by allowing for the consideration of multiple factors and stakeholder preferences [9]. This approach not only facilitates the identification of high-risk areas but also supports the development of targeted mitigation strategies that can significantly reduce flood impacts. Geospatial technologies, including Geographic Information Systems (GIS) and remote sensing, provide valuable tools for collecting, analyzing, and visualizing spatial data related to flood risk factors [10]. These technologies enable the creation of detailed maps and models that can be used to identify areas with high flood vulnerability [11,12]. MCDA, on the other hand, offers a structured framework for incorporating multiple criteria, often conflicting, into the decision-making process [9,13]. By combining geospatial data with MCDA, it is possible to evaluate the relative importance of different flood risk factors and identify areas with the highest overall risk [14]. Recent research such as Koralay & Kara [14] and Aladejana & Ebijuoworih [15] highlighted the effectiveness of utilizing Geographic Information Systems (GIS) in conjunction with MCDA to assess flood vulnerability and risk. Ugwu et al. [6] conducted a comprehensive spatial assessment of flood vulnerability in Port Harcourt, revealing that a significant proportion of developed properties are situated in areas of moderate to high flood vulnerability. Their findings indicated that approximately 79% of developed properties fall within moderately vulnerable zones, emphasizing the urgent need for proactive flood management interventions in the metropolis [6]. This study serves as a critical reference point for understanding the spatial dynamics of flood risk in the region. Moreover, the application of MCDA methodologies allows for the incorporation of diverse datasets, including hydrological, topographical, and socio-economic factors, into the flood risk assessment process. This multidimensional analysis is crucial for capturing the complex interactions between various flood risk drivers, thereby enabling more informed decision-making. For example, recent studies have demonstrated the utility of MCDA in identifying flood hazard drivers and vulnerability factors, which can then be mapped to produce comprehensive flood risk profiles for urban areas [15,16]. Such methodologies not only enhance the accuracy of flood risk assessments but also promote stakeholder engagement by incorporating local knowledge and preferences into the decision-making process. In the context of Port Harcourt, the integration of geospatial technologies and MCDA is particularly relevant given the city's unique geographical and socio-economic characteristics. The Niger Delta region, where Port Harcourt is located, is prone to seasonal flooding due to its low-lying topography, high rainfall, and inadequate drainage infrastructure. Consequently, the city faces significant challenges related to flood management, including the need for effective urban planning, infrastructure development, and community engagement in flood risk reduction initiatives. This study aims to conduct a spatial assessment of flood risk in Port Harcourt using a geospatial and MCDA approach. By analyzing various flood risk factors and their spatial distribution, the research seeks to identify areas most at risk of flooding and provide recommendations for mitigating flood impacts. The findings will contribute to the existing body of knowledge on flood risk management in Nigeria and provide valuable insights for policymakers, urban planners, and disaster management authorities. In conclusion, the combination of geospatial analysis and MCDA represents a powerful tool for understanding and addressing flood risks in urban environments like Port Harcourt. As the impacts of climate change and urbanization continue to intensify, the need for comprehensive flood risk assessments becomes increasingly critical. This study will not only enhance our understanding of flood dynamics in Port Harcourt but also support the development of effective strategies for flood risk reduction and resilience building in Obio-Akpor.

2. LOCATION AND ACCESSIBILITY OF THE STUDY AREA

Obio-Akpor is part of Port Harcourt city located in Rivers state, south eastern Nigeria, situated at the mouth of River Bonny and lies between latitude $4^0$43'0"N – latitude $4^0$57'3"N and longitude $6^0$0'0"E – longitude $7^0$5'54"E (Figures 1a and 1b). It is the capital of Rivers state which boasts Nigeria's largest oil and gas reserves making it a city of great economic importance [17]. Port Harcourt is Nigeria's fourth largest city after Lagos (Southwest), and regional centres Kano (Northwest) and Ibadan (Southwest). The city is positioned between the Dockyard creek and the Amadi creek at an average altitude of about 12m above mean sea level.

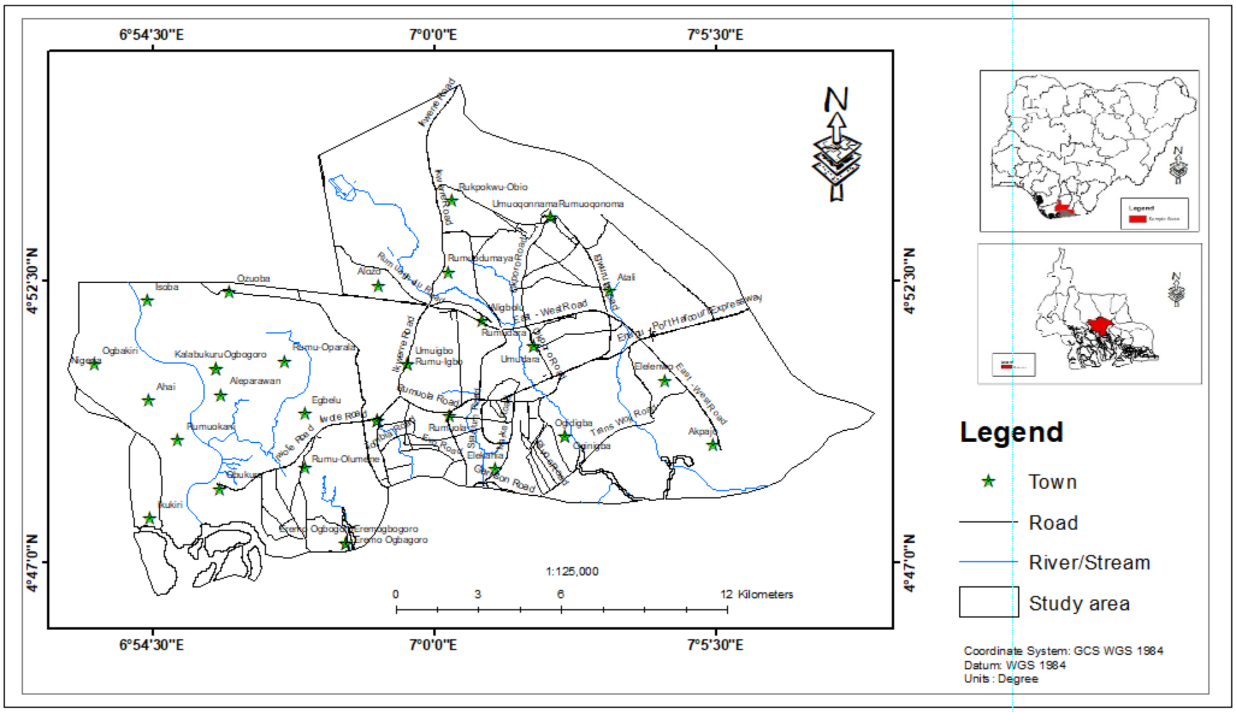


Figure 1a: Study area map

The Niger Delta is a geological wonder, being one of the world largest river-dominated deltas. Its formation is closely linked to the interplay of tectonic activity, sedimentation, and sea-level changes [18] The delta foundation is within the Benue Trough, a rift basin formed during the Cretaceous period. As the Atlantic Ocean opened, extensional forces acted on the African plate, creating the structural framework for the delta. Over millions of years, the Niger River and its tributaries deposited vast amounts of sediment, forming the delta's substantial thickness [19]. The delta stratigraphy comprises three main lithofacies : the marine claystones and shales of the Akata Formation, the alternating sandstones and shales of the Agbada Formation, and the overlying alluvial sands of the Benin Formation [20,21]. These units display a regressive sequence, indicating a gradual shift from marine to continental environments [18, 22]. The Niger Delta is noted for its abundant hydrocarbon resources, primarily from the organic-rich shales of the Akata Formation. The porous sandstones of the Agbada Formation act as excellent reservoirs, while the overlying shales provide effective seals, creating optimal conditions for oil and gas accumulation [23].

3. MATERIALS AND METHODS

Data Acquisition

The following spatial data were collected for the analysis: The Shuttle Radar Topographic Mission (SRTM) DEM was obtained from the official website of the United States Geological Survey (USGS) (http://www.earthexplorer.usgs.gov/) to be used in flood risk assessment. The boundary of the study area was defined using an administrative map, also obtained from the USGS website. High-resolution satellite imagery from Sentinel-2 was downloaded from the European Space Agency website for use in the flood risk assessment. Geological data for the study area were acquired from the Nigeria Geological Survey Agency, and historical rainfall data were obtained from the Nigerian Meteorological Agency (NIMET).

Methodology

Data Integration and Preprocessing

The first step in the process was the collection of relevant datasets. Maps and satellite images were obtained from reliable sources. The DEM, a crucial input for terrain analysis, was acquired from sources like the Shuttle Radar Topography Mission (SRTM). Once these datasets were obtained, they were imported into ArcGIS 10.6 for preprocessing.

Preprocessing involved several steps, including georeferencing, resampling, and reprojection, to ensure that all data layers were in the same spatial reference system. This uniformity is critical for accurate spatial analysis. Georeferencing was performed by aligning the raster and vector layers to a common coordinate system, typically WGS 1984. Resampling was used to standardize the pixel size of raster data, ensuring consistency across datasets. Reprojection was then applied to ensure that all datasets conformed to the same projection, which minimizes spatial distortions during analysis.

Generation of Flood Conditioning Factor Maps

Once the data was preprocessed, the next step involved generating the flood conditioning factor maps. These maps represent the environmental and hydrological factors that influence flood risk in the study area.

1. **Elevation**: Elevation data, also extracted from the DEM, was crucial for identifying low-lying areas prone to flooding. The Elevation tool was used to create this map, which provides a visual representation of the terrain's height above sea level.
2. **Flow Accumulation**: Flow accumulation was derived from the DEM using hydrological analysis tools in ArcGIS. This map identifies areas where water is likely to converge, indicating potential zones of water accumulation that could lead to flooding.

3. **Slope**: The slope was derived from the DEM using the Slope tool in ArcGIS. This map highlights areas of steep terrain, which can influence the velocity and direction of surface runoff, thus impacting flood risk.
4. **Curvature**: The curvature map was created to assess the convexity or concavity of the terrain. Areas with high curvature values can influence water flow patterns, making them critical in flood risk analysis.
5. **Drainage Density**: The drainage density map was generated by calculating the total length of drainage channels per unit area. This factor is important as areas with higher drainage density are more efficient at channeling water, potentially reducing the risk of surface water accumulation and flooding.
6. **Land Use/Land Cover (LULC)**: Satellite images were classified into different land use and land cover categories, such as Built up areas, vegetation, water bodies, and bare land. The LULC map was created using supervised classification techniques, helping to identify regions where human activities might exacerbate flood risks.
7. **Normalized Difference Water Index (NDWI)**: NDWI, calculated using satellite imagery, was used to highlight water bodies and moisture content in vegetation. The NDWI map is particularly useful for identifying areas that are already saturated with water and thus more susceptible to flooding.
8. **Rainfall**: Rainfall data, usually obtained from meteorological stations or satellite-derived precipitation products, was interpolated using Inverse Distance Weighting (IDW) technique to create a continuous rainfall distribution map. This map illustrates the spatial variability of rainfall, a primary driver of flood events
9. **Geology**: Geological data, including soil types and rock formations, was integrated into the analysis. The geology map was created using vector layers that depict different geological formations, which can affect infiltration rates and surface runoff.

Generation of Thematic Maps

The final step in the data processing involved the creation of thematic maps for each flood conditioning factor. These maps—rainfall, slope, elevation, land use/land cover, drainage density, NDWI, flow accumulation, curvature, and geology—were generated using the Raster Calculator and Map Algebra tools in ArcGIS. Each map was carefully examined and validated to ensure accuracy.

Reclassification: Reclassification is a critical step in flood risk assessment, allowing for the transformation of raw spatial data into a format that highlights the relative importance of different flood-influencing factors. In this study, nine factors were reclassified: curvature, drainage density, digital elevation model (DEM), flow accumulation, geological type, land use/land cover (LULC), Normalized Difference Water Index (NDWI), rainfall distribution, and slope degree (Figure 2a). Each factor was assigned a weight based on its contribution to flood risk, which was then used to develop the flood risk assessment map.

Multi-Criteria Evaluation (MCE) and Analytical Hierarchy Process (AHP): The AHP method employed pair-wise comparisons to weigh the relative influence of each factor on flood risk [24-

26] This approach facilitated judgments and calculations. The AHP model assigned weights and ranks to each flood factor and its classes (1-5) based on their contribution to flood risk in the study area. For some factors, the ranking was reversed, with the highest impact category receiving the highest weight. The AHP extension in ArcGIS 10.6 was used for these calculations. The weight Wi of each factor iii was calculated using the formula:

$$W_i = \frac{A_i}{\sum_{i=1}^{n} A_i} \qquad \text{Eq. 1}$$

where Ai represents the eigenvalue of the factor iii obtained from the pairwise comparison matrix, and n is the total number of factors.

Weighted Overlay Method: This method involved assigning weights to each raster layer based on its importance in flood risk. The values in each raster were then reclassified on a common scale of 1 to 5. Subsequently, the raster layers were overlaid, with each cell's preference value multiplied by its layer weight. The resulting values were summed to derive a final preference value for each cell. The weighted overlay formula is:

$$R_j = \sum_{i=1}^{n} W_i * Sij \qquad \text{Eq. 2}$$

where R_j is the risk score for cell j, Wi is the weight of factor iii, and Sij is the score of factor iii in cell $_j$. Finally, these values were used to create a flood risk map.

Flood Risk Criteria Ranking: Nine criteria were identified as crucial for flood risk assessment. These criteria were reclassified, and a linear function was used to assign preference values (1-5) to different classes within each criterion. The preference values ranged from 1 (low risk) to 5 (high risk). This combined approach of GIS analysis and AHP allowed for a comprehensive assessment of flood risk in the chosen region.

4. RESULTS AND DISCUSSION

4.1 Results

Utilizing various parameters such as curvature, drainage density, digital elevation model (DEM), flow accumulation, geological type, land use/land cover, Normalized Difference Water Index (NDWI), rainfall distribution, and slope degree. The results are presented below with findings from Tables 1 to 9 and Figure 2a.

Table 1: Curvature description level on flood risk

Rate of curve	Ranking	Unified Value	Flood Risk Class
-4.09 – -0.55	1	20	Very low
-0.54 – -0.23	2	40	Low
-0.22 – 0.08	3	60	Moderate
0.09 – 0.39	4	80	High
0.4 – 7.34	5	100	Very High

Table 2: Drainage Density description level on flood risk

Drainage Density (km^2)	Ranking	Unified Value	Flood Risk Class
0 – 198.04	1	20	Very low
198.05 – 396.08	2	40	Low
396.09 – 594.12	3	60	Moderate
594.13 – 792.16	4	80	High
792.17 – 990.2	5	100	Very High

Table 3: Digital Elevation Model description level on flood risk

Digital Elevation Model (m)	Ranking	Unified Value	Flood Risk Class
-17 – 5	5	100	Very High
5.01 – 11	4	80	High
11.01 – 17	3	60	Moderate
17.01 – 22	2	40	Low
22.01 – 43	1	20	Very Low

Table 4: Flow Accumulation description level on flood risk

Flow Accumulated Value	Ranking	Unified Value	Flood Risk Class
0 – 2,449.52	1	20	Very low
2,449.53 – 10,070.24	2	40	Low
10,070.25 – 22,590	3	60	Moderate
22,590.01 – 38,647.95	4	80	High
38,647.96 – 69,403	5	100	Very High

Table 5: Geological type description level on flood risk

Vegetation type	Ranking	Unified Value	Flood Risk Class
Coastal plain sands	1	20	Very low
Deltaic basins and tidal flats	2	40	Low
Mangrove swamps	3	60	Moderate
Recent alluvium	4	80	High
Recent alluvium and coastal plain sands	5	100	Very High

Table 6: Land use/ land cover description level on flood risk

Land use/land cover	Ranking	Unified Value	Flood Risk Class
Vegetation	1	25	Low
Bare land	2	50	Moderate
Built up area	3	75	High
Water bodies	4	100	Very High

Table 7: NDWI description level on flood risk

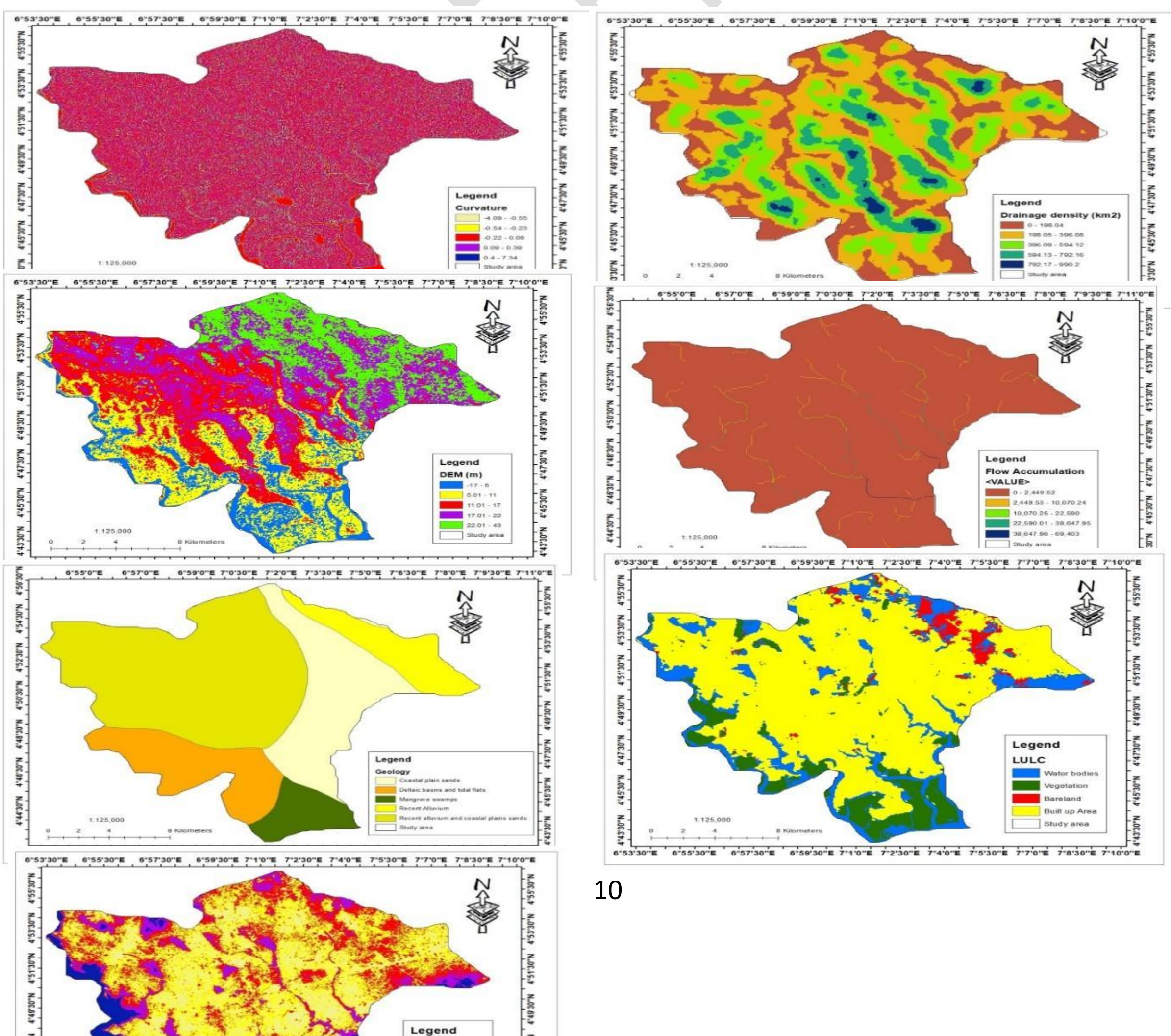
Index Value	Ranking	Unified Value	Flood Risk Class
-0.7 – 0.06	1	20	Very low
0.07 – 0.11	2	40	Low
0.12 – 0.19	3	60	Moderate
0.2 – 0.3	4	80	High
0.31 – 0.43	5	100	Very High

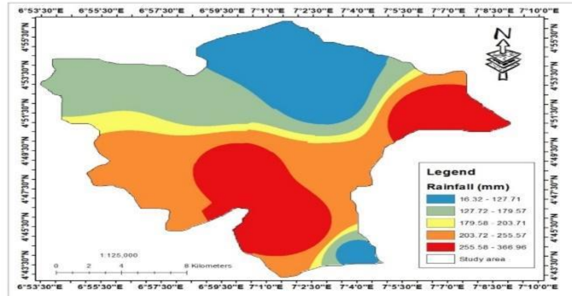
Table 8: Rainfall distribution description level on flood risk

Rainfall distribution (mm)	Ranking	Unified Value	Flood Risk Class
16.32 – 127.71	1	20	Very low
127.72 – 179.57	2	40	Low
179.58 – 203.71	3	60	Moderate
203.72 – 255.57	4	80	High
255.58 – 366.96	5	100	Very High

Table 9: Slope description level on flood risk

Slope (Degree)	Ranking	Unified Value	Flood Risk Class
0 – 10	2	100	Very high
10.01 – 25	1	50	High





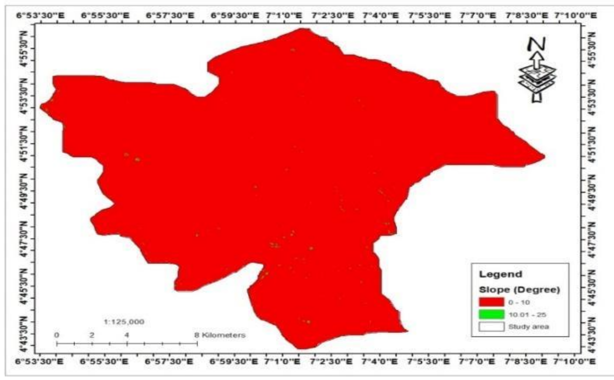


Figure 2a: Curvature, drainage density, digital elevation model (DEM), flow accumulation, geological type, land use/land cover, Normalized Difference Water Index (NDWI), rainfall distribution

4.2 Discussion

Flood risk assessment is critical for urban planning and disaster management, especially in flood-prone areas like Port Harcourt, Rivers State, Nigeria. This study employs a Geospatial and Multi-Criteria Decision Analysis (MCDA) approach to assess flood risk, utilizing various parameters such as curvature, drainage density, digital elevation model (DEM), flow accumulation, geological type, land use/land cover, Normalized Difference Water Index (NDWI), rainfall distribution, and slope degree. The results are discussed in detail and compared with other recent studies to validate the findings.

Curvature is an important geomorphological factor influencing flood risk. Table 1 illustrates the unified preference values for curvature, showing that areas with a curvature range of -4.09 to -0.55 have a very low flood risk (Figure 2b), while areas with a curvature range of 0.4 to 7.34 have a very high flood risk. This trend is consistent with findings by Otokiti et al., [27] who noted that higher curvature values are associated with increased surface runoff and flood potential [28].

Drainage density is a measure of the total length of streams and rivers per unit area, affecting flood dynamics. Table 2 shows that areas with lower drainage density (0 – 198.04 km^2) exhibit very low flood risk, whereas areas with higher drainage density (792.17 – 990.2 km^2) have a very high flood risk (Figure 2b). This relationship aligns with the study by which highlighted that regions with higher drainage density are more susceptible to flooding due to higher runoff potential.

DEM is crucial for understanding topographic variation and flood risk. As indicated in Table 3, areas with lower elevation (-17 to 5 m) have a very high flood risk (Figure 2b), while higher elevation areas (22.01 to 43 m) have very low flood risk. This observation is supported by Ugwu et al., [6] and Sahraei et al., [29] who found that low-lying areas are more prone to flooding due to limited drainage and higher water accumulation [30]

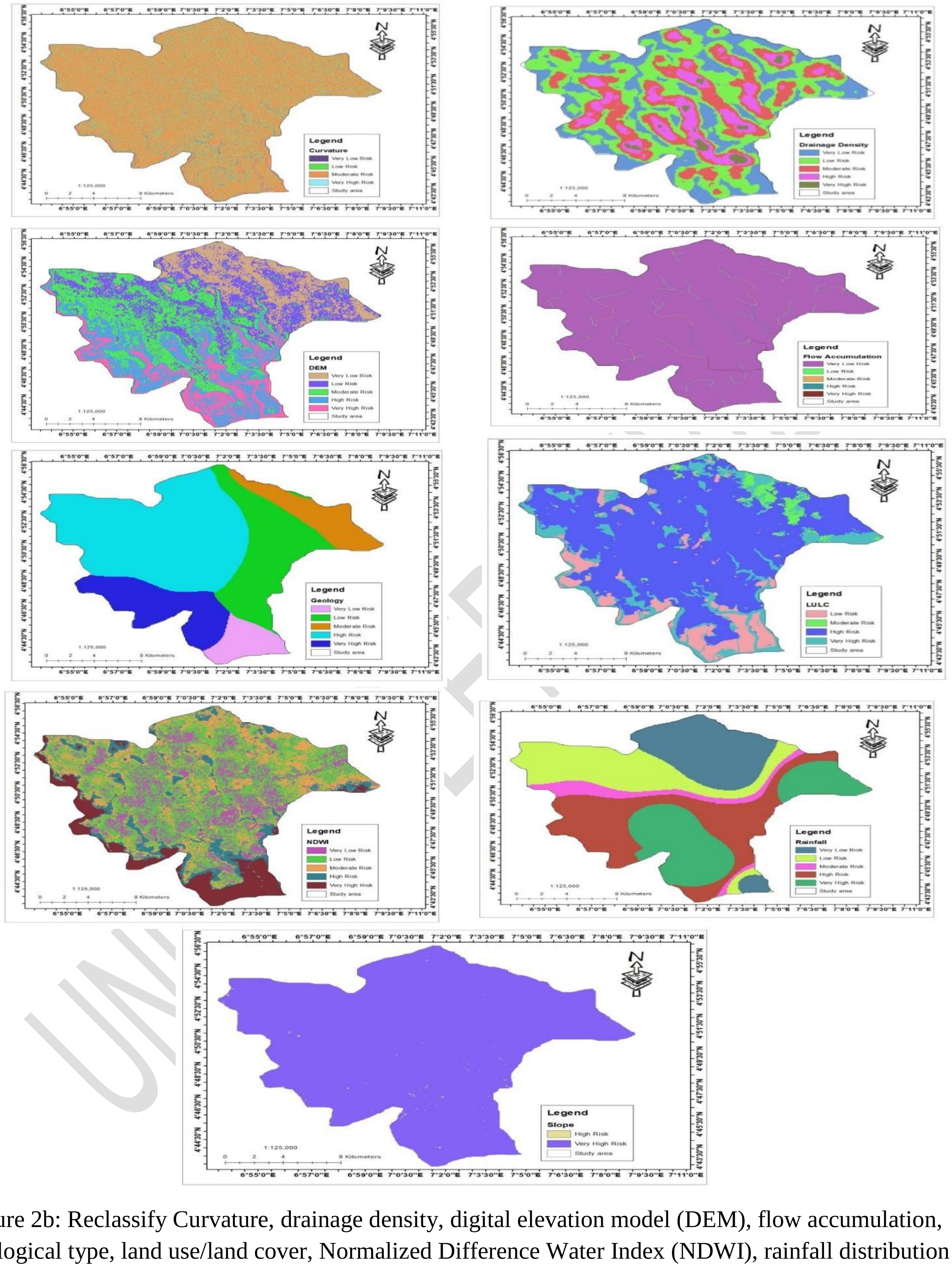


Figure 2b: Reclassify Curvature, drainage density, digital elevation model (DEM), flow accumulation, geological type, land use/land cover, Normalized Difference Water Index (NDWI), rainfall distribution

Flow accumulation reflects the convergence of water flow in a particular area. According to Table 4, regions with lower flow accumulation (0 – 2,449.52) have very low flood risk, whereas regions with higher flow accumulation (38,647.96 – 69,403) have very high flood risk (Figure 2b). These results are in line with those of Kazakis et al., [31] which demonstrated that areas with higher flow accumulation are more likely to experience flooding due to greater water convergence [32].

Geological characteristics influence flood risk due to varying permeability and water retention properties. Table 5 indicates that coastal plain sands exhibit very low flood risk (Figure 2b), whereas recent alluvium and coastal plain sands have very high flood risk. Similar findings were reported by Ghosh and Kar [33] who identified that alluvial regions are more flood-prone due to their high permeability and water retention capacity [34].

Land use and cover types significantly affect flood risk. Table 6 reveals that areas with vegetation have low flood risk, while built-up areas and water bodies have high to very high flood risk (Figure 2b). This trend is corroborated by Ugwu et al., [6] and Bui et al., [35] who noted that urbanization and the presence of water bodies increase flood susceptibility due to reduced infiltration and increased surface runoff [34].

NDWI is used to identify water content in vegetation and soil. Table 7 shows that areas with higher NDWI values (0.31 – 0.43) have very high flood risk (Figure 2b), while areas with lower NDWI values (-0.7 – 0.06) have very low flood risk. This observation is consistent which found that higher NDWI values are associated with increased soil moisture and flood risk [32].

Rainfall intensity and distribution are critical factors in flood risk assessment. Table 8 demonstrates that areas with higher rainfall distribution (255.58 – 366.96 mm) have very high flood risk, while areas with lower rainfall distribution (16.32 – 127.71 mm) have very low flood risk (Figure 2b). This relationship aligns with the findings of Chapi et al., [36] and Wu et al., [37] who emphasized that regions with higher rainfall are more susceptible to flooding [32].

Slope degree affects the velocity and volume of runoff. Table 9 indicates that areas with lower slopes (0 – 10 degrees) have very high flood risk, whereas steeper slopes (10.01 – 25 degrees) have high flood risk (Figure 2b). This trend is supported by Pham et al., [38] and Eteh et al., [39], who found that flatter areas are more prone to flooding due to slower water movement and greater accumulation.

4.2.2 Development of the Pairwise Comparison Matrix

The Analytic Hierarchy Process (AHP) was employed to develop a pairwise comparison matrix. This involved expert judgment to assign relative importance to various flood-inducing factors based on the Saaty scale, ranging from 1 (equal importance) to 9 (extremely important) as shown in Tables 10 and 11. The factors considered included Digital Elevation Model (DEM), Land Use/Land Cover (LULC), Slope, Drainage Density (DD), Flow Accumulation, Rainfall, Geology, Normalized Difference Water Index (NDWI), and Curvature. This method facilitates the comparison of criteria by assigning a numerical value to the importance of one criterion over another.

Table 10: The intensity of pair wise comparison ranking [40]

The intensity of pair wise comparison	Interpretation
1	Equal importance
2	Equal to Moderately importance
3	Moderately to the strong importance
4	Moderate to the strong importance
5	Strong importance
6	Strong to the very strong importance
7	Very strong importance
8	Very to the extremely importance
9	Extremely importance

Table 11: Pairwise comparison of a 9-point continuous scale

Criterion	DEM	LULC	Slope	DD	Flow Acc	Rainfall	Geology	NDWI	Curvature
DEM	1								
LULC	1/2	1							
Slope	1/3	1/2	1						
DD	1/4	1/3	1/2	1					
Flow Acc	1/5	1/4	1/3	½	1				
Rainfall	1/6	1/5	1/4	1/3	½	1			
Geology	1/7	1/6	1/5	¼	1/3	1/2	1		
NDWI	1/8	1/7	1/6	1/5	¼	1/3	1/2	1	
Curvature	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1
	2.8	4.7	7.5	11.3	16.3	22.1	28.8	36.5	45.0

4.2.3 Pairwise Comparison and Eigenvector Weight Calculation

Using the pairwise comparison matrix, the eigenvector weights for each criterion were calculated. Table 12 presents these weights, showing the relative importance of each factor in determining flood risk in Port Harcourt. The consistency ratio (CR) was found to be 0.03, indicating that the comparisons were consistent and acceptable. The calculated weights were then used to derive the relative importance percentages for each criterion, as detailed in Table 13.

Table 12: Pair wise comparison matrix

	DEM	LULC	Slope	DD	Flow Acc	Rainfall	Geology	NDWI	Curvature	Eigenvector weight	Percentage (%)
DEM	0.35	0.43	0.40	0.35	0.31	0.27	0.24	0.22	0.20	0.31	30.85
LULC	0.18	0.21	0.27	0.27	0.25	0.23	0.21	0.19	0.18	0.22	21.92
Slope	0.12	0.11	0.13	0.18	0.18	0.18	0.17	0.16	0.16	0.15	15.49
DD	0.09	0.07	0.07	0.09	0.12	0.14	0.14	0.14	0.13	0.11	10.92
Flow Acc	0.07	0.04	0.03	0.03	0.06	0.09	0.10	0.11	0.11	0.07	7.26
Rainfall	0.06	0.04	0.03	0.03	0.03	0.05	0.07	0.08	0.09	0.05	5.34
Geology	0.05	0.04	0.03	0.02	0.02	0.02	0.03	0.05	0.07	0.04	3.71
NDWI	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.04	0.03	2.60
Curvature	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	1.90
Total										1	100

Consistency ratio = 0.03, consistency is acceptable

Flood Influencing Factors

The results indicate that the Digital Elevation Model (DEM) is the most significant factor, with a relative weight of 30.85%. This is followed by Land Use/Land Cover (LULC) at 21.92% and Slope at 15.49%. Drainage Density (DD) and Flow Accumulation have weights of 10.92% and 7.26%, respectively. Rainfall, Geology, Normalized Difference Water Index (NDWI), and Curvature are less influential, with relative weights of 5.34%, 3.71%, 2.60%, and 1.90%, respectively.

Table 13: Flood influencing factor relative weight percent

S/N	Parameters	Relative Weight (%)
1	Digital Elevation Model	30.85
2	Landuse/Landcover	21.92
3	Slope	15.49
4	Drainage Density	10.92
5	Flow Accumulation	7.26
6	Rainfall	5.34
7	Geology	3.71
8	NDWI	2.60
9	Curvature	1.90

4.2.4 Spatial Assessment of Flood Risk

The flood risk map (Figure 3 and 4) generated from the analysis reveals the spatial distribution of flood risk in Port Harcourt. The map categorizes areas into four flood risk classes: Low, Moderate, High, and Very High. The final flood assessment results, shown in Table 14, indicate that 33% of the area is at low risk, 37% at moderate risk, 20% at high risk, and 10% at very high risk.

Table 14: Final flood assessment results

Flood Risk Class	Area (km^2)	Percentage (%)
Low	35.97	33
Moderate	40.33	37
High	21.8	20
Very High	10.9	10

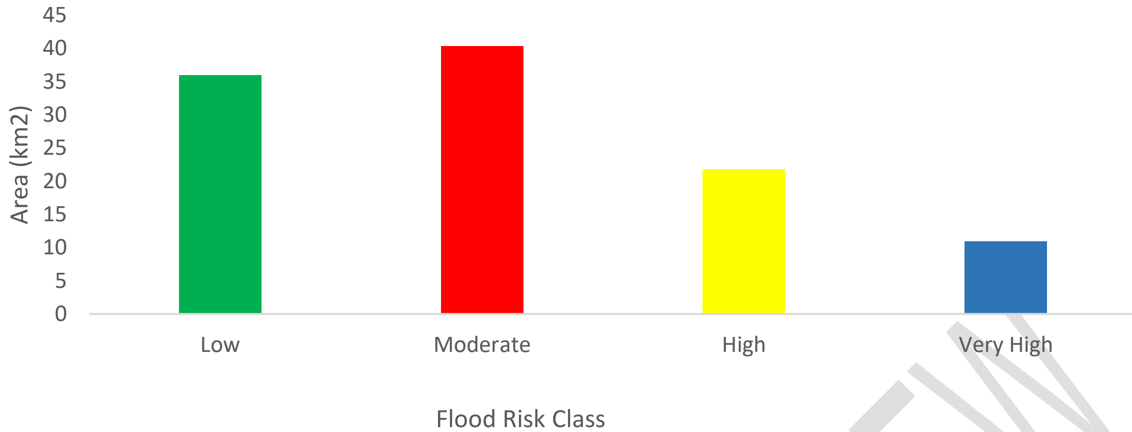


Figure 3: bar chart of flood assessment

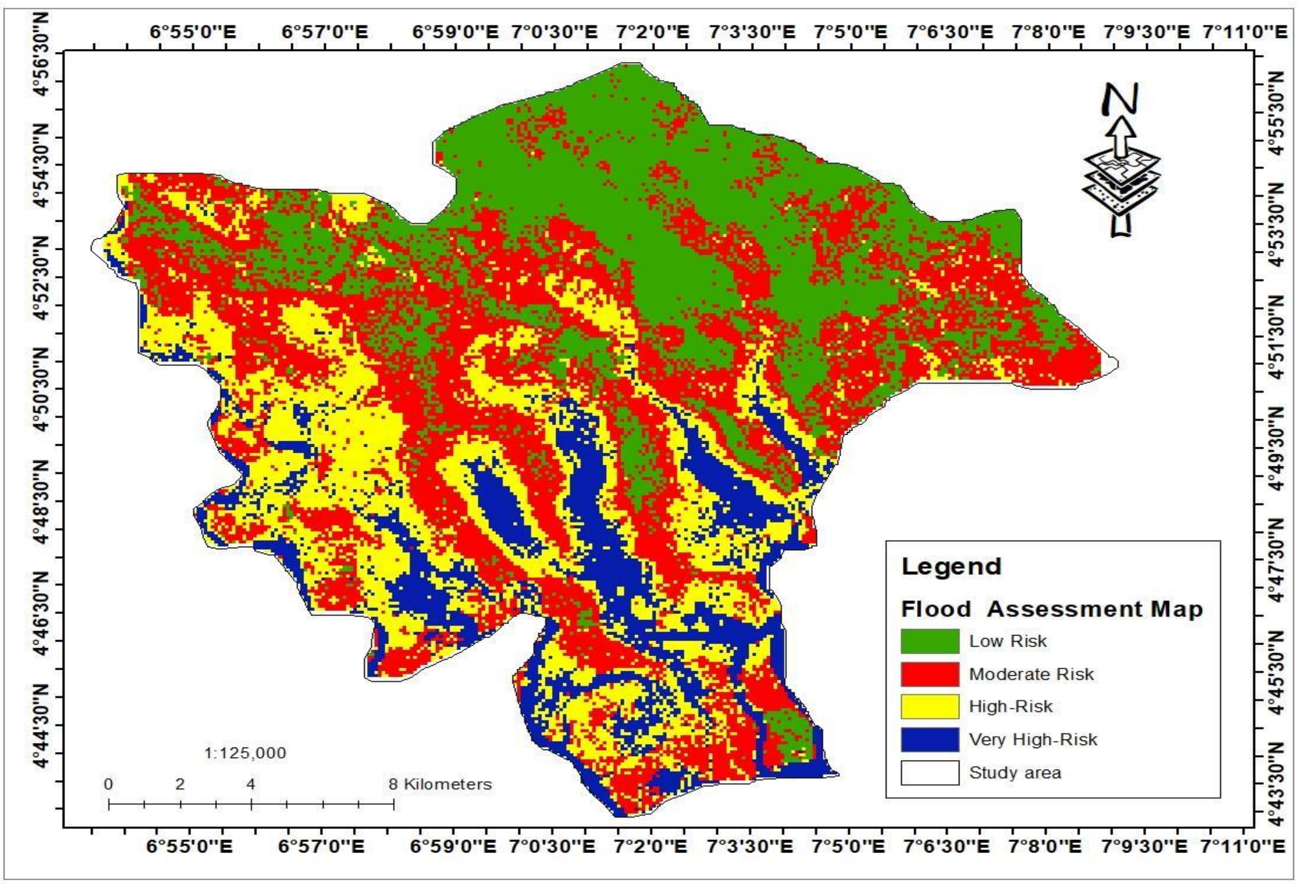


Figure 4: Flood sensitive map in Obio-Akpor, Rivers State, Nigeria

The spatial assessment of flood risk using the MCDA approach provides a comprehensive understanding of flood-prone areas in Port Harcourt. The high influence of DEM indicates that elevation variations significantly affect flood risk. Low-lying areas are more susceptible to flooding due to their inability to effectively drain excess water. Similarly, LULC and slope are critical factors, as they influence surface runoff and water retention. The moderate to high importance of DD and flow accumulation indicates that areas with dense drainage networks and significant water flow accumulation are more likely to experience flooding. Rainfall, though a direct contributor to flood events, has a lower relative weight, possibly due to the uniformity of precipitation patterns in the study area. Geology, NDWI, and curvature have minimal impact on flood risk, reflecting their lesser role in the specific context of Port Harcourt.

5. CONCLUSION

Flood risk assessment is essential for urban planning and disaster management, particularly in flood-prone areas such as Port Harcourt, Rivers State, Nigeria. This study utilized a Geospatial and Multi-Criteria Decision Analysis (MCDA) approach, incorporating factors like curvature, drainage density, digital elevation model (DEM), flow accumulation, geological type, land use/land cover (LULC), Normalized Difference Water Index (NDWI), rainfall distribution, and slope degree. The findings highlight that the DEM is the most significant factor affecting flood risk, with a relative weight of 30.85%. This indicates that low-lying areas are more prone to flooding due to poor drainage and higher water accumulation. LULC (21.92%) and slope (15.49%) also play crucial roles, influencing surface runoff and water retention. Areas with dense drainage networks and significant flow accumulation exhibit higher flood risk, aligning with the moderate to high importance of these factors. The study found that curvature, NDWI, and geology have minimal impacts, suggesting their lesser role in this context. The reclassification of these factors allowed for the development of a detailed flood risk map, categorizing areas into low, moderate, high, and very high risk. The results show that 33% of Port Harcourt is at low risk, 37% at moderate risk, 20% at high risk, and 10% at very high risk. The analysis validates previous studies, confirming that areas with higher curvature, drainage density, lower elevation, and greater flow accumulation are more susceptible to flooding. Additionally, it was observed that built-up areas and water bodies have high flood risk due to reduced infiltration and increased runoff. Rainfall intensity, despite being a direct contributor to flood events, showed a lower relative weight due to uniform precipitation patterns in the region. Therefore, this comprehensive flood risk assessment using MCDA and geospatial techniques provides valuable insights for urban planners and disaster management authorities. The findings underscore the need for targeted interventions in high-risk areas to mitigate flood impacts, emphasizing the critical roles of elevation, land use, and drainage characteristics in flood risk management.

Conflict of Interest:

The authors have no conflicts of interest to disclose related to the content of this article.

Funding Declaration:

No financial support, grants, or other funding was received for this study.

Author Contributions:

P.M. and W.T. conceptualized the study and contributed to the writing and formatting. T.I. and A.G.W handled the data processing and assisted with the writing. All authors collaboratively wrote the final version of the manuscript.

Acknowledgments:

We sincerely thank Eteh, Desmond Rowland for his valuable contributions and supervision during this research. We also extend our gratitude to the anonymous reviewers for their insightful feedback and suggestions, which significantly improved this work.

References

[1]. Kundzewicz, Zbigniew & Buda, Su & Wang, Yanjun & Xia, Jun & Huang, Jinlong & Tong, Jiang. (2019). Flood risk and its reduction in China. Advances in Water Resources. 130. 10.1016/j.advwatres.2019.05.020.

[2]. Desmond, Eteh & Oborie, Ebiegberi. (2022). Hazard Flood Mapping and Monitory in Parts of the Niger Delta Region Using Sentinel 1 Synthetic Aperture Radar. Sumerianz Journal of Scientific Research. 44-52. 10.47752/sjsr.52.44.52.

[3]. Eteh, Desmond Rowland and Okechukwu Okpobiri. “Floodplain mapping and risks assessment of the Orashi River using Remote Sensing and GIS in the Niger Delta Region, Nigeria.” Journal of Geographical Research (2021): n. pag.

[4]. IPCC, 2021 Climate Change 2021: the Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change

[5]. Cambridge University Press In Press (2021) IPCC, 2022 IPCC Sixth Assessment Report, 2022. Climate change 2022: Impacts, adaptation and vulnerability (2022)

[6]. Ugwu, M. O., Elenwo, E. I., Obafemi, A. A., & Eludoyin, O. S. (2022). Spatial Assessment of Flood Vulnerability of Developed Properties in Port Harcourt Metropolis, Rivers State, Nigeria. Journal of Geography, Environment and Earth Science International, 26(11), 47-61. doi:10.9734/jgeesi/2022/v26i11645.

[7]. Di Baldassarre, G., Kemerink, J. S., Kooy, M., & Brandimarte, L. (2014). Floods and societies: The spatial distribution of water-related disaster risk and its dynamics. WIREs Water, 1(2), 133–139. https://doi.org/10.1002/wat2.1015

[8]. Nkwunonwo, Ugonna & Whitworth, Malcolm & Baily, Brian. (2020). A review of the current status of flood modelling for urban flood risk management in the developing countries. Scientific African. 7. e00269. 10.1016/j.sciaf.2020.e00269.

[9]. Taherizadeh, M., Niknam, A., Nguyen-Huy, T. et al. Flash flood-risk areas zoning using integration of decision-making trial and evaluation laboratory, GIS-based analytic network process and satellite-derived information. Nat Hazards 118, 2309–2335 (2023). https://doi.org/10.1007/s11069-023-06089-5

[10]. Merga, B.B., Mamo, F.L., Moisa, M.B. et al. Assessment of flood risk by using geospatial techniques in Wabi Shebele River Sub-basin, West Hararghe Zone, southeastern Ethiopia. Appl Water Sci 13, 214 (2023). https://doi.org/10.1007/s13201-023-02019-9

[11]. Desmond Rowland Eteh, Samuel Oseji, Erazua Iziegbe , Osi Nnamdi Claude, Abaye Ebinyo Oreikio. “Water Quality Assessment Using GIS Based Multi-Criteria Evaluation (MCE) and Analytical Hierarchy Process (AHP) Methods in Yenagoa Bayelsa State, Nigeria”. International Journal of Advanced Engineering Research and Science, vol. 10, no. 4, Apr. 2023.

[12]. Bhattacharjee, Sutapa & Kumar, Pramod & Thakur, Praveen & Gupta, Kshama. (2021). Hydrodynamic modelling and vulnerability analysis to assess flood risk in a dense Indian city using geospatial techniques. Natural Hazards. 105. 1-29. 10.1007/s11069-020-04392-z.

[13]. Eteh Desmond Rowland, Francis Omonefe, Jonathan Lise Erebi. (2021-01-18). "Site Suitability Study for Solid Waste Dumpsite Selection Using Geospatial-Based Multi-Criteria Analysis inYenagoa, Bayelsa StateNigeria." *Volume 4*, 1, 1-12

[14]. Koralay, N., Kara, Ö. Assessment of flood risk in Söğütlü stream watershed of Trabzon province in Turkey using geographic information systems and analytic hierarchy process approach. Nat Hazards (2024). https://doi.org/10.1007/s11069-024-06594-1

[15]. Aladejana, O.O., Ebijuoworih, E.J. Flood risk assessment in Kogi State Nigeria through the integration of hazard and vulnerability factors. Discov Geosci 2, 31 (2024). https://doi.org/10.1007/s44288-024-00036-y

[16]. Osman, S.A., Das, J. GIS-based flood risk assessment using multi-criteria decision analysis of Shebelle River Basin in southern Somalia. SN Appl. Sci. 5, 134 (2023). https://doi.org/10.1007/s42452-023-05360-5

[17]. Orazulike, N. C., Justina, J. O., Christopher, C. C., Tamunomie, K. N., & Samuel, A. U. (2017). A 3-year retrospective review of mortality in women of reproductive age in a tertiary health facility in Port Harcourt, Nigeria. International journal of women's health, 9, 769–775. https://dx.doi.org/10.2147/IJWH.S138052.

[18]. Reijers TJ. Stratigraphy and sedimentology of the Niger Delta. Geologos. 2011;17:133-162.

[19]. Tuttle LWM, Charpentier RR, Brownfield EM. The Niger Delta Petroleum System: Niger Delta Province, Nigeria Cameroon and Equatorial Guinea, Africa. US Geological Survey Open-File Report 99-50-H. Denver: US Geological Survey; 1999. p. 70.

[20]. Short KC, Stauble AJ. Outline of Geology of Niger Delta. AAPG Bull. 1967;51:761-779.

[21]. Ngah S, Eze C. Typical Hydraulic Properties of Deep Aquifers of Niger Delta from Pumping Test Data. J Geosci Environ Prot. 2017;5:139-148. doi:10.4236/gep.2017.511010.

[22]. Wiener RW, Mann MG, Angelich MT, Molyneux JB. Mobile Shale in the Niger Delta: Characteristics, Structure, and Evolution. AAPG Memoir. 2010;145-161.

[23]. Reyment RA. Aspects of the geology of Nigeria—The Stratigraphy of the Cretaceous and Cenozoic Deposits. Ibadan: Ibadan University Press; 1965. p. 133.

[24]. AlAli, Abdulrahman Mubarark, Abdelrahim Salih, and Abdalhaleem Hassaballa. 2023. "Geospatial-Based Analytical Hierarchy Process (AHP) and Weighted Product Model (WPM) Techniques for Mapping and Assessing Flood Susceptibility in the Wadi Hanifah Drainage Basin, Riyadh Region, Saudi Arabia" Water 15, no. 10: 1943.

[25]. OGUNWUMI TS, WAZIRI ES, UDOH JC. GEOSPATIAL MAPPING OF FLOOD HAZARD USING MULTI-CRITERIA APPROACH IN FUFORE LOCAL GOVERNMENT AREA, NORTH EASTERN NIGERIA. Journal of Basic and Applied Research International 27, no. 3 (June 3, 2021): 13–26. Accessed August 28, 2024.

[26]. Ihinegbu, C., Ogunwumi, T. Multi-criteria modelling of drought: a study of Brandenburg Federal State, Germany. Model. Earth Syst. Environ. 8, 2035–2049 (2022). https://doi.org/10.1007/s40808-021-01197-2

[27]. Otokiti, K., Akinola, O., Adeniji, K. (2020). Geospatial mapping of flood risk in the coastal megacity of Nigeria. American Journal of Geophysics, Geochemistry, and Geosystems. 5(4), 129-138.

[28]. Vojtek, Matej & Vojteková, Jana. (2016). Flood hazard and flood risk assessment at the local spatial scale: a case study. Geomatics, Natural Hazards and Risk. 7. 1973-1992. 10.1080/19475705.2016.1166874.

[29]. Sahraei, Roya & Kanani-Sadat, Yousef & Safari, Abdolreza & Homayouni, Saeid. (2023). Flood Susceptibility Modelling Using Geospatial-Based Multi-Criteria Decision Making in Large Scale Areas. X-4/W1-2022. 677-683. 10.5194/isprs-annals-X-4-W1-2022-677-2023.

[30]. Ikram, Qiyamud Din & Jamalzi, Abdur Rashid & Hamidi, Abdur Rahim & Ullah, Irfan & Shahab, Muhmmad. (2023). Flood risk assessment of the population in Afghanistan: A spatial analysis of hazard, exposure, and vulnerability. Natural Hazards Research. 10.1016/j.nhres.2023.09.006

[31]. Kazakis, Nerantzis & Kougias, Ioannis & Patsialis, Thomas. (2015). Assessment of flood hazard areas at a regional scale using an index-based approach and Analytical Hierarchy Process: Application in Rhodope–Evros region, Greece. Science of The Total Environment. 538. 555–563. 10.1016/j.scitotenv.2015.08.055.

[32]. Kelly, Matthew, Imogen Schwarz, Mark Ziegelaar, Andrew B. Watkins, and Yuriy Kuleshov. 2023. "Flood Risk Assessment and Mapping: A Case Study from Australia's Hawkesbury-Nepean Catchment" Hydrology 10, no. 2: 26.

[33]. Ghosh, S., & Kar, S. K. (2018). "Application of analytical hierarchy process (AHP) for flood risk assessment: a case study in Malda district of West Bengal, India," Natural Hazards: Journal of the International Society for the Prevention and Mitigation of Natural Hazards, Springer;International Society for the Prevention and Mitigation of Natural Hazards, vol. 94(1), pages 349-368, October.

[34]. Efraimidou, E., Spiliotis, M. A GIS-Based Flood Risk Assessment Using the Decision-Making Trial and Evaluation Laboratory Approach at a Regional Scale. Environ. Process. 11, 9 (2024). https://doi.org/10.1007/s40710-024-00683-w

[35]. Bui, Dieu & Pradhan, Biswajeet & Nampak, Haleh & Bui, Quang-Thanh & Tran, Quynh-An & Phi, Quoc. (2016). Hybrid Artificial Intelligence Approach Based on Neural Fuzzy Inference Model and Metaheuristic Optimization for Flood Susceptibility Modelling in A High-Frequency Tropical Cyclone Area using GIS. Journal of Hydrology. 540. (Accepted, in press). 10.1016/j.jhydrol.2016.06.027.

[36]. Chapi, K., Singh, V. P., Shirzadi, A., Shahabi, H., Bui, D. T., Pham, B. T., & Khosravi, K. (2017). A Novel Hybrid Artificial Intelligence Approach for Flood Susceptibility Assessment. Environmental Modelling & Software, 95, 229-245.

[37]. Wu, Zening, Wanjie Xue, Hongshi Xu, Denghua Yan, Huiliang Wang, and Wenchao Qi. 2022. "Urban Flood Risk Assessment in Zhengzhou, China, Based on a D-Number-Improved Analytic Hierarchy Process and a Self-Organizing Map Algorithm" Remote Sensing 14, no. 19: 4777. https://doi.org/10.3390/rs14194777

[38]. Pham, B. T., Pradhan, B., Bui, D. T., Prakash, I., & Dholakia, M. B. (2016). A Comparative Study of Different Machine Learning Methods for Landslide Susceptibility Assessment: A Case Study of Uttarakhand Area (India). Environmental Modelling & Software, 84, 240-250.

[39]. Eteh Desmond Rowland, Francis Omonefe, Jonathan Lise Erebi. (2021-01-18). "Site Suitability Study for Solid Waste Dumpsite Selection Using Geospatial-Based Multi-Criteria Analysis inYenagoa, Bayelsa StateNigeria." *Volume 4*, 1, 1-12

[40]. Saaty T. L., Decision making with the analytic hierarchy process, International Journal of Services Sciences. 2008a, 1, no. 1, 83–98,

.