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Flood Vulnerability and Risk Assessment of Onitsha, Anambra State Using Remote Sensing and GIS: AHP Method

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Abstract
Flooding remains one of the most devastating natural hazards affecting both rural and urban communities in Nigeria, resulting in the loss of lives, destruction of property, disruption of socioeconomic activities, and environmental degradation. Onitsha, Anambra State, is particularly vulnerable to recurrent flooding due to its low-lying terrain, rapid urbanization, proximity to the River Niger, inadequate drainage infrastructure, and poor waste management practices that obstruct natural drainage channels. This study assessed the flood vulnerability of Onitsha using Remote Sensing and Geographic Information Systems (GIS) integrated with the Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Analysis (MCDA). Spatial datasets including Digital Elevation Model (DEM), Topographic Wetness Index (TWI), slope, rainfall, land use/land cover (LULC), Normalized Difference Vegetation Index (NDVI), and Euclidean distance from water bodies were processed, reclassified, weighted, and integrated using weighted overlay analysis to generate a flood vulnerability map. The results revealed that topography, proximity to water bodies, land cover characteristics, and surface wetness were the major factors influencing flood susceptibility within the study area. The final flood vulnerability map classified the area into three vulnerability zones, with approximately 8.45% (18,054 m²) identified as highly vulnerable, 90.40% (193,141 m²) as moderately vulnerable, and 1.15% (2,454 m²) as having low vulnerability to flooding. The predominance of the moderate vulnerability class indicates that a substantial proportion of Onitsha remains susceptible to flooding, particularly during periods of intense rainfall and River Niger overflow. The study demonstrates the effectiveness of integrating GIS and AHP for flood vulnerability assessment and provides valuable spatial information to support flood risk reduction, sustainable urban planning, disaster preparedness, and evidence-based decision-making by government agencies and environmental managers.

Keywords: Flood Vulnerability, Flood Risk Mapping, Geographic Information System (GIS), Remote Sensing, Analytic Hierarchy Process (AHP), Multi-Criteria Decision Analysis (MCDA), Onitsha, Nigeria

1. Introduction

Nigeria is one of the countries that experience recurrent flooding with both riverine and urban floods posing serious threats to lives, property, agriculture and economic development. The devastating nationwide floods of 2012, 2018 and 2022 affected millions of people, displacing thousands of households and caused a great amount of damage to agriculture, transportation and public infrastructure (National Emergency Management Agency [NEMA], 2022) [9]. These flood events have underscored the urgent need for effective flood risk assessment and management strategies, particularly in rapidly urbanizing areas where human activities have altered natural drainage systems.

Flooding is one of the most frequent and destructive natural hazards globally, causing significant loss of life, damage to infrastructure, environment degradation and disruption of socioeconomic activities. The increasing frequency and intensity of flood events have been attributed to a combination of climate change, rapid urbanization, population growth and inadequate land use planning. According to the Intergovernmental Panel on Climate Change (IPCC), rising global temperatures have intensified the hydrological cycle, leading to more frequent extreme rainfall events and increasing flood risks in many regions of the world (IPCC, 2023) [8]. Onitsha as Nigeria's second largest business city contends with flooding as a pervasive consequence of climate change (Efobi and Anierobi, 2013) [3]. Despite its importance, Onitsha faces a pressing challenge of flooding, disrupting economy, displacing populations and triggering humanitarian crisis (Ebhoka and Okoyeh, 2019; Umar and

Gray, 2022; Nkiruka, Chinedu and Smart, 2023 [10]).

Onitsha, located in Anambra State in southeastern Nigeria serves as a major economic hub within the lower Niger Basin. The city lies on the eastern bank of River Niger and is characterized by a low lying topography, dense population and extensive impervious surfaces resulting from rapid urban expansion. These characteristics coupled with inadequate drainage infrastructures, indiscriminate waste disposal fluvial and pluvial flooding (Anambra State Emergency Management Agency [SEMA], 2022) [2]. Seasonal flooding in Onitsha frequently disrupts commercial activities, damages residential and public infrastructure and threatens public health through the contamination of water sources and increased incidence of waterborne diseases. Drainage channels are blocked with buildings as development continuous unregulated. Building codes are not adhered to (Fabiyi, Adagbasa, Efosa and Enaruvbe, 2012) [6]. If more runoff id generated than the drainage channel can accommodate, the water will overrun thereby leading to flooding (Ikhuoria, Yesuf, Enaruvbe and Ige-Olumide, 2012) [7]. Another cause of flooding is through releases of water from dam, which is the major causes of flooding that happened in 2012. Runoff water from Lagdo dam in Cameroon, Shiroro and Kainji dams were released to prevent the dams from breaking.

Flood vulnerability refers to the degree to which people, infrastructure and the environment are susceptible to the adverse impacts of flooding, while flood risk represents the interaction between flood hazard, exposure and vulnerability (United Nations Office for Disaster Risk Reduction [UNDRR], 2022) [14]. Effective flood risk assessment therefore requires not only the identification of flood prone areas but also an understanding of the spatial distribution of vulnerable populations, critical infrastructure and socioeconomic activities as carried out in this study. This assessment provides valuable information for disaster preparedness, urban planning, emergency response and climate adaptation strategies.

Recent advances in Geographic Information Systems (GIS) and Remote Sensing (RS) have transformed flood risk assessment by enabling the integration an analysis of diverse spatial datasets. GIS provides the robust platform and environment needed for acquiring, managing, analyzing and visualizing geospatial information, while remote sensing facilitates the acquisition of up-to-date spatial data over large geographic areas. The integration of these technologies allows researchers to evaluate multiple flood conditioning factors such as elevation, slope, land use and land cover, rainfall, drainage density, soil characteristics and proximity to rivers (Elkhrachy, 2015) [5]. Consequently, GIS-based flood mapping has become one of the most widely adopted approaches to identifying flood hazards zones and supporting evidence-based flood management decisions.

Among the various GIS-based techniques, multi-criteria decision analysis (MCDA), particularly the Analytic Hierarchy Process (AHP) has gained considerable acceptance for flood vulnerability and risk assessment. The AHP method enables the systematic weighting of flood conditioning factors based on judgment and pairwise comparison, thereby improving the objectivity and reliability of spatial decision making (Saaty, 1980) [12]. When combined with weighted overlay analysis in GIS, AHP provides a transparent and reproducible framework for producing flood hazard and risk maps that can guide policy makers in prioritizing flood mitigation interventions.

Despite the increasing application of GIS in flood studies world word, there remains limited comprehensive research focusing on flood vulnerability and risk assessment in Onitsha using integrated geospatial techniques. Many existing studies have concentrated primarily on flood hazard mapping without adequately incorporating vulnerability and exposure components necessary for comprehensive flood risk assessment. Furthermore, the rapid urban growth experienced by Onitsha over the past flooding times has altered land-use patterns and drainage characteristics, bringing about the necessary updated spatial analyses that reflect current environmental conditions. Also contributing to the growing body knowledge on GIS-based flood risk assessment in Nigeria and provide a methodological framework that can be adapted for similar urban environments across the country.

2. Materials and Methods

2.1 Study Area

Onitsha is located lat 6.14978° N and long 6.78569° E on the eastern region, the eastern bank if the Niger River, in Anambra state, Nigeria. It is A metropolitan city, and is known for its river port and as an economic hub for commerce, business, education and trades. The largest market in Africa- main market in terms of geographical size and population. As at 2016, the greater Onitsha area had an estimated population of around eight (8) million people in central and southern Anambra state extending into neighboring Delta State to the west and the Imo State to the south, (Africapolis 2023). The continuous urban sprawl of continuation of greater Onitsha spreads across several separate cities and their satellite towns and suburbs including Asaba, Obosi, Ogidi, Oba and Ogbaru. The capital city Awka. As od 2025, Onitsha city has an estimated population of 5,628,000, (Onitsha, Nigeria Metro Area Population 2022).

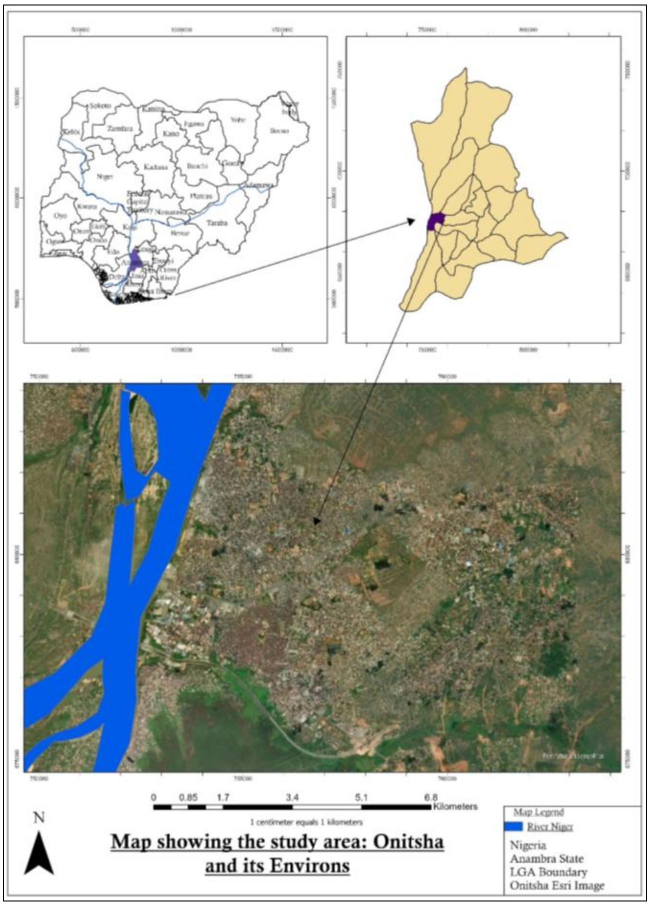

Fig 1: Showing Map of the Study Area

2.2 Data and Method

Data used for this study are; Satellite Imagery – LandSat 8/9 with 30m resolution for the year 2022 downloaded from www.earthexplorere.usgs.gov, administrative shapefile of study area, SRTM Imagery of the study area showing the DEM OF 90m resolution, rainfall dataset for the year 2022 downloaded from CHIRPS.

The method used is the Analytic Hierarchy Process (AHP). Since the aim of the study is to carry out a flood vulnerability assessment of the area, different datasets where processed and reclassified to be in the same classes so they can be weighed against each other, datasets include; TWI, Elevation map of the area, Slope, Rainfall data, Land Use Land Cover (LULC), NDVI and distance from the road to develop the end produce.

Firstly, a TWI was generated from the downloaded DEM. Topographic Wetness Index - this measures how land shape affects the flow and pooling of water across the ground. It uses two main parts: the size of the land area above that drains water down and the steepness of the local slope. An elevation map was done and reclassified into 5 to show the topography of the area, a slope map was also generated from the DEM. Rainfall data was downloaded and reclassified into 5 for the purpose of this study, LULC was also done to see how the land use also affects flooding in the area. We trained using supervised classification method on the image to produce 5 classes below;

1. Bare surface
2. Built up area
3. Vegetation
4. Farmland
5. Wetlands

3. Data Processing

3.1 TWI - Topographic Wetness Index

In mapping the topographic wetness index of the area. The DEM fill, flow accumulation and slope with the shapefile of the area was used to generate the wetness index of the area. Then was later reclassified to show just 5 class. TWI calculations were based on the topography of the area represented by DEM (Digital Elevation Model). The highest value of the TWI is 8.856 and is associated with high flood vulnerability, whilst lowest TWI value of -5.916 is associated with low flood vulnerability. Based on the calculation of TWI value, flood-prone areas in Onitsha covers most of the riverine areas.

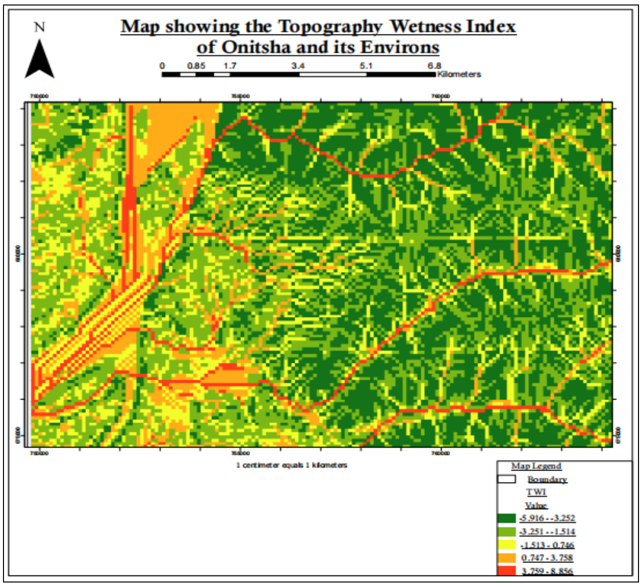

Fig 2: Showing TWI map of the Study Area without classification

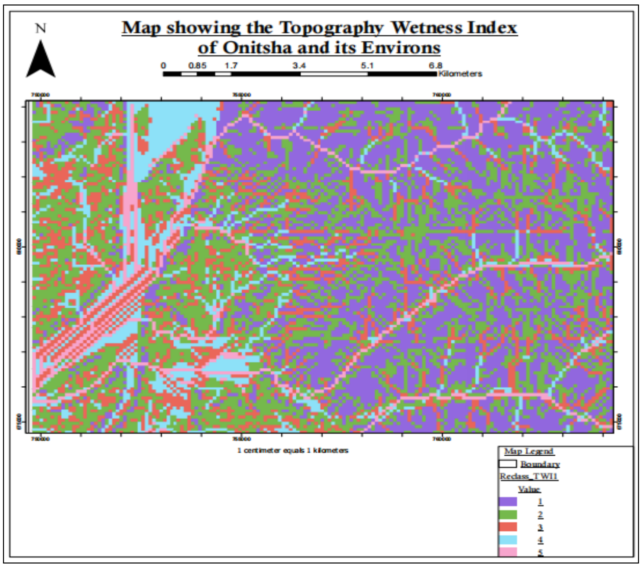

Fig 3: Showing TWI after classification

The TWI was generated using Map Algebra, utilizing raster calculator, given by:

*TWI = Ln (flow accumulation Scaled / Tan Slope) Flow Accumulation Scaled was derived using raster calculator, given by: (Flow Accumulation + 1) * 0.00027774796, with 0.00027774796 as pixel size (x, y) and number of bands as 1.*

TWI layers are displayed with colour scheme indicating areas with less wetness in purple and areas with high wetness in pink. The other colour illustrating TWI in the study area is green, red and blue indicating mid wetness level.

3.2 Elevation Map of the Area

Elevation map of the area was visualized from the downloaded DEM of the study area. And reclassified into 5 classes. The color dark red leveled at 1 is associated with the highest points in the area and a low vulnerable to flooding while the color light yellow 5 is lowest and highly vulnerable to flooding.

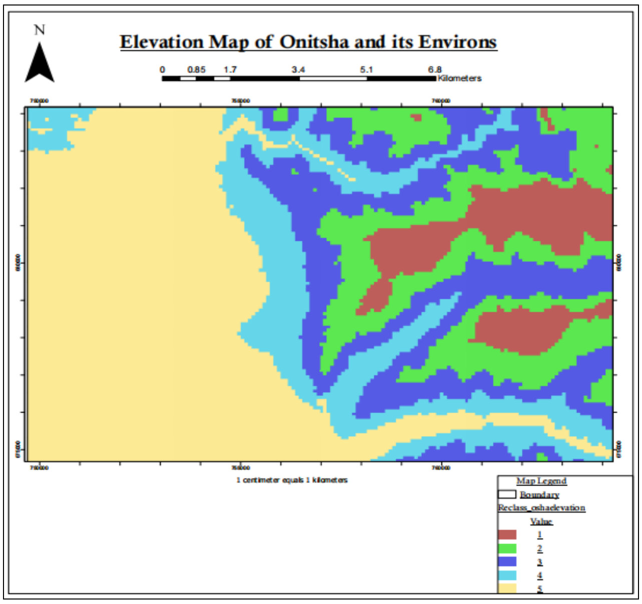

Fig 4: Elevation Map of the Area

3.3 Slope

Slope of the area is calculated from the fill DEM. The lowest point starting from 0.001 is the highest vulnerable to flooding while the highest 31.585 area is the lowest vulnerable to flooding.

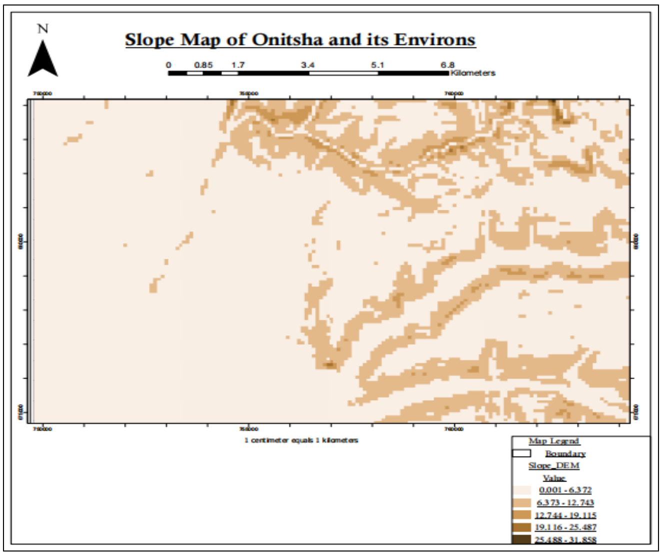

Fig 5: Showing Slope Map of the Area

3.4 Precipitation

Rainfall data set as downloaded for the year 2022 from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) was visualized and reclassified into 5 classes. The minimum rainfall for the year is 3068 the maximum rainfall for the year is 3207.199951171875. the mean is calculated to be 3160.375015258789 while the SD that is standard deviation for the year is 44.236038988024.

Table 1: Showing the statistics value for rainfall

Statistics

Build Parameters: skipped columns: 1, rows: 1, ignored value(s):

Band Name	Minimum	Maximum	Mean	Std. Deviation
Band_1	3068	3207.199951171875	3160.375015258789	44.236038988024

The lowest value 3068.001 for rainfall is represented with yellow while the highest values for rainfall 3207.200 is represented by red color.

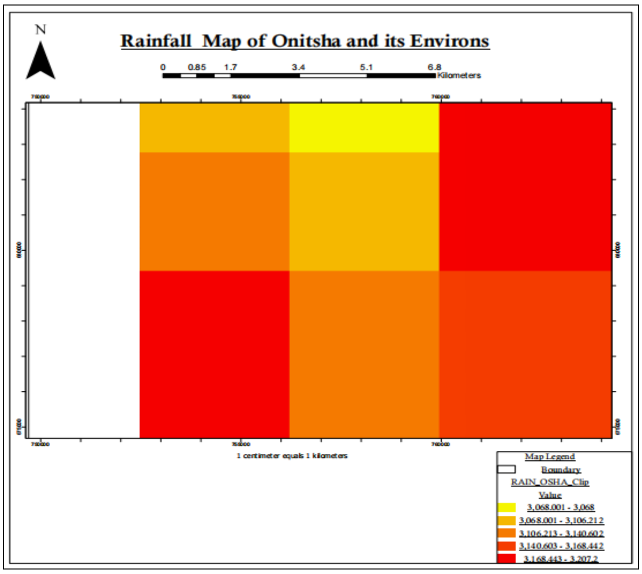

Fig 6: Rainfall Map of the study Area

3.5 Land Use/Land Cover

In the study, the image was classified into 5 to show usage of land in the area. The following were identified; Developed, Forest, wetlands, barren and water and reclassified so that forest is 1 and less vulnerable to flood while water and wetlands is 5 and 4 respectively and is highly vulnerable to flooding as shown below;

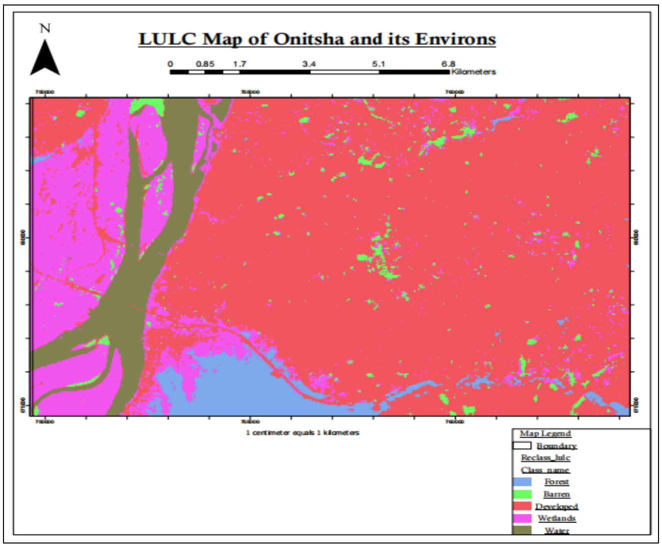

Fig 7: Map showing LULC

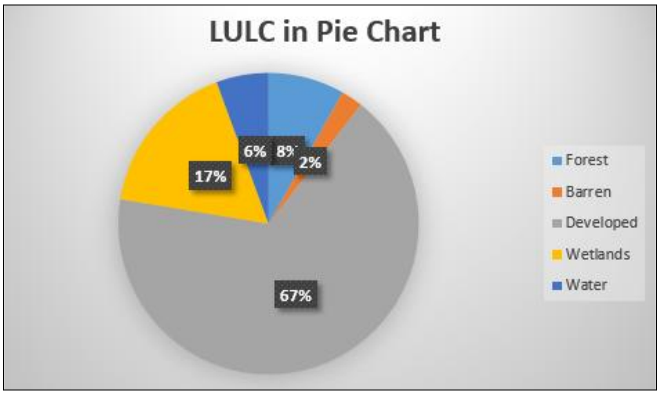

Fig 8: Showing LULC Pie Chart

Are covered by forest is 8%, barren area is 2%, wetlands is 17%, water is 6% while developed area is 67%. This is represented in a table below.

Table 2: Showing LULC area in percentage

S. No	Area	Class	%
1	22,923	Forest	8.226272
2	6,514	Barren	2.337649
3	186,793	Developed	67.03355
4	46,752	Wetlands	16.77768
5	15,674	Water	5.624856
Total	**278656**		

3.6 NDVI

NDVI (Normalized Difference Vegetation Index) is a simple numerical indicator used to measure and analyze plant health by evaluating near-infrared (NIR) and red light. It operates on the principle that healthy green leaves absorb visible red light while strongly reflecting near-infrared light.

$$\textit{Calculated as } NDVI = \frac{NIR-RED}{NIR+RED}$$

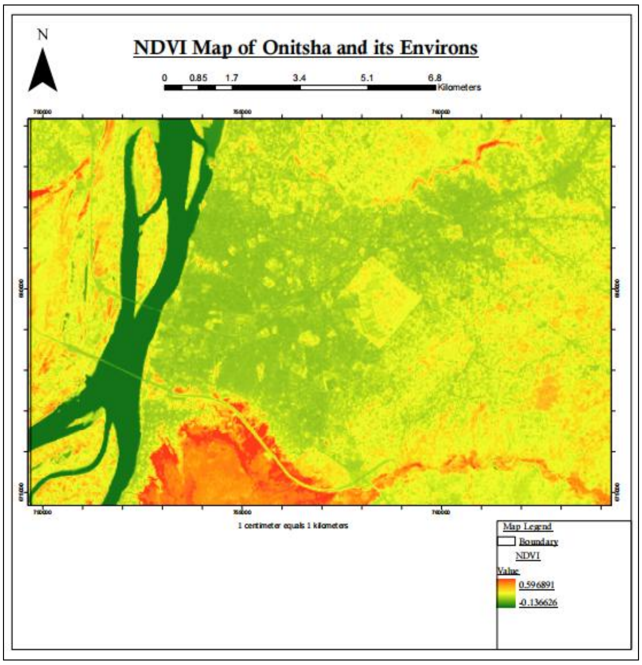

Fig 9: Showing NDVI Map of the Area

Results are -1.0 to 0.0: Water bodies, snow, or non-vegetated surfaces like bare rock and man-made structures. 0.0 to 0.1: Barren ground, rock, sand, or snow. 0.2 to 0.5: Sparse vegetation such as shrubs, grasslands, or early-stage crops. 0.6 to 1.0: Dense, healthy green vegetation like temperate forests and thriving agricultural crops. This was followed to get the result below;

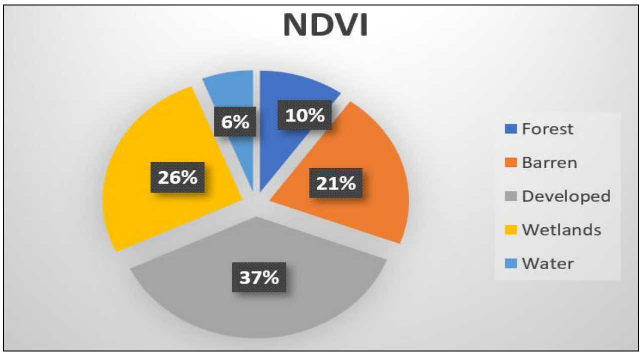

Fig 10: Showing NDVI Pie Chart

Are covered by forest is 10%, barren area is 26%, wetlands is 17%, water is 6% while developed area is 37%. This is represented in a table below.

Table 3: Showing LULC area in percentage

S. No	Area	Class	%
1	27561	Forest	9.845781
2	58585	Barren	20.92867
3	104011	Developed	37.15647
4	73126	Wetlands	26.12324
5	16644	Water	5.945836
Total	**279927**		

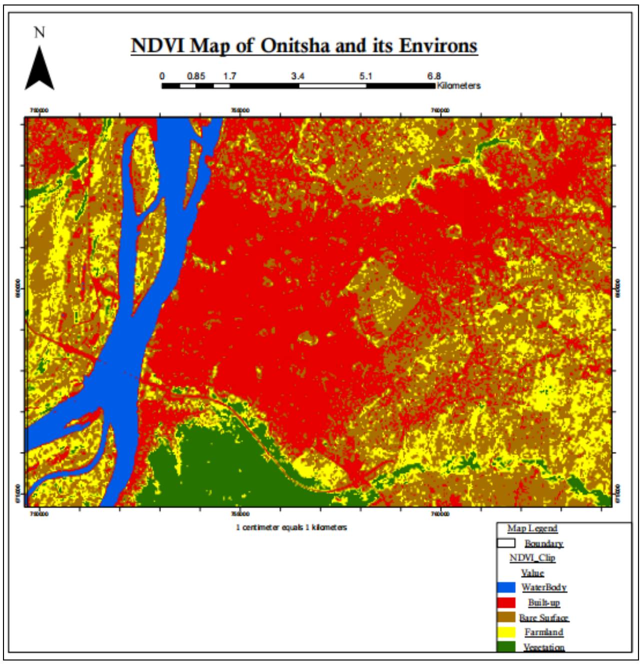

Fig 11: Showing NDVI Map after reclassification

The above image was reclassified to give water area highly vulnerable to flood vegetation area low vulnerable to flooding. With built up area, bear surface and farmland to follow in second, third and fourth respectively.

3.7 Euclidean Distance From Water

This is a straight-line measurement from any point in a landscape to the nearest water body or stream. Calculated using spatial analysis tools from map algebra to determine the shortest direct path from grid cells to water sources. This was done and the result is visualized below;

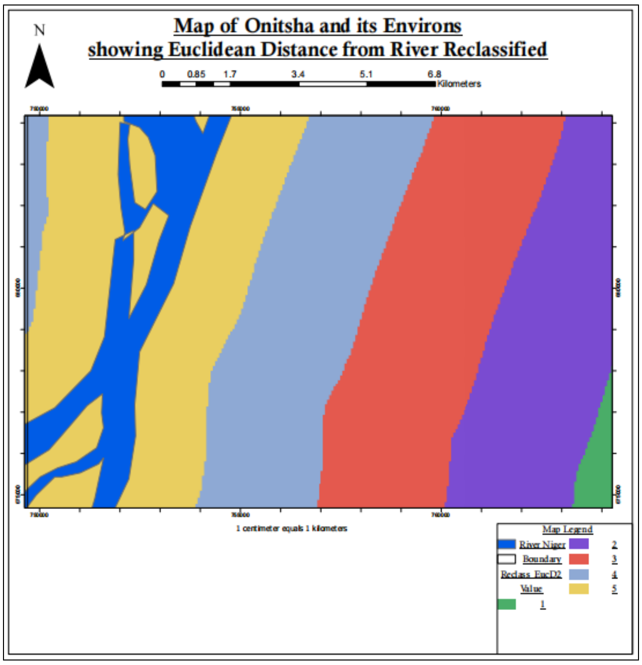

Fig 12: Showing Euclidean Distance from Water

The color green is represented to showing the farthest distance from water, followed by purple, then red, blue and lastly yellow. Which is highly vulnerable to flooding in the area.

4. Final Results

The results of the weighted AHP analysis allowing TWI to weight 25%, Elevation 20%, Slope 12%, Rainfall 15%, LULC 8%, NDVI 8%, Distance from River 12% which then produced the map showing three (3) vulnerable stages; Lowly, moderately and highly vulnerable flood zones. The result shows that 18,054sqm is highly vulnerable to flooding occupying 9% of the area, while 90% of the area being 193,141sqm is moderately vulnerable to flooding and 1% is lowly vulnerable to flooding. See the pie chart and table below.

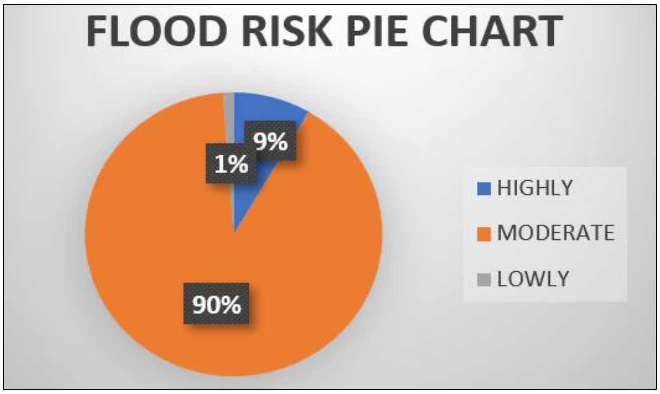

Fig 13: Showing the pie chart of the flood risk

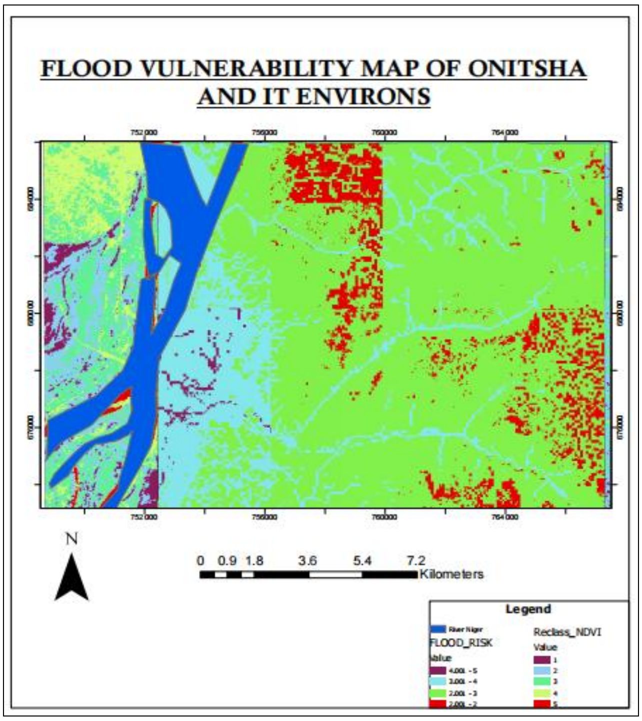

Fig 14: Showing Flood Vulnerability Map of the Area

Table 4: Showing the flood risk Study Area

S. No	Area	Class	%
1	18,054	HIGHLY	8.450309
2	193,141	MODERATE	90.40108
3	2,454	LOWLY	1.148613
Total	**213649**		

5. Conclusion

This study successfully applied Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP) to assess flood vulnerability in Onitsha, Anambra State, through the integration of multiple flood-conditioning factors, including Topographic Wetness Index (TWI), elevation, slope, rainfall, land use/land cover (LULC), Normalized Difference Vegetation Index (NDVI), and Euclidean distance from water bodies. The integration of these datasets within a GIS environment provided a systematic and spatially explicit approach for identifying areas susceptible to flooding and producing a comprehensive flood vulnerability map.

The findings indicate that the spatial distribution of flood vulnerability in the study area is strongly influenced by topography, proximity to water bodies, land cover characteristics, and surface wetness conditions. The Topographic Wetness Index revealed that riverine and low-lying areas possess the highest potential for water accumulation and are therefore more susceptible to flooding. Similarly, the elevation analysis showed that areas at lower elevations exhibited greater flood vulnerability due to their limited drainage capacity, while slope analysis demonstrated that gently sloping terrains are more prone to flood inundation than steeper areas because runoff tends to accumulate rather than flow rapidly away.

The rainfall analysis further established that the study area receives relatively high annual precipitation, which contributes significantly to flood occurrence, particularly when combined with inadequate drainage infrastructure and extensive impervious surfaces. The land use/land cover classification revealed that developed areas account for approximately **67%** of the study area, indicating a high level of urbanization. This extensive urban development reduces infiltration, increases surface runoff, and consequently elevates flood risk. In contrast, vegetated areas contribute to increased infiltration and reduced runoff, thereby lowering flood susceptibility. Likewise, the NDVI analysis confirmed that areas with sparse vegetation and extensive built-up surfaces are generally more vulnerable to flooding than densely vegetated locations.

The Euclidean distance analysis demonstrated that locations situated closer to rivers and other water bodies exhibit significantly higher flood susceptibility than areas farther away. This finding is consistent with the physical characteristics of Onitsha, which lies adjacent to the River Niger and experiences seasonal river overflow and urban flooding. The influence of proximity to water bodies, combined with low elevation and high surface wetness, explains the concentration of flood-prone areas within the riverine portions of the study area.

The final flood vulnerability map generated through the weighted overlay analysis using AHP classified the study area into three flood vulnerability zones: **high**, **moderate**, and **low**. The analysis revealed that approximately **9%** of the study area is highly vulnerable to flooding, **90%** is moderately vulnerable, and only **1%** falls within the low vulnerability category. The predominance of the moderate vulnerability class indicates that although only a relatively small proportion of the area is currently classified as highly vulnerable, a large portion of Onitsha remains susceptible to flooding under conditions of prolonged rainfall, river overflow, blocked drainage systems, or future urban expansion. This finding suggests that flood risk in the study area should not be considered only in terms of the highly vulnerable zones, as moderate vulnerability areas could easily transition into high-risk zones under changing environmental and climatic conditions.

Overall, the study demonstrates the effectiveness of integrating GIS and Multi-Criteria Decision Analysis (MCDA) using the Analytic Hierarchy Process (AHP) for flood vulnerability assessment. The approach provides a reliable, cost-effective, and scientifically robust framework for identifying flood-prone areas and supporting evidence-based decision-making. The resulting flood vulnerability map serves as an important spatial planning tool that can assist government agencies, urban planners, disaster management authorities, and policymakers in prioritizing flood mitigation measures, improving land-use planning, enhancing drainage infrastructure, and developing sustainable flood management strategies.

Finally, the study contributes to the growing application of geospatial technologies in environmental management by demonstrating how the integration of remotely sensed data, topographic information, climatic variables, and spatial analysis techniques can support disaster risk reduction. Future studies should incorporate additional flood-conditioning factors such as drainage density, soil infiltration characteristics, historical flood records, population density, building footprints, and climate change scenarios to further improve the accuracy of flood vulnerability assessments. Validation of the generated flood vulnerability map using observed flood events and field data would also enhance the reliability of the model and strengthen its application in flood risk management and urban resilience planning.

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