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Flood Vulnerability Assessment of AWKA South LGA in Anambra State Using Flood Simulation Model

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Abstract- *This study aimed at performing a flood vulnerability assessment of Awka South LGA in Anambra State, using flood simulation model with a view of identifying flood vulnerable areas within the study area. The objectives of the study are to; determine the pattern of landcover/landuse in Awka South LGA; determine the surface runoff potential within the study area; ascertain the flood frequency within the study area and to model the extent of flood vulnerability within the study area using HEC-RAS. The methodology comprises of the collection of Sentinel-2 data, Alos Palsar, Rainfall Data and Soil Data covering Awka South LGA, preprocessing of the acquired data to remove noise and ensure accuracy of the data, image classification to determine the pattern of landcover/landuse in the study area, surface runoff analysis to determine the infiltration levels, and hydraulic flood modelling with HEC-RAS to determine the flood frequency and flood extents.Treveals significant patterns influencing flood vulnerability and risk management. The results revealed that Built-up areas dominated the landscape, occupying 52.588% (89.791 km²), impacting surface runoff patterns due to impervious surfaces. Open spaces and vegetation, covering 25.738% (43.947 km²) and 19.427% (33.171 km²), respectively, play a role in flood mitigation through natural retention and infiltration. Cropland (1.979%, 3.380 km²) and water bodies (0.268%, 0.457 km²) are also integral to understanding flood dynamics. Surface runoff analysis showed that 42.14% (71.963 km²) of the area has low infiltration potential, contributing to higher runoff and flood susceptibility. Meanwhile, 51.59% (88.110 km²) of the area shows moderate infiltration potential, and only 6.25% (10.686 km²) exhibits high infiltration, essential for flood mitigation and groundwater recharge. Flood frequency analysis using the HEC-RAS model identifies inundation extents for various return periods, highlighting significant risks even for frequent events. A 2-year return period shows an inundation extent of 23.675 km², reducing to 10.869 km² for a 5-year period, with dynamic changes in flood extents observed over time. Vulnerability mapping delineated high (18.77%, 32.057 km²), moderate (69.41%, 118.528 km²), and low (11.81%, 20.176 km²) vulnerability zones, guiding flood risk management strategies. Landcover within high vulnerability zones includes 27.053% built-up areas (8.659 km²) and 43.085% open spaces (13.790 km²), necessitating targeted mitigation efforts. Validation of the flood model using an error matrix shows an overall accuracy of 79.6%. The study recommends improving the drainage systems in high vulnerability zones (Ziks Avenue, Emma Nnaemeka Street, Ogechukwu Street, Majuo Street, Unizik Tempsite Junction, Nnedioramma Junction, Unizik tempsite bus-stand, Abakiliki junction, Alex Ekwueme Road, Old English Hotel Road, Real Estate Road, Onitsha-Enugu expressway, and Kwatta Junction) as it is a major factor contributing to flooding in these areas.*
Keywords: *Awka South, Flooding, Hec Ras, Vulnerability*

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I. Introduction

Arguably, the rate of flooding occurrence in recent times has been unprecedented. With 70 million people globally exposed to flooding every year, and more than 800 million living in flood prone areas (Peduzzi *et al* 2009) climate change with more frequent and severe rainfall events, sea level rise, rapid population growth and urbanization, the rate of development on floodplains, the level of awareness of flood risk and the ineffectiveness of efforts towards tackling flooding in many places are factors of concern within the global (Raaijmakers *et al* 2008). The economic consequences of flooding reported in the last two decades amount to tens of billions of US dollars (Guha-Sapir 2013). Over 3700 flood disasters globally are recorded in the EM-DAT database, covering the period 1985 to 2014. These events were responsible for hundreds of thousands of deaths mainly in Asia (most notably China, Thailand and Bangladesh) and adversely affected billions of people mostly through homelessness, spread of diseases, physical injuries, mortality (mainly through drowning) and psychological conditions mainly depression, anxiety and posttraumatic stress (Ahern *et al* 2005, Tapsell 2008, Hunter 2003, Tunstall *et al* 2006). In the US, 32.9% of the total natural disasters in 2012 were hydrological with floods accounting for the most part, affecting more than 9 million people and causing about US$ 0.58 billion worth of damage. The same source shows, for that year, more than US$4.7 billion worth of damage recorded for Europe, and about US$0.83 billion and US$19.3 billion damage for Africa and Asia respectively resulting from flooding. Four different floods that hit cities in UK in 2012 caused a total loss of $2.9 billion, with hundreds of people who were affected Guha-Sapir D *et al* 2012). In many African countries for example Nigeria, flooding has impoverished hundreds of thousands of people through displacement from homes and loss of tangible properties (Action Aid 2006). Historically, flooding in Nigeria which dates back to the early 1950' are fluvial, coastal and pluvial in nature and have been a major cause of concern for rural areas and cities within the country (Bashir *et al* 2012 and Douglas *et al* 2008). Fluvial and coastal flooding both of which affected mainly coastal environments were influenced by seasonal interruption of major rivers and water overtopping their natural and artificial defences and overflowing areas not typically submerged (Akintola *et al* 1994). Fluvial floods account for the majority of the flood threats experienced in locations along the plains adjoining major rivers in the country, including rivers Niger, Benue and Hadeja. The states in Nigeria mostly affected by such floods are Adamawa, Kano, Niger, Jigawa, Kaduna, Cross River and Kebbi (Iloje2004, Agbola *et al* 2012). The worst fluvial flood in Nigeria was the Kaduna flood disaster of 2006 which affected hundreds of thousands of human lives with economic loss worth millions of US dollars (Adebayo *et al*2013, Obeta 2009). Coastal floods in Nigeria affect the low-lying areas in the southern part of the country (comprising for examples Lagos, Oyo, Ondo, Akwa-Ibom and Bayelsa states).

The impacts of such floods have been severe due to the number of human populations exposed following the attractions of coastal areas for economic and social reasons (Adelekan 2010). Nigeria is globally ranked with the top 20 countries whose present population and future scenarios in the 2070s (including climate change and socio-economic factors) are exposed to coastal flooding (Nicholls 2008). Pluvial floods usually occur annually during rainy seasons (between July and October) and affect mainly the urban areas in Nigeria. Such floods which are arguably unprecedented in recent times are caused by more frequent and severe rainfall which overwhelms the efficiency of drainage systems and soil infiltration capacity (Houston *et al*2011, Merz *et al* 2007). The significance of urban areas in the economic and political development of Nigeria is generally acknowledged (Ujoh *et al* 2009). However, urbanization is a critical anthropogenic influence on climate change and hydrological cycle in the country given that much impervious surfaces increase surface water runoffs and reduce soil infiltration capacity (Mujumdar 2001-Seto 2009). Along with urbanization is the rapid population increase in many Nigerian cities which is also a global concern within the context of flooding in urban areas (UNSTTPUNDA 2012). It is estimated that more than half of the world's population has been residing in cities since the last 6 years and by 20Merz *et al* 2007 the number of people living in urban areas (with urban areas of developing countries (DCs) accounting for the most part) will grow to 5 billion (i.e. 60% of the world's population) (UN (United Nations) 2007-Li 2009). Regrettably, a major challenge with rapid population growth and urbanization in Nigeria which also seems to influence the risk of flooding in the country both presently and in the future (if not addressed) has been poor urban planning (in particular inadequate drainage system and the range of poorly serviced urban utilities). In recent years, the urban area of Awka in Anambra State has faced a growing threat from recurrent flooding incidents, which have significantly jeopardized the safety, livelihoods, and infrastructure of its residents. Despite concerted efforts to address these challenges, the lack of a comprehensive understanding of flood vulnerability within the urban landscape continues to impede effective disaster management and adaptation strategies.

Existing research efforts in the study area have made strides in assessing flood vulnerability, but they have often fallen short in providing the depth and precision necessary for targeted interventions. Many previous studies have primarily relied on traditional methodologies, such as field surveys, historical data analysis, and basic hydrological models (Efobi *et-al.*, 2013). While these approaches have yielded valuable insights into the general flood risk landscape of Awka, they have often lacked the spatial and temporal resolution required to accurately capture the intricacies of urban flood dynamics.

Additionally, the limitations of existing methodologies have become apparent in the face of increasingly complex urban environments and changing climatic conditions. Traditional flood vulnerability assessments may struggle to account for factors such as rapid urbanization, land use changes, hydraulic infrastructure developments, and the intensification of extreme weather events. As a result, these assessments may overlook critical vulnerabilities or inaccurately identify at-risk areas, leading to suboptimal allocation of resources and inadequate preparedness measures (Agba, 2021; Egbuzoeme, 2015), uses questionnaires method to sample resident's opinion concerning flood activities in their areas.

By utilizing advanced flood simulation models, this study aims to address the shortcomings of previous research efforts and provide a more comprehensive understanding of flood vulnerability in Awka. These advanced models, such as 2D hydrodynamic models or coupled hydrological-hydraulic models, offer enhanced capabilities for simulating complex urban flood scenarios with greater accuracy and detail. By integrating high-resolution topographic data, hydrological parameters, land use information, and climate projections, these models can generate spatially explicit flood hazard maps, assess potential impacts on critical infrastructure and vulnerable communities, and evaluate the effectiveness of various flood mitigation measures.

II. Materials and Methods

2.1 Study Area

Awka South is a local government area in Anambra State, Nigeria. It is located in the southeastern part of the country. The local government area is situated in the capital city of Anambra State, which is Awka. Awka South is bordered by other local government areas such as Awka North, Njikoka, and Dunukofia. It covers a land area of about 73 square kilometers. The area is predominantly urban, with a growing population and various infrastructural developments. Awka South is known for its administrative, commercial, and educational significance. It is home to government institutions, including the Anambra State Secretariat, which houses various government offices. The area also hosts several markets, shopping centers, and business establishments, contributing to its economic vibrancy.

In terms of education, Awka South boasts of several primary and secondary schools, as well as tertiary institution like Nnamdi Azikiwe University. These institutions attract students from different parts of Nigeria and beyond. Overall, Awka South is a bustling and strategically located local government area in Anambra State, playing a vital role in the socio-economic development of the region.

2.2 Methods

2.2.1 Pre-Processing

The pre-processing stage began with the acquisition of medium-resolution satellite imagery and ancillary datasets, including Landsat-8 OLI and ALOS PALSAR. The raw images underwent geometric correction to align them accurately with a common coordinate system, thus ensuring spatial consistency across all datasets. Radiometric calibration was applied to correct sensor-induced distortions, and atmospheric correction was performed to remove atmospheric effects that could obscure surface features.

Additionally, DEM was pre-processed to ensure a continuous and accurate surface representation. This involved filling any sinks within the DEMs to prevent artificial depressions that could affect hydrological modeling. The DEMs were then resampled to match the spatial resolution of the satellite imagery. The preprocessing steps were completed with rigorous quality checks to confirm that the data were suitable for detailed analysis and modeling.

2.2.2 Image Classification

Image classification was performed to delineate various land cover and land use types within the study area. A supervised classification approach was employed using the Maximum Likelihood Classifier, which is well-suited for distinguishing between different land cover types based on their spectral signatures. Training samples for classification were carefully selected from the image to represent key land cover categories: built-up areas, open spaces, vegetation, cropland, and water bodies. Training samples were collected using the *Sampling Tool* in ArcGIS to extract representative pixels from different land cover types. These samples were used to train the classification algorithm. After which, The *Maximum Likelihood Classification* tool was applied to classify the imagery based on the training samples. The algorithm evaluated the probability that each pixel belonged to a particular class based on spectral properties. This was used to achieve objective no 1.

Post-classification, the accuracy of the land cover map was assessed through accuracy assessment procedures, including confusion matrix analysis. Ground-truthing was conducted to verify the classification results, and adjustments were made as necessary to improve classification accuracy. The final classified maps were analyzed to understand the spatial distribution of land cover types, which is essential for evaluating their impact on flood dynamics.

2.2.3 Surface Runoff Analysis

Surface runoff analysis was conducted using the Soil Conservation Service Curve Number (SCS-CN) method, which relates land cover and soil characteristics to runoff potential. The curve numbers were assigned based on land cover types derived from the classification results and soil properties. Areas with different infiltration capacities were identified by calculating the potential surface runoff for various rainfall scenarios. Curve numbers for different land cover types were assigned using the *Reclassify* tool in ArcGIS. The *Raster Calculator* was then used to compute surface runoff by applying the SCS-CN method, which incorporated land cover and soil properties. Thereafter, The *Zonal Statistics* tool was used to calculate runoff potential across different zones. This tool aggregated runoff values and provided insights into spatial variability in surface runoff potential. This was used to achieve objective no 2.

2.2.4 Flood Modelling Using HEC-RAS

Flood modeling was performed using the Hydraulic Engineering Center's River Analysis System (HEC-RAS). This involved the setup of the model by importing pre-processed DEMs and integrating land cover data to define roughness coefficients, which are critical for simulating the flow of water through different surface types. The model was calibrated using historical flood data to ensure accuracy.

Various flood scenarios were simulated for different return periods (2-year, 5-year, 10-year) to assess inundation extents under varying conditions. The model outputs provided detailed maps of flood extents, which were analyzed to understand the spatial and temporal variations in flood risk. This was used to achieve objective no 3 and 4.

2.2.5 Flood Validation Using Error Matrix

To validate the accuracy of the flood model, an error matrix was constructed by comparing the model's flood predictions with ground-truth observations. This matrix provided a detailed assessment of classification performance across different flood risk categories (low, moderate, high). The accuracy metrics derived from the error matrix included:

a) Producer's Accuracy: Measures the likelihood that a given category on the ground was correctly identified by the model.

b) User's Accuracy: Assesses the probability that a category shown on the map corresponds to the actual class on the ground.

The *Tabulate Area* tool was used to calculate the area of each flood risk category within the model output. The *Field Calculator* was employed to derive metrics for the error matrix, comparing predicted flood extents with ground-truth data. An error matrix was then constructed to evaluate classification accuracy for flood risk categories. The matrix provided key accuracy metrics, including producer's and user's accuracy, to gauge the reliability of the flood model predictions.

III. Results

3.1 Pattern of Landcover/Landuse within Awka

The analysis of landcover/landuse distribution in Awka South LGA in 2023, depicted in Figure 1 and Table 1, offers valuable insights for flood modeling endeavours. It reveals that built-up areas constitute the predominant land cover/use, occupying approximately 52.588% of the total area and spanning 89.791 km^2. This indicates a significant expanse of urban infrastructure, which can influence the hydrological response to flooding by altering surface runoff patterns and impervious surface coverage.

Open spaces, comprising 25.738% of the area and covering 43.947 km^2, provide critical green infrastructure that may play a role in flood mitigation through natural retention and infiltration processes. Vegetation, accounting for 19.427% and encompassing 33.171 km^2, serves as another important component in flood modeling, as it can influence soil permeability, evapotranspiration rates, and overall hydrological processes.

Cropland, while occupying a smaller proportion (1.979% and 3.380 km^2), may still impact flood modeling due to potential alterations in land surface roughness and infiltration rates. Conversely, water bodies, representing the smallest fraction at 0.268% and 0.457 km^2, play a crucial role in flood modeling as they serve as primary receptors of excess water during inundation events.

Understanding the spatial distribution of these land cover/use categories is vital for accurate flood modeling and risk assessment. It enables planners and policymakers to identify areas of vulnerability, prioritize mitigation measures, and develop resilient urban infrastructure to minimize the impacts of flooding on communities and the environment. Moreover, it underscores the importance of incorporating land use changes into flood modeling efforts to account for evolving urban landscapes and their implications for flood risk management.

Table 1: Landcover/Landuse distribution for Awka South LGA (2023)

S/N	*Class Category*	*Area (km^2)*	*Percentage (%)*
1	Water Body	0.457	0.268
2	Vegetation	33.171	19.427
3	Cropland	3.380	1.979
4	Built Up Area	89.791	52.588
5	Open Space	43.947	25.738
6	Total	170.7446	100

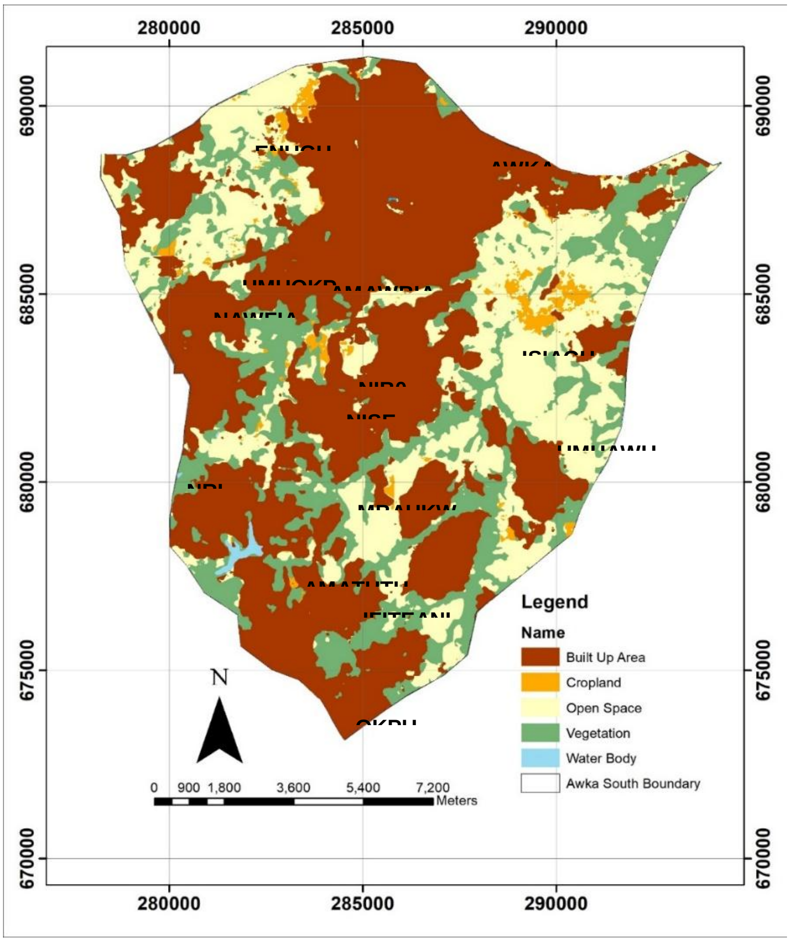

Figure1: Landcover/landuse of Awka South LGA in 2023

3.2 Surface Runoff Modelling

Surface runoff is the movement of water across the ground surface, typically observed during periods of heavy rainfall or when the soil's capacity to absorb water is exceeded. This phenomenon is particularly pronounced in areas where soil saturation occurs rapidly, surpassing the ground's ability to absorb water effectively. Impervious surfaces exacerbate surface runoff by preventing water from permeating into the soil, leading to increased flow over the ground.

In this study, various factors such as land cover/land use patterns, rainfall data, and soil characteristics were analyzed to model the potential for surface runoff.

Utilizing land cover/land use maps, soil maps, and rainfall data, a curve number map was derived to assess the surface runoff potential. The curve number represents a crucial parameter influencing the amount of runoff generated after accounting for all losses and hydrological processes within a catchment area. A curve number of zero signifies a scenario where all rainfall infiltrates into the soil as subsurface flow, whereas a curve number of 100 indicates complete surface runoff, typically occurring during prolonged rainfall events when the soil reaches saturation.

By analysing the relationship between curve number and runoff, it was found that an increase in curve number corresponds to an escalation in runoff from the watershed. This insight underscores the importance of considering factors such as soil saturation and land cover characteristics in predicting and managing surface runoff.

The culmination of this effort was the creation of a runoff potential map derived from the curve number analysis (Figure 2).

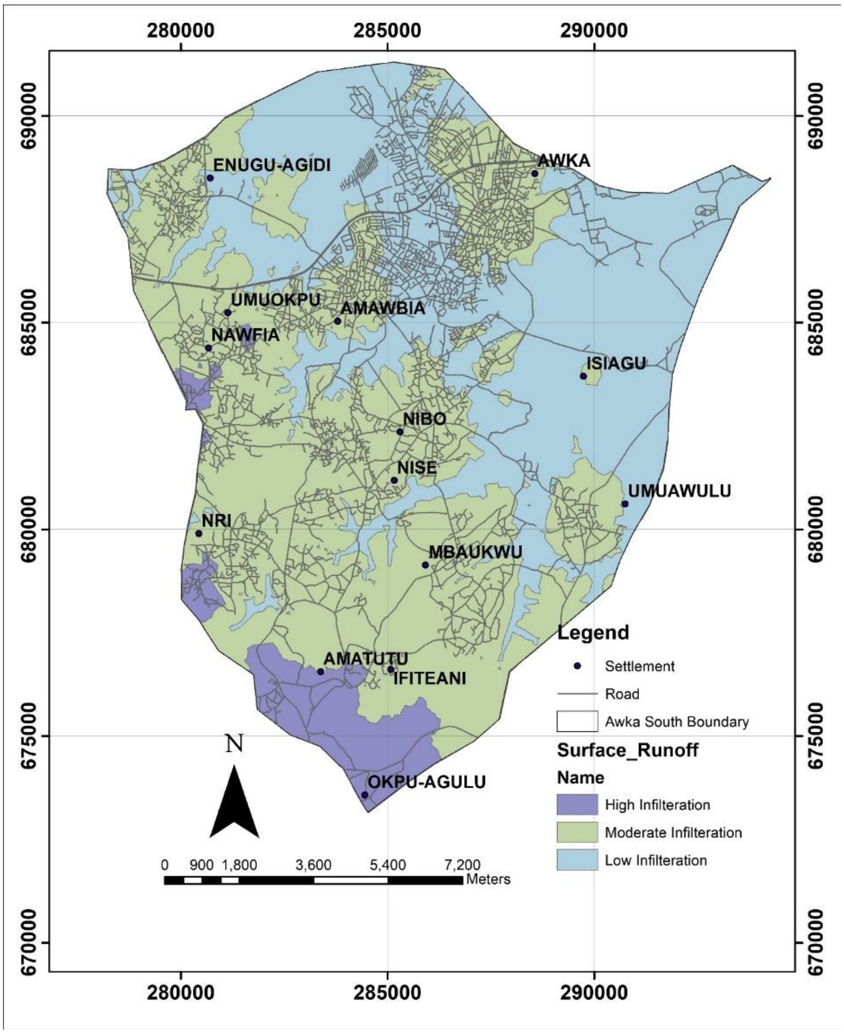

Figure 2: Surface runoff potential in Awka South LGA.

The analysis depicted in Figure 2 unveils crucial insights into the surface runoff potential within the studied area. It reveals a nuanced distribution of infiltration potential across the landscape, shedding light on the varying degrees of susceptibility to surface runoff.

Notably, the data indicate that a significant portion of the area, comprising 42.14% and spanning 71.963 km^2, exhibits low infiltration potential. This implies that a considerable portion of the land surface is prone to generating runoff, as rainfall is more likely to accumulate and flow over the ground rather than infiltrate into the soil. The implications of such a finding are substantial, as areas with low infiltration potential are more susceptible to soil erosion, waterlogging, and flooding, which can have detrimental effects on both natural ecosystems and human infrastructure.

In contrast, the analysis also identifies areas with moderate infiltration potential, encompassing 51.59% of the studied area and covering 88.110 km^2. While these regions demonstrate a relatively higher capacity for water absorption compared to those with low infiltration potential, they still pose significant risks of surface runoff during periods of intense rainfall. However, the moderate infiltration potential suggests that these areas may exhibit a more balanced hydrological response, with a portion of rainfall infiltrating into the soil while excess water contributes to surface runoff.

Furthermore, the findings highlight pockets of land with high infiltration potential, comprising 6.25% of the total area and spanning 10.686 km^2. These areas are characterized by their ability to effectively absorb water, minimizing the likelihood of surface runoff. High infiltration potential areas play a crucial role in mitigating the impacts of rainfall, as they help regulate water flow and reduce the risk of erosion and flooding downstream. Additionally, such regions may serve as important recharge zones for groundwater, contributing to the sustainability of local water resources.

Overall, the delineation of infiltration potential presented in Figure 2 carries significant implications for land management, urban planning, and environmental conservation efforts. By identifying areas prone to surface runoff and those with higher infiltration capacities, policymakers and stakeholders can implement targeted strategies to mitigate the adverse effects of runoff, enhance water retention, and promote sustainable land use practices. Moreover, the findings underscore the importance of considering hydrological dynamics in landscape planning and decision-making processes to ensure the resilience and long-term viability of ecosystems and communities in the studied area.

3.3 Flood Frequency Analysis

In the specific context of the Awka South LGA, flood frequency was modelled using HEC-RAS, a sophisticated hydraulic modeling software. The results of this modeling endeavour are encapsulated in Figure 3, providing a visual representation of flood frequency dynamics within the study area.

This modeling effort holds significant implications for urban planning, disaster management, and infrastructure development in Awka and beyond. By quantifying flood frequencies, stakeholders gain essential insights into the frequency and severity of potential flood events, allowing for informed decision-making regarding land use, infrastructure design, and emergency preparedness measures.

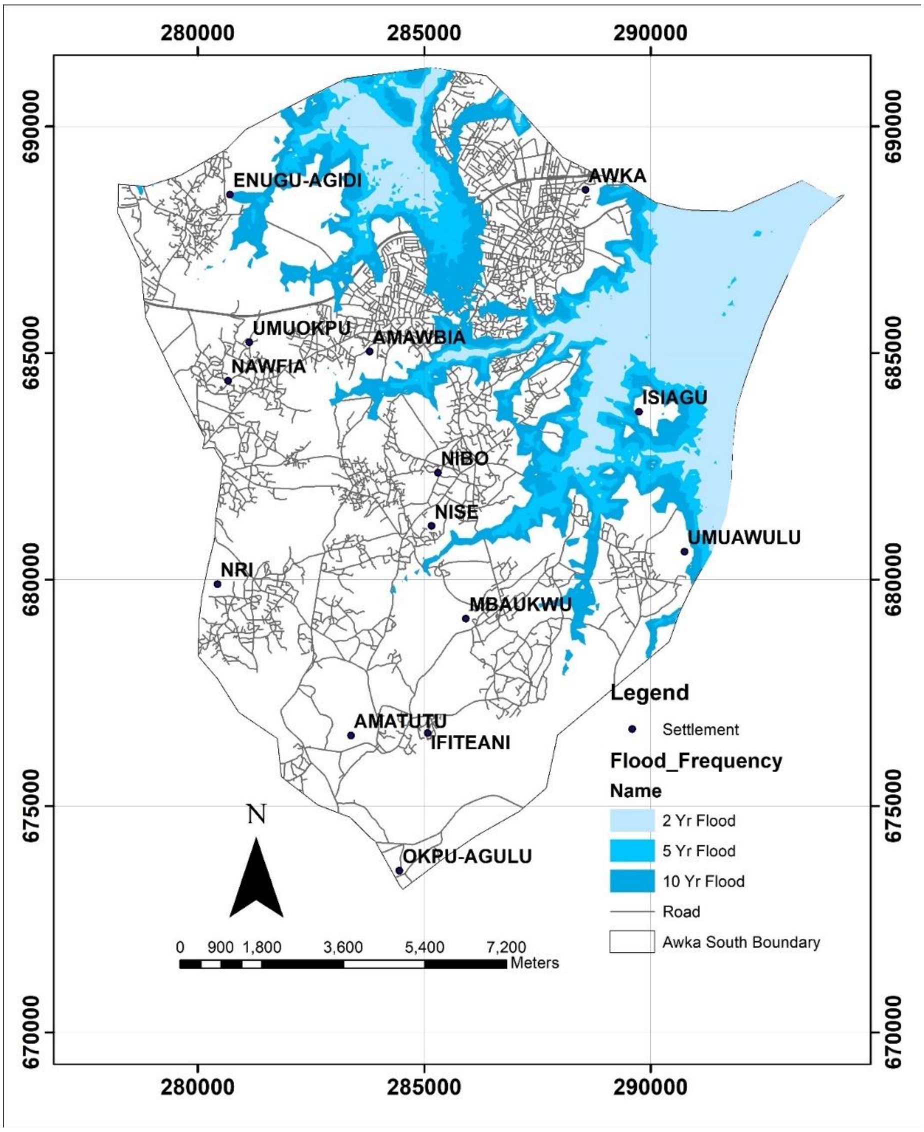

Figure 3: Flood frequency as modeled by HEC-RAS

The outcome derived from the HEC-RAS model (Figure 4.3) provide vital insights into flood dynamics, offering a comprehensive understanding of inundation extents across different return periods. These findings are essential for informing flood risk management strategies, infrastructure planning, and disaster preparedness efforts.

The data reveal significant variations in inundation extents across various return periods. For instance, for a 2-year return period, the predicted inundation extent is recorded at 23.675 km2, indicating the area prone to flooding during relatively frequent events. As the return period increases to 5 years, there is a notable decrease in inundation extent, with the area reduced to 10.869 km2. This reduction suggests a relative decrease in flood-prone areas but underscores the persistent risk of flooding even in less frequent events.

Furthermore, the analysis highlights dynamic changes in inundation extents over time. By the fifth-year return period, there is a considerable decrease in flood extent, with a reduction of 24.80% compared to the 2-year return period. However, this trend reverses by the tenth-year return period, with a subsequent increase of 12.022% in inundation extent. Notably, the peak inundation extent is observed at the 2-year return period, indicating the potential severity of even relatively frequent flood events.

These findings, elucidated in Table 2, offer valuable insights into the temporal and spatial dynamics of flooding, aiding policymakers and stakeholders in devising effective mitigation strategies and adaptation measures. By understanding how inundation extents vary across different return periods, communities can better anticipate and respond to flood hazards, thereby reducing vulnerability and enhancing resilience to future flood events.

Moreover, these results underscore the importance of proactive planning and investment in flood risk reduction measures, such as improved drainage infrastructure, land-use zoning regulations, and early warning systems. By incorporating such strategies based on comprehensive flood modeling data, communities can minimize the socio-economic impacts of flooding, safeguarding lives, livelihoods, and critical infrastructure in the face of increasingly unpredictable weather patterns and climate change.

Table 2: HEC-RAS model flood frequency

HEC-RAS	*Extent (Km2)*	*Percentage*
2-year return period	23.675	32.1%
5-year return period	17.075	35.55%
10-year return period	12.022	33.75%
Total	80.19	100

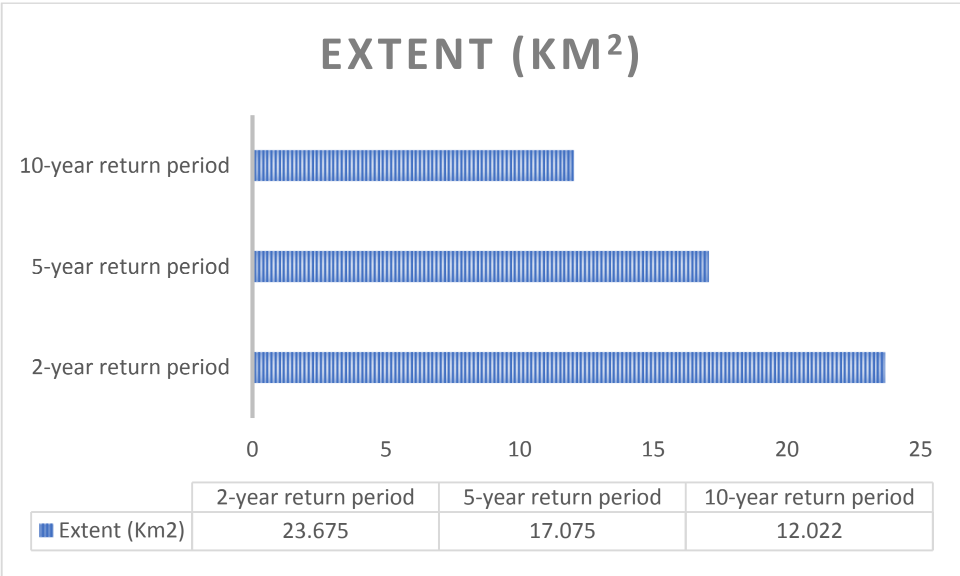

Figure 4: HEC-RAS modelled flood extent for 2yr, 5yr, 10yr returns.

3.4 Flood Vulnerability Mapping

The vulnerability modeling conducted using HEC-RAS delineated three distinct flood vulnerability zones within the study area, categorizing them as high, moderate, and low vulnerability zones. This spatial analysis is pivotal for understanding the susceptibility of different areas to flood hazards, guiding decision-making processes related to disaster preparedness, land-use planning, and infrastructure development.

The results obtained from the vulnerability modeling illustrate the varying degrees of vulnerability across the study area. The high vulnerability zone encompasses 18.77% of the total area, spanning 32.057 km2, indicating regions highly susceptible to flood impacts. These areas are at greater risk of experiencing severe inundation and associated damages during flood events, necessitating urgent attention from authorities and stakeholders in terms of mitigation measures and resilience-building initiatives.

In contrast, the moderate vulnerability zone covers a significant portion of the study area, occupying 69.41% and encompassing 118.528 km2. While exhibiting a lower level of vulnerability compared to the high vulnerability zone, these areas still face notable risks of flood-related impacts. Understanding the extent of moderate vulnerability zones is crucial for prioritizing resources and implementing targeted interventions to reduce vulnerability and enhance community resilience.

Furthermore, the analysis identifies low vulnerability zones, comprising 11.81% of the study area and covering 20.176 km2. These areas are relatively less prone to flood hazards, indicating a lower risk of inundation and associated damages. However, it is essential to recognize that even low vulnerability zones are not immune to flood events, emphasizing the need for comprehensive risk management strategies that consider the entire spectrum of vulnerability.

The distribution of vulnerability zones, as depicted in Figure 5, provides a visual representation of the spatial patterns of flood vulnerability within the study area. This information serves as a valuable resource for policymakers, urban planners, and disaster management agencies in prioritizing mitigation efforts, allocating resources, and implementing land-use policies aimed at reducing vulnerability and enhancing community resilience to flood hazards.

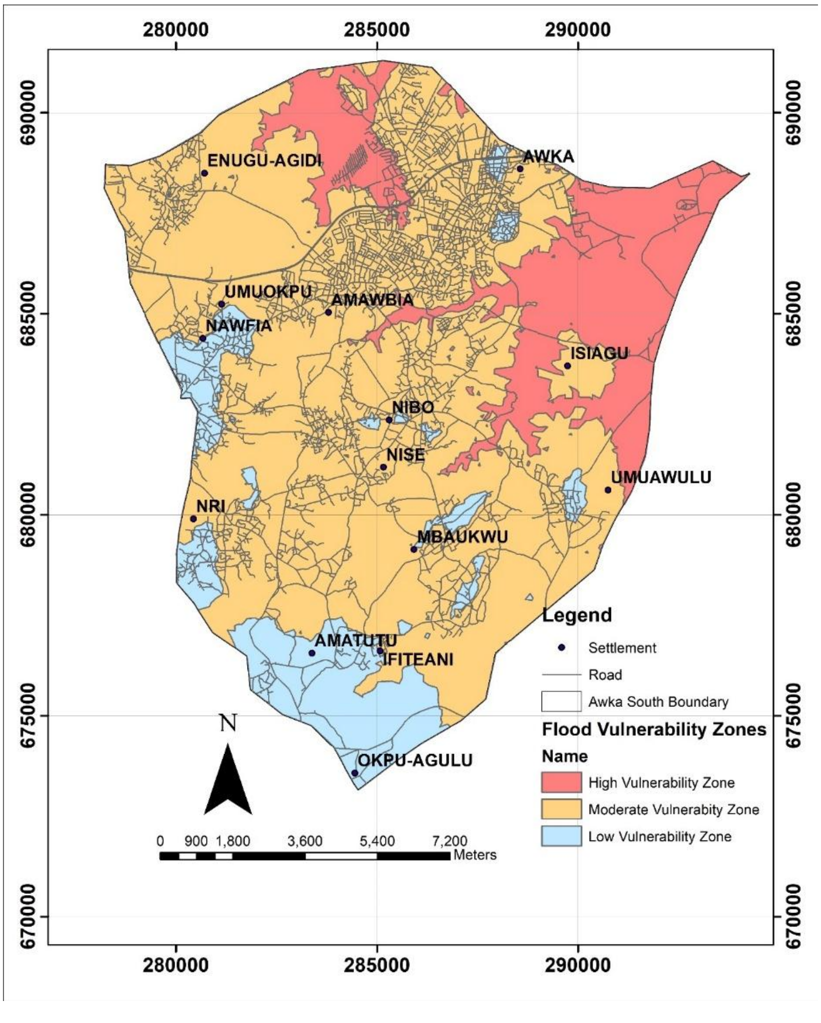

Figure 5: Flood Vulnerability Zone Map

3.4.1 Features at High Flood Vulnerability Zone

A comprehensive overlay analysis was conducted by merging the flood vulnerability layer with the land cover/land use layer, aiming to delineate areas of high vulnerability as modelled by HEC-RAS.

The findings revealed that within the high flood vulnerability zone, vegetation covered a significant portion, accounting for 24.612% and spanning an area of 7.877 km^2. Cropland occupied 5.249% of the zone, totalling 1.680 km^2, while built-up areas comprised 27.053%, covering 8.659 km^2. Open spaces were prevalent within the high vulnerability zone, constituting 43.085% and encompassing 13.790 km^2. Also, these areas include major roads and intersections such as Ziks Avenue, Ifebi Crescent Street, Emma Nnaemeka Street, Ogechukwu Street, Majuo Street, Unizik Tempsite Junction, Nnedioramma Junction, Unizik tempsite bus-stand, Abakiliki junction, Alex Ekwueme Road, Old English Hotel Road, Real Estate Road, Onitsha-Enugu expressway, and Kwatta Junction.

The distribution of land cover classes within the high flood vulnerability zone is meticulously detailed in Table 3 and visually depicted in Figure 6. These findings carry profound implications for urban planning, disaster risk reduction, and environmental management. Understanding the spatial distribution of land cover within areas of high flood vulnerability is crucial for implementing targeted mitigation measures, enhancing resilience, and safeguarding both human settlements and natural ecosystems from the adverse impacts of flooding.

Table 3: Distribution of feature class at High Flood Vulnerability

S/N	*Class Category*	*Area (km^{2})*	*Percentage (%)*
1	Vegetation	7.877	24.612
2	Cropland	1.680	5.249
3	Built Up Area	8.659	27.054
4	Open Space	13.790	43.085
5	Total	32.006	100.000

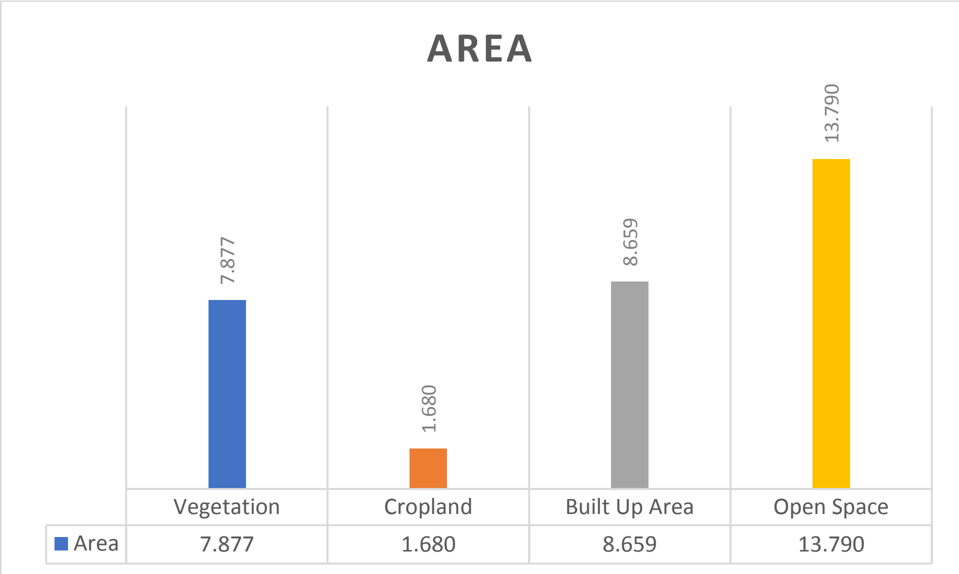

Figure 6: Features within High flood vulnerability zone

3.4.2 Features at Moderate Flood Vulnerability

The analysis indicated that within the moderate flood vulnerability area, water bodies covered a minimal 0.386% of the region, totalling an area of 0.457 km^2. Conversely, vegetation occupied a substantial portion, accounting for 19.323% and spanning 22.877 km^2. Cropland constituted 1.420% of the area, with a total land area of 1.681 km^2. Notably, built-up areas dominated the moderate vulnerability zone, encompassing 54.206% and covering an extensive area of 64.174 km^2. Open spaces also played a significant role, comprising 24.664% of the zone and occupying 29.200 km^2.

This distribution of land cover classes within the moderate flood vulnerability zone is further detailed in Table 4 and graphically depicted in Figure 7. These findings hold critical implications for urban planning, disaster management, and environmental conservation efforts. Understanding the composition of land cover within areas susceptible to moderate flood vulnerability is essential for implementing effective mitigation measures, enhancing resilience, and promoting sustainable development practices to minimize the potential impact of flooding on communities and ecosystems.

Table 4: Distribution of feature class at Moderate Flood Vulnerability

S/N	*Class Category*	*Area (km^{2})*	*Percentage (%)*
1	Water Body	0.457	0.386
2	Vegetation	22.877	19.323
3	Cropland	1.681	1.420
4	Built Up Area	64.174	54.206
5	Open Space	29.200	24.664
6	Total	118.389	100

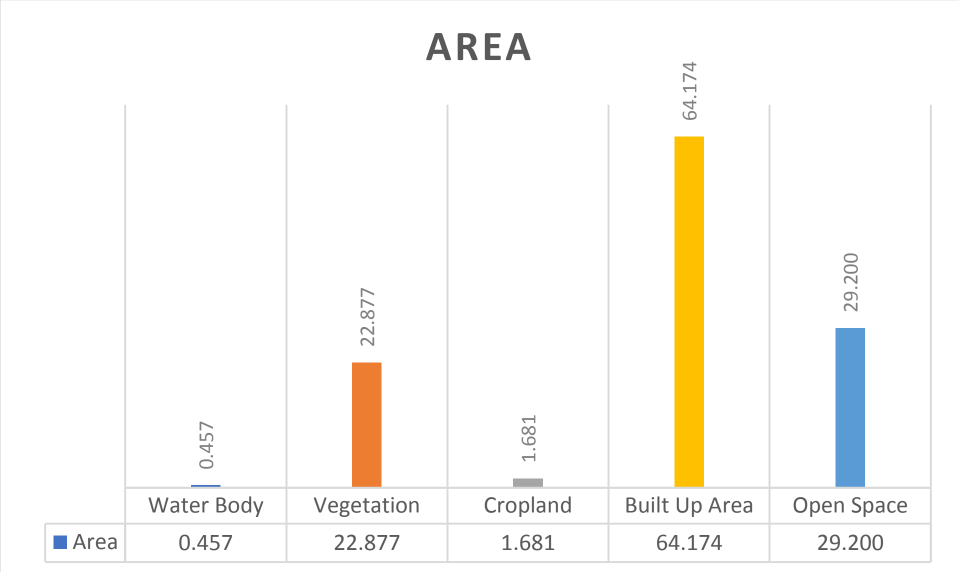

Figure 7: Features within moderate flood vulnerability zone

3.4.3 Features at Low Flood Vulnerability

The analysis revealed that within the low vulnerability area, vegetation covered 11.727% of the region, accounting for an area of 2.358 km^2. Cropland constituted a mere 0.060% of the area, totalling 0.012 km^2. In stark contrast, built-up areas dominated the low vulnerability zone, encompassing 83.773% and occupying an area of 16.849 km^2. Additionally, open spaces comprised 4.441% of the zone, covering 0.893 km^2.

This distribution of land cover classes within the low vulnerability flood zone is further detailed in Table 4.5 and depicted graphically in Figure 8. These findings hold significant implications for land management and urban planning, as they provide valuable insights into the composition of areas less susceptible to flood risk. Understanding the distribution of land cover within low vulnerability zones can inform decisions regarding land use, infrastructure development, and disaster resilience strategies, ultimately contributing to more sustainable and resilient communities.

Table 5: Distribution of feature class at Low Flood Vulnerability

S/N	*Class Category*	*Area (km^2)*	*Percentage (%)*
1	Vegetation	2.358	11.727
2	Cropland	0.012	0.060
3	Built Up Area	16.849	83.773
4	Open Space	0.893	4.441
5	Total	20.112	100

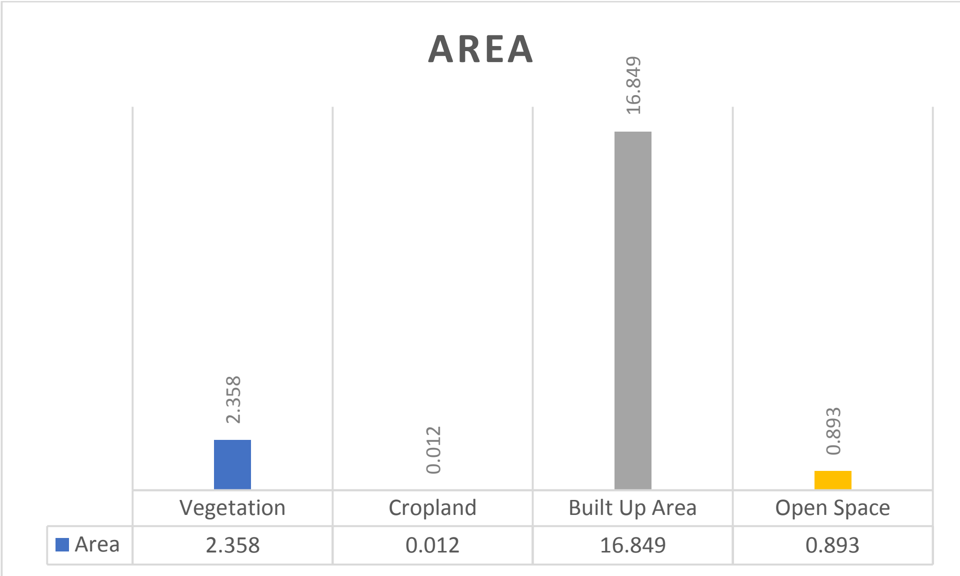

Figure 8: Features within low flood vulnerability zone

The overlay analysis integrating flood vulnerability with land cover/land use layers yielded critical insights into the spatial distribution of vulnerability across different zones. In the high flood vulnerability zone, characterized by significant susceptibility to flooding, a diverse array of land cover types was observed. Vegetation covered a substantial portion, indicating potential flood mitigation through natural barriers, while built-up areas constituted a significant proportion, reflecting heightened risk to human settlements and infrastructure. Open spaces, though prevalent, may offer some resilience against flooding but could also serve as pathways for flood propagation.

Conversely, the moderate vulnerability zone exhibited a distinct composition, with built-up areas dominating the landscape. This concentration suggests heightened exposure to flood risk for urban centers and infrastructure within this zone. The prevalence of vegetation and open spaces may offer some buffering capacity against flooding, but their effectiveness could be compromised by the extensive built-up areas.

In the low vulnerability zone, built-up areas overwhelmingly dominated, indicating limited susceptibility to flooding. However, the presence of vegetation and open spaces, though relatively smaller in extent, may still play a role in mitigating flood impacts by providing natural flood retention areas and reducing runoff. The scarcity of cropland suggests minimal agricultural vulnerability to flooding in this zone.

The significance of these findings lies in their implications for urban planning, disaster management, and environmental resilience. Areas identified as high or moderate vulnerability zones require targeted interventions to reduce flood risk, such as implementing green infrastructure, enhancing drainage systems, and adopting land use policies that prioritize flood resilience. Additionally, efforts to preserve and enhance natural vegetation and open spaces can contribute to flood mitigation and improve overall ecosystem health. Conversely, low vulnerability zones should not be overlooked, as they may still face localized flood risks, especially in rapidly urbanizing areas.

This analytical assessment underscores the importance of integrating spatial data analysis with flood vulnerability mapping to inform evidence-based decision-making and foster sustainable development practices that enhance resilience to natural hazards.

3.5 Flood Modeling Validation

Assessing the accuracy of flood modeling results is essential to ensure their reliability and validity. A key aspect of this process involves comparing the coordinates of flow accumulation points obtained from the flood model with those observed during ground verification. This comparison helps evaluate the positional accuracy of the model and serves as a critical validation step. The resulting error matrix and overall accuracy, which provide a detailed assessment of the model's performance, are presented in Table 6.

Table 6: Error Matrix

`Class		Ground Reference			Total	Error of Commission	Users Accuracy
		Low Risk	Moderate Risk	High Risk			
Flood Modeling	Low Risk	65	10	5	80	0.187	81.25%
	Moderate Risk	5	55	16	76	0.276	72.36%

	High Risk	5	10	79	94	0.159	84.04%
	Total	75	75	100	250		
Error of Omission		0.133	0.260	0.21			
Producers Accuracy		86.66%	73.33%	79%			

Table 6 illustrates the error matrix, a tool used to assess the performance of a classification model by comparing predicted results with ground reference data, category by category. This matrix provides a visual representation of the classification results, where each cell indicates the number of observations assigned to a specific category.

The off-diagonal elements in the error matrix highlight misclassification errors. Errors of omission occur when a category is incorrectly excluded or misclassified, and these are represented by non-diagonal elements in the columns. Errors of commission arise when a category is incorrectly included or misclassified, represented by non-diagonal elements in the rows.

Producer's accuracy measures the likelihood that a given category on the ground has been correctly identified by the model, reflecting the model's ability to accurately detect the presence of a particular class. Conversely, User's accuracy indicates the probability that a category shown on the map corresponds to the actual class on the ground, measuring the model’s success in confirming the absence of misclassified categories.

Tables 7 and 8 present the producer’s and user’s accuracy calculations for flood hazard modeling. These accuracy metrics were derived by dividing the number of correctly classified observations by the total observations for each category. The producer's accuracy was 86.66% for low risk, 73.33% for moderate risk, and 79% for high risk. For user’s accuracy, the values were 81.25% for low risk, 72.36% for moderate risk, and 84.04% for high risk, indicating the reliability of the flood model across different risk categories.

Table 7: Producers Accuracy

Producers Accuracy		
Low Risk	65 / 75	86.66%
Moderate Risk	55 / 75	73.33%
High Risk	79 / 100	79%

Table 8: Users Accuracy

Producers Accuracy		
Low Risk	65 / 80	81.25%
Moderate Risk	55 / 76	72.36%
High Risk	79 / 94	84.04%

The overall accuracy was computed by dividing summation of the diagonal to the total number in the matrix.
Overall Accuracy = $(65 + 55 + 79) / 250 = 79.6\%$.

The model shows relatively strong performance, with an overall accuracy of 79.6%. although, misclassification occurred, particularly with moderate-risk zones, which have the highest error rates (error of commission: 27.6%, error of omission: 26%). This indicates that moderate-risk areas share characteristics with both low and high-risk zones, leading to more confusion in classification.

The high-risk class performed the best in terms of both user’s accuracy (84.04%) and producer’s accuracy (79%). This indicates that the model was relatively more successful in identifying areas that are truly at high risk of flooding.

The low-risk class had a strong producer’s accuracy of 86.66%, meaning most low-risk areas were correctly identified by the model. However, its user’s accuracy (81.25%) and error of commission (18.7%) indicate that some areas were wrongly classified as low risk, which could lead to underestimation of flood threats in this area.

The moderate-risk class is the weakest, with relatively low producer’s and user’s accuracies, indicating that the model struggled to distinguish moderate-risk areas accurately. Further refinement, possibly by adjusting classification thresholds or incorporating additional variables, may be necessary to improve performance in this category.

IV. Conclusion

The findings from the comprehensive analysis of land cover/land use distribution, surface runoff modeling, flood frequency analysis, and vulnerability mapping in Awka South LGA yield several key conclusions such as the dominance of built-up areas, underscoring the significant influence of urbanization on hydrological responses. This urban expansion alters surface characteristics, leading to increased surface runoff and flood risk.

Flood frequency analysis revealed dynamic changes in inundation extents over time, highlighting the need for adaptive planning and mitigation strategies to address evolving flood risks. Also, the vulnerability mapping identified areas highly susceptible to flooding, guiding prioritization of mitigation efforts and resilience-building initiatives. Understanding the spatial distribution of vulnerability zones is essential for effective risk management and land-use planning.

The integration of land cover/land use data with flood modeling and vulnerability mapping provides a holistic understanding of flood dynamics. This integrated approach facilitates evidence-based decision-making for mitigating flood risks, enhancing resilience, and promoting sustainable development.

The findings emphasize the importance of proactive planning and adaptive management strategies to address the complex challenges posed by flooding in urban areas like Awka. By considering the interplay between land cover characteristics, hydrological processes, and vulnerability assessments, policymakers and stakeholders can develop targeted interventions to minimize flood risks, protect communities and infrastructure, and foster sustainable urban development in the face of changing climate conditions.

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