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ASSESSING FLOOD RISK LEVELS IN YOLA NORTH LGA, ADAMAWA STATE, NIGERIA

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Abstract

This research analyzes the flood risk level of Yola North LGA, Adamawa State, Nigeria, by analyzing the Land Use Land Cover and Digital Elevation Model (DEM) of Yola North, identifying flood risk level, and areas vulnerable to flood risk level in the study area using geospatial techniques. The data used include ASTER with 30m spatial resolution, Landsat 9 OLI multispectral data (2023), and 140 locations of flood and non-flood points of the study area was collected. The data were analyzed in ArcGIS 10.8 software. An Artificial Neural Network (ANN) was employed in ArcGIS 10.8 software to classify LULC types through supervised classification using maximum likelihood algorithms. Confusion matrix was used for the 2023 satellite image accuracy assessment. The analysis derived a Land Use/Land Cover (LULC), Digital Elevation Model, and Flood Risk level and area vulnerable to flood risk. The ArcTool Box, Spatial Analysis Tools, Map Algebra, and Raster Calculator of the software were utilized for the data analysis. The results show that the elevation ranges from 151m to 226m above sea level. The 2023 LULC reveals that built-up areas cover about 33% of the study area, followed by farmland (25%), bare land (18%), vegetation (15%), and water bodies (9%). The flood risk level varies in the study area, with 59% being flood-free, 28.1% at high risk (levels 3 and 4), and 12.7% at moderate to low risk (levels 1 and 2). The analysis also shows that a 5m flood would affect about 3.7% of the study area, while increases of 10m, 15m, and 20m would affect 13.3%, 23%, and 35% of the area, respectively. This implies that elevation plays a major role in flood susceptibility risk, highlighting the need to consider elevation in planning to reduce vulnerability to flood risk. Based on the research findings, this research recommends the needs to incorporate flood risk susceptibility into urban planning and develop flood mitigation and preparedness strategies in Yola North LGA.

Keywords: Flood, Risk, Geospatial Techniques, Yola North and Adamawa State.

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1.0 INTRODUCTION

Flood is commonly defined as an overflow of water onto lands that are used or are usable by man, and are not normally covered by water. Floods have two essential characteristics: the inundation of land is temporary; and the land is adjacent to and inundated by overflow from a river, stream, lake, or ocean [1]. Another, more general definition states that flood is determined as a general and temporary condition of partial or complete inundation of normally dry land areas from overflow of inland or tidal waters, or from the unusual and rapid accumulation or runoff of surface water from any source [1]. A river channel is formed by the forces of nature to be able to convey the flow that is found most of the time. When the volume exceeds this, the water level rises above the banks and spreads in to the adjacent lands. This area is usually called the flood plain of the river e.g. when rainfall exceeds absorption capacity of the soil, which in turn causes significant environmental consequences [2].

Flood disaster is generally defined as the function of hazard, the probability of a flood event; exposure, the population and value of assets subject to flooding; and vulnerability, the capacity of a society to deal with the event [3]. While the understanding of hazard and exposure has greatly improved over the years, knowledge of vulnerability remains one of the biggest hurdles in flood risk assessment to date [4] [5]. Traditionally, studies assessing flood disaster and the feasibility of flood risk management (FRM) policies include the physical vulnerability of structures and goods as an indicator of flood risk [6] [7].

Flooding as one of the most common and destructive natural disasters has caused approximately 7 million deaths and more than $US 700 billion losses around the world since 1900 [8]. Worse still, some studies have declared that flooding events may increase in many coastal regions in the future due to global and regional climate change that will cause rising sea levels [9]. There are many events happenings around the world every day, some of which become natural disasters [10]. Natural disasters are a disaster or disaster caused by a high-risk natural phenomenon such as floods, droughts, earthquakes, landslides, hurricanes or volcanoes that cause extensive damage to human communities, but in areas where direct contact with humans These events do not turn into natural disaster [11] [12]. Floods are the most destructive catastrophe worldwide and cause the highest number of deaths and injuries [13]. In recent years, assessments and estimates of

floods have increased significantly due to increased urbanization and the concentration of residential areas around rivers and floodplains. Estimate that ‘1.47 billion people, or 19% of the world population, are directly exposed to substantial risks during 1-in-100-year flood events. In developing countries, flooding results from climate change, excessive precipitation, building on waterways, sea-level rise, soil moisture regime, dam operations, especially along borders, uncontrolled rapid population growth, inadequate preparedness, and lack of political will [14] [15]. [15] identified excessive levels of precipitation as the main natural cause of flooding, caused by climate change.

The definitions and conceptual frameworks of flood risk exhibit variability, leading to divergent methods of calculation. [16] clarified that risk indicates the probability and potential loss based on different intensity floods. The flood hazard risk implies people's or any region's exposure, sensitivity, and ceaselessness to flood threats and the failure to deal with their consequences [17]. The need to understand the vulnerability of floods arises because of flood natural hazards assessment and evaluation, which will contribute to effective flood control and reduce its effect on different sectors of society [18]. Vulnerability is a phenomenon that emerged in the social sciences and is now becoming more common in disaster studies. The idea of vulnerability comprises numerous parts such as risk, exposure, and sensitivity and is multidimensional.

[19] described Flood susceptibility as the process of identifying flood-prone areas by analyzing a series of flood-triggering and causal parameters, such as elevation, slope, aspect, and rainfall. The selection of these parameters depends on the physical and natural characteristics of the study area and data availability. El-Haddad emphasized the assessment of areas likely to experience flooding based on hydro-geomorphological factors, such as flow accumulation, slope, and permeability. The methodology involves correlating these factors with historical flood data to produce susceptibility maps that differentiate areas by risk levels [20].

The intersection of risk and exposure is defined to be the vulnerability of a system to floods. However, there is a distinction between vulnerability and susceptibility. flood vulnerability can be assessed through various criteria such as literacy rate, land use, quality of building, building density, green area ratio (vegetation type), age of buildings, population density, drainage density, density of transportation networks and age [21]. As it seems, flood vulnerability is a

multidimensional concept, involving various social, physical, and environmental components. Considering the journal papers centered around "susceptibility" term, various criteria influencing flood susceptibility have been highlighted such as vegetation Index, DEM, Topographic position index, flow accumulation, distance from river, land use, soil type, precipitation (rainfall), lithology (geology), stream power index, curvature, river density, building materials, disabled people, slope, Topographic wetness index, drainage density and average monthly household's [22] [16] [23].

Floods are among the most devastating natural disasters in the world, claiming more lives and causing more property damages than any other natural phenomena. According to the latest Adamawa State Emergency Management Agency [24] report, the floods have caused a large-scale displacement of more than 8,504 households (51,043 individuals), the majority of whom are women, children, and the elderly, currently living in 11 temporary settlements across Yola South, Yola North, Lamude, Madagali, and Demsa LGAs. 33 casualties were reported. Flood risk Mapping is one of the critical tools for studies such as identifying flood-prone areas, land use planning, emergency preparedness, and disaster risk reduction [25]. The accuracy and reliability of these maps require a broad understanding of the parameters and methods used in FSM. FSM Combines hazard, vulnerability, and exposure data to produce flood risk susceptibility maps. Machine learning techniques, such as Random Forest and XGBoost, are increasingly used. Machine learning models have become central to flood susceptibility mapping.

In recent times (2023), Nigeria witnessed much milder flooding than in 2022. The National Emergency Management Agency (NEMA) reported that as of October 2023, 157,159 people were affected country-wide, with 68,000 displaced as a result of flooding across the country. The flood alert in Adamawa State in Northeast Nigeria and bordering Cameroon on October 7th was prompted by the release of water from Cameroon's Lagdo Dam, a situation that the Nigeria Hydrological Services Agency [26] had been monitoring since August 2023. Initially, there was a controlled release at 200 cubic meters per second from August 14th to 28th, followed by a well-managed release at 650 cubic meters per second on September 17. The Highly Probable Flood Risk States are; Adamawa, Abia, Akwa-Ibom, Anambra, Bauchi, Bayelsa, Benue, Cross-River, Delta, Eboyin, Ekiti, Edo, Gombe, Imo, Jigawa and Kadunna, others are, Kano, Kebbi, Kogi,

Kwara, Lagos, Nasarawa, Niger, Ogun, Ondo, Osun, Oyo, Rivers, Sokoto, Taraba and Yobe, as well as Zamfara and FCT [26].

Over 4 million people have needed urgent food assistance annually in the BAY states since June 2020. Trend analysis indicates consistently high or rising food insecurity levels since 2018. The year 2019, Yola North and South have left both the government and the governed devastated. It is no longer news that flooding and its attendant consequences are injurious to man while the spatial dimensions are often not mapped. Following heavy rains on 26-27 October 2019, a large number of people have been displaced in Yola North, Yola South, Lamurde, Numan,Demsa, Guyuk, Girei, Fufore, Local Government Areas (LGAs) of Northeastern state of Adamawa. An estimated 381 houses have been damaged, 493 houses partially damaged, with over 365 water and sanitation facilities destroyed, affecting 12,092 individuals (2,325 households). In Purakayo ward of Guyuk LGA, 2 people were reportedly killed by the flash floods and an unconfirmed number of people injured in the eight affected LGAs of Adamawa. Most of the farmlands have been submerged in water leading to heavy loss of farm produce, livestock and other valuable items worth millions of Naira destroyed. Demsa LGA is the most affected with an estimated 5,050 individuals (842 households), followed by Numan LGA with 2,149 individuals (456 households). Yola North, Girei, Yola South, Fufore, Guyuk and Lamurde LGAs account for the remaining 4,893 (1,027 households) displaced individuals [27].

The flood water contaminated water points in several communities causing water-borne and vector-borne diseases like cholera, diarrhoea, malaria and dengue fever. Moreover, an outbreak of scabies, a parasitic skin infestation, was reported in riverine communities like Bawaranji. The risk of infection is higher for vulnerable groups, such as malnourished children whose immune systems are already compromised. Disease outbreaks are putting pressure on the already threadbare healthcare system in Adamawa State [24].

Within the last two decades, the most widely used approaches in modelling flooding in Nigeria include geospatial techniques and Geographic Information Systems (GIS), and hydrological modelling and fitting of probability distributions [28] using GIS techniques to describe vulnerable areas prone to flooding close to the Ogun River basin, Nigeria. [28] in related work on the Ogunpa River basin, Ibadan, Oyo state, combined three methods, viz., the HAND model,

GIS-based multi-criteria decision analysis and event-based flood simulation using the FLO-2D model, to develop flood risk level maps. This justifies the need for this research in Yola North LGA, because it falls within the Highly Probable flood risk areas based of Annual Flood Outlook 2021 to map out areas vulnerable to flood risk and provide information that will be useful for flood mitigation in the study area. Hence, this research Assessing Flood Risk Levels in Yola North LGA, Adamawa State, Nigeria by analyzing he Land Use Land Cover and Digital Elevation Model (DEM) of Yola North, identifying flood risk level, and areas vulnerable to flood risk level in the study area using geospatial techniques.

2.0 MATERIALS AND METHODS

2.1 Study Area

Yola-North LGA is one of the largest cities in Adamawa state, Nigeria, situated at a height of 215 meters Above Mean Sea Level and located between Latitudes 9° 12' 0." and 9° 21' 0" North of the Equator and Longitudes 12° 19' 12" and 12° 30' 0" East of the Greenwich Meridian. The area is located at the bank of River Benue and is bounded by Giere in the North and East, and in South and West by Yola-South local government area. Yola-North Local Government is composed of eleven Wards namely; Yelwa, Nasarawo, Jambutu, Luggere, Alkalawa, Doubeli, Limawa, Rumde, Karewa, Ajiya and Gwadabawa (See Figure 1).

Yola North Local Government area experiences a tropical sub humid climate, the wet and dry seasons. Over the course of the year, the temperature typically varies from 17° Celsius (C) to 39° Celsius (C) and is rarely below 14°Celsius (C) or above 42° Celsius (C) (Weather spark, 2021). The study area is underlain by Bima Sandstone which marks the base of the sedimentary succession in the Upper Benue Trough. It varies in thickness from 100m to 300m and has a maximum thickness at the Lamurde anticline where it exceeds 3000m. The differing degree of sediment accumulation in the trough and the irregular relief of the underlying crystalline basement on which the sediments accumulated are probably responsible for the variation in thickness. The Bima Sandstone rocks in the Upper Benue Basin have been sub-divided from base to top into three sandstone members. These include the lower Aptian/Albian Bima, the Middle Albian Bima Sandstone and the late Albian/Cenomanian Upper Bima Sandstone [29].

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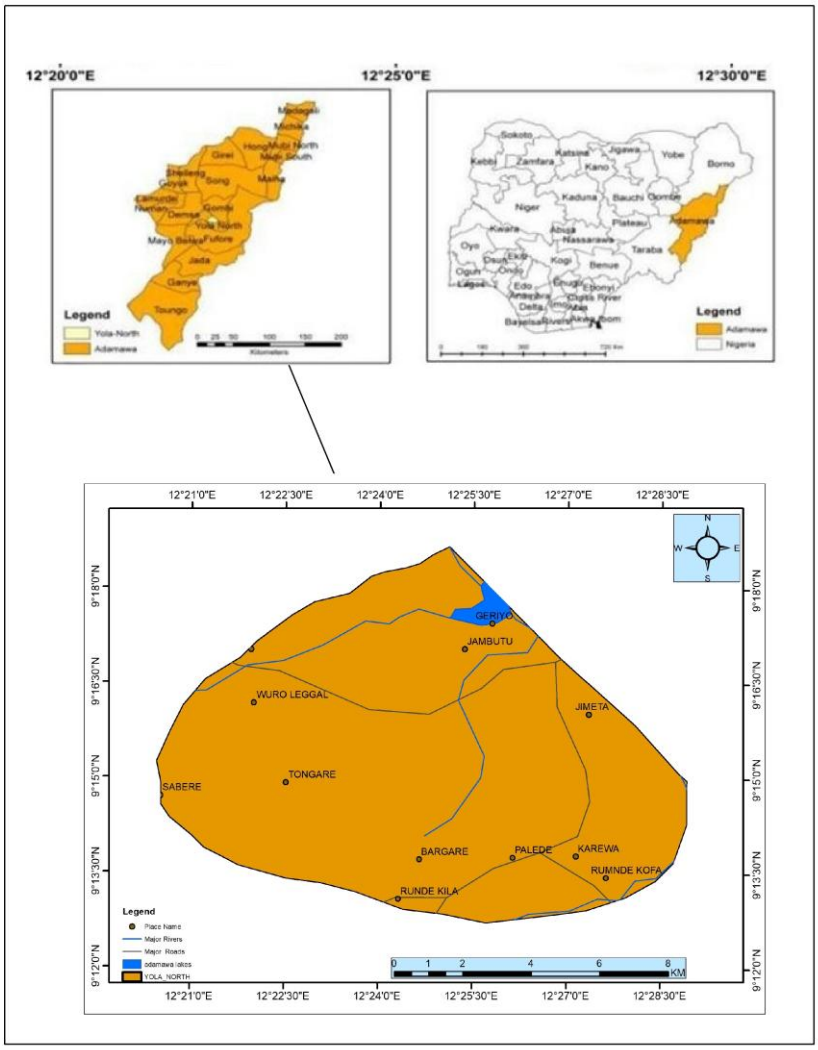


Figure 1: Map of Study Area

Like most areas in northern Nigeria, the soil of Yola-North is derived from the basement complex rock, however, there is some alluvial soil along the Benue flood plains. The soil of the study area is loamy and it drains easily when it rains. The vegetation consists of short, medium and shrubs, more especially in the months of August and September during which the area records higher amount of rainfall. The population of the area is approximately the projected Population as at the year 2022 is 307,900 based on exponential growth model with an annual growth rate of 2.7 percent. The city is clearly stratified in terms of population densities such as low, medium and high-density areas.

2.2 Methods

2.2.1 Reconnaissance Survey

The survey was carried out to get acquainted with the study area for data sources and to aid in the method of field observation and generation/taking coordinate of floodable and non-floodable areas.

2.2.2 Types and Sources of Data

Tables 1 show the type and sources of data and the parameters to be used as input for Geospatial techniques and machine learning algorithm used for flood susceptibility modeling.

Table 1a: Types and Sources of Data

S/NO	Type of Data	Source of Data
1	Digital Elevation Model	ASTER with 30m spatial resolution, Global Landcover
2	Land Use/Land Cover (LULC)	Wusgs. Landsat 9 OLI/TIRS, 30 (Multispectral).
3	Flood Points and Non-Flood Points	Historical data sources, Fieldwork, Perception of local residents, and Google Earth Engine

Source: Thlakma, 2024.

2.2.3 Data Processing and Accuracy Assessment

Arc Tool box of Spatial Analyst Tools was applied using Segmentation and Classification in creating the Create Accuracy Assessment Points using ArcGIS 10.8 software, the points were converted to kml to be able to view the point on google map and later verified on the attribute table of the LULC classification image of the year 2023 (ArcGIS 10.8). The Arc Tool box of Spatial Analyst Tools was used to calculating confusion matrix in the software.

The result for the accuracy assessment of the classification is presented on Table 1.

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Table 1b: Accuracy assessment table Yola North

Land Use Classes	Water body	Built Up areas	Vegetation	Bare land	Agriculture Land	Total(user)
Water body	**4**	0	0	0	0	4
Built Up areas	1	**7**	0	0	0	8
Vegetation	0	1	**3**	0	1	5
Bare land	0	0	0	**7**	0	7
Agriculture Land	0	0	0	2	**4**	6
Total(producer)	5	8	3	9	5	30

Source: Author's Analysis, 2025

Overall accuracy =total number of correctly classified pixels(diagonal)÷total number of referenced pixels ×100

=25/30×100 = 83.3%

User accuracy =total number of correctly classified pixels in each category ÷total number of referenced pixels in that category (the row total) ×100

1. Water body = 4/4 × 100 = 100%
2. Built Up areas = 7/8 × 100 = 87.5%
3. Vegetation = 3/5 × 100 = 60%
4. Bare land = 7/7 × 100 = 100%
5. Agriculture land= 4/6 × 100= 66.6%

Producer accuracy =total number of correctly classified pixels in each category ÷ total number of referenced pixels in that category (the column total) ×100

1. Water body = 4/5 × 100 = 80%
2. Built Up areas = 7/8 × 100 = 87.5%
3. Vegetation = 3/3 × 100 = 60%
4. Bare land = 7/9 × 100 = 77.7%
5. Agriculture land= 4/5 × 100= 80%

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2.2.4 Data Analysis Techniques

The data were assessed and examined based on the stated objectives as follows:

Objective I: Land Use/Land Cover (LULC) Analysis

This study utilized a 2023 LULC map derived from Landsat imagery with a 30m spatial resolution. An Artificial Neural Network (ANN) was employed in ArcGIS 10.8 software to classify LULC types through supervised classification using maximum likelihood algorithms. Post-classification comparison was then used to detect land use transitions over the selected period. The classification scheme adopted five LULC classes (see Table 2), adapted from [30] and modified to suit the specific characteristics of Yola North and the research objectives.

Table 2: Land Use Land Cover Classification Scheme

LULC Class	Description
Built-up Area	Residential, commercial, industrial, transportation, and other constructed areas
Vegetation	Trees, shrubs, grasslands, and other vegetated areas
Bare Land	Exposed soil, sand, rocks, and areas with little or no vegetation
Farmland	Cultivated areas and agricultural fields
Water Bodies	Rivers, streams, ponds, and other surface water features

***Source: Adapted from* [30].**

The study employed a supervised classification approach using the Maximum Likelihood Classifier (MLC), a method widely recognized for its effectiveness in urban and environmental land cover mapping [31]. Representative training samples for each Land Use/Land Cover (LULC) class were collected from high-resolution reference imagery and verified with ground truth data. For historical images lacking direct ground observations, training samples were derived from areas with well-documented historical land uses. The MLC was applied with optimized parameters to produce LULC maps for each study year. To enhance map coherence, post-classification refinement included applying a majority filter, reducing the salt-and-pepper effect common in pixel-level classifications. Accuracy assessment used an independent set of

validation points, computing key metrics such as overall accuracy, user's accuracy, producer's accuracy, and the Kappa coefficient to evaluate classification performance and reliability. Although alternative machine learning classifiers like Support Vector Machines (SVM) and Random Forest (RF) have gained popularity for handling complex, non-linear relationships, MLC was chosen for its robustness with well-defined and relatively limited training data. Unlike RF and SVM, which require larger training datasets and parameter fine-tuning, MLC assumes normal distribution of class signatures and performs reliably when this condition is met. Given the study's scope, available training samples, and need for comparability across multi-decadal Landsat datasets, MLC provided a consistent and computationally efficient classification approach.

Objective II: Flood Risk Level

Floodable and Non-floodable Points. The floodable and non-floodable points, including their heights and locations (140 points), collected during fieldwork were input using Spatial Analysis Tools of ArcGIS 10.8 software. Raster interpolation of the software was performed using the Inverse Distance Weighting (IDW) method and saved as a DEM (Digital Elevation Model). The ArcGIS 10.8 ArcTool Box, Spatial Analysis Tools, Map Algebra, and Raster Calculator were utilized, and the output was saved as IDW-DEM. This was then reclassified using the Reclassify tool in ArcGIS 10.8 software, resulting in the following flood level classifications: 0-0.3: Flood-free area; 0.3-0.9: Flood Level 1; 0.9-1.8: Flood Level 2; 1.8-3.6: Flood Level 3and 3.6+: Flood Level 4.

Objective III: Areas Vulnerable to Flood Risk

This was achieved using ArcGIS 10.8 software. The ArcTool Box, Spatial Analysis Tools, and Map Algebra of the software was used. The DEM values for the study area ranged from its lowest point (151m) to higher values. To model flood risk, 5m, 10m, 15m, and 20m were added to the DEM. The resulting values ranged from 0 to 1. The output was then reclassified, removing 0 values and replacing them with NoData. Additionally, the value 2 was reassigned to 1. The final outputs were saved according to the corresponding flood height scenarios (5m, 10m, 15m,

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and 20m). The analysis utilized flood influencing factors, along with current and historical flooding points, which were processed in an ArcGIS 10.8 environment.

3.0 RESULTS AND DISCUSSION

The results for this research were discussed based on subsections.

3.1 Land Use Land Cover and Digital Elevation Model (DEM) of Yola North

The result for the landuse land cover of Yola North is presented on Figure 2 and Table 3 and Digital Elevation Model Figure 3.

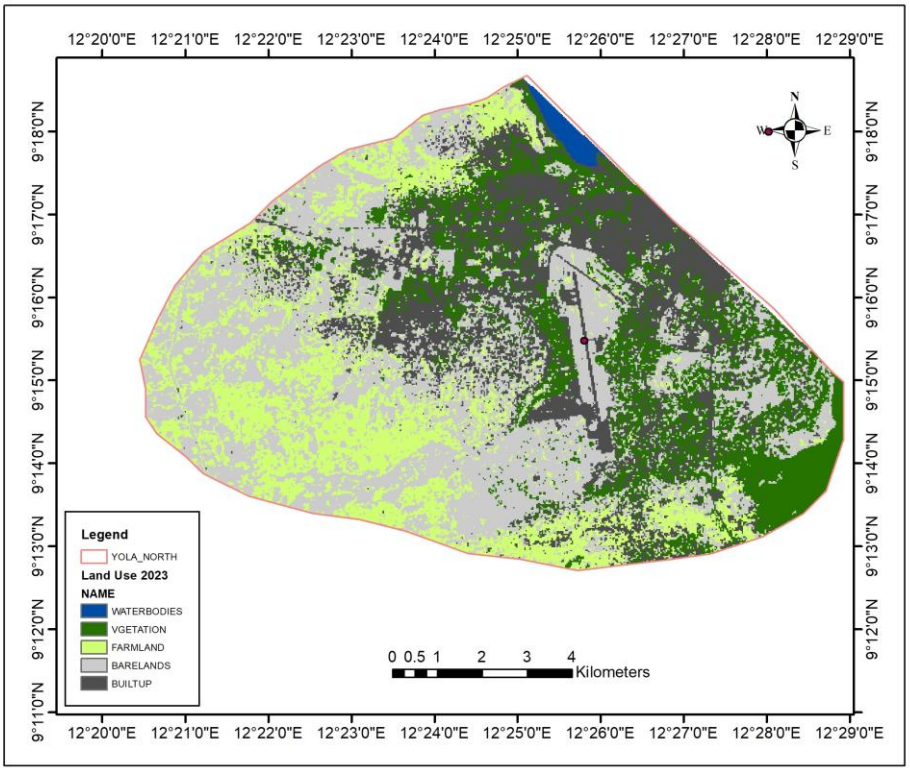


Figure 2: Land Use Land Cover of Yola North for the Year 2023
Source: Authors Analysis (2025)

Table 3. Land Use Land Cover of 2023

Land Use	Years 2023 (%)
Buildup	33.32

Bare land	18.22
Vegetation	14.57
Farmland	24.84
Water Bodies	9.06
Total	100%

Source: Authors Analysis (2025)

The 2023 Land Use Land Cover (LULC) analysis on Figure 2 and Table 3 shows the study area's land use distribution. Built-up Area (33%) indicate a high urbanization, increased impervious surfaces, and altered hydrology contribute to flood risk. This could altered hydrological processes, such as increased stormwater runoff and decreased groundwater recharge. Farmland (25%) reveled a soil compaction and crop management practices increase runoff and soil erosion, exacerbating flood risk. Bare Land (18%) indicates an increased runoff and erosion due to lack of vegetation cover. Vegetation (15%) helps mitigate flood risk by absorbing rainfall and stabilizing soil and waterbodies (9%) regulates flood flows and provides ecosystem services such as habitat provision and water filtration. The results imply that the LULC analysis indices have significant implications for flood risk susceptibility in the study area as supported by [16] [27] clarified that risk indicates the probability and potential loss based on different intensity floods. Also supported by [21] [24] [22] [16] [23].

The result from Figure 3 indicates that the study area has a varying elevation, with a maximum height of 226 meters above sea level and a minimum height of 151 meters above sea level. This elevation range suggests that the area is not extremely mountainous but has noticeable variations in topography. The elevation data has significant implications for flood risk susceptibility. Areas with lower elevations of 151m are more susceptible to flooding, especially during heavy rainfall events or when water bodies overflow. This can lead to accumulation of water in low-lying areas, increasing flood risk. This revealed that the areas with low elevations 151m are likely to be at high risk of flooding, areas with moderate elevations between 180m and 200m may experience moderate flood risk and those with higher elevations 226m are likely to be at lower risk of flooding. As supported by [22] [16] [23] that criteria influencing flood susceptibility have been highlighted such as vegetation Index, DEM, Topographic position index amongst others.

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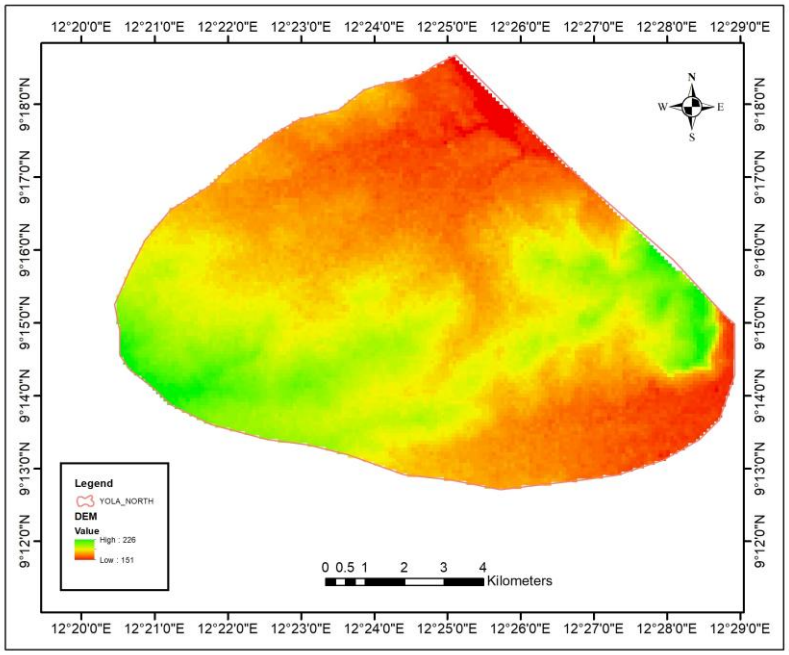


Figure 3: Digital Elevation Model (DEM) of Yola North
Source: Authors Analysis (2025)

3.2 Flood Risk Level

Figure 4 and Table 4 presents the results for Flood Risk Level of the Yola North Local Government area.

Figure 4 and Table 4 reveal varying flood risk levels in the study area: 59% is flood-free, 28.1% is high-risk (levels 4 and 3), and 12.7% is low to moderate risk (levels 2 and 1). The study's findings indicate that the flood risk susceptibility level in the study area is varied, with different proportions of the area falling into different risk categories. Specifically, 59% of the area is at no flood risk (free flood level), indicating that more than half of the study area is not prone to flooding. The 28.1% of the area is at high risk (levels 4 and 3), suggesting that a significant portion of the area is susceptible to flooding while 12.7% of the area is at low to moderate risk (levels 2 and 1), indicating that a smaller portion of the area is at relatively lower risk of flooding. as supported by [20] flood data to produce susceptibility maps that differentiate areas by risk levels.

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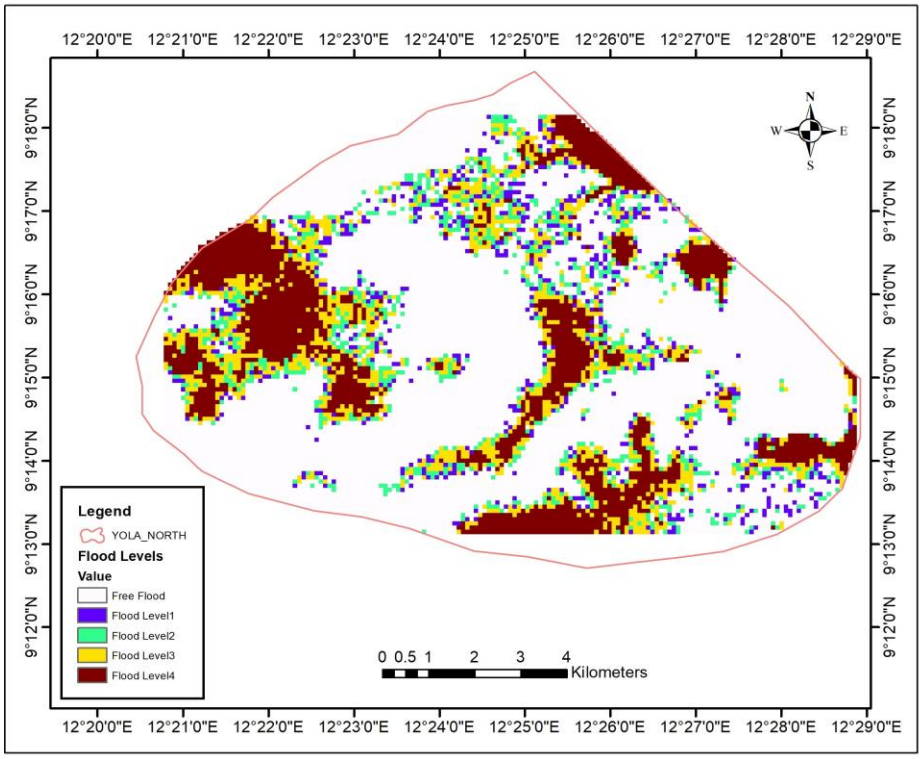


Figure 4: Flood Risk Level
Source: Authors Analysis (2025)

Table 4. Flood Risk Level

Flood Levels	Areas Covered (Pixel Counts)	Percentage Covered
Flood Level 0	514	59.2%
Flood Level 1	46	5.3%
Flood Level 2	64	7.4%
Flood Level 3	98	11.3%
Flood Level 4	146	16.8%
Total	868	100%

Source: Authors Analysis (2025)

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3.3 Areas Vulnerable to Flood Risk Level

The Areas Vulnerable to Flood Risk Level is presented in Figure 5. The results from Figure 5 and Table 5 indicate that if the floodwater rises to 5 meters, approximately 3.7% of the study area will be susceptible to flood risk. Furthermore, an increase of 10 meters will affect about 13.3% of the area, while increases of 15 meters and 20 meters will lead to around 23% and 35% of the area being susceptible to flood risk, respectively. This suggests that elevation plays a significant role in determining flood susceptibility risk, highlighting the need to consider elevation in planning to reduce vulnerability to flood risk. This revealed that the results from Figure 4 and Table 5 demonstrate a clear relationship between floodwater levels and flood risk susceptibility.

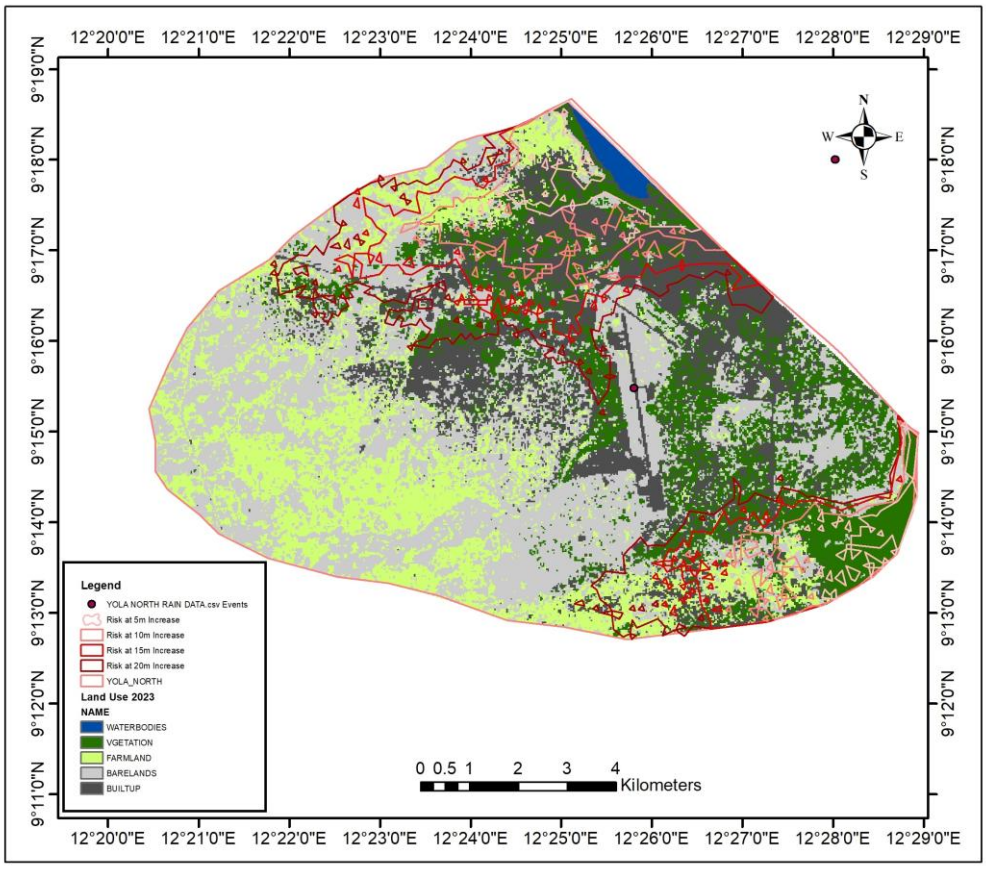


Figure 5: Overlay Areas Vulnerable to Flood Risk Level
Source: Authors Analysis (2025)

Table 5. Areas Vulnerable to Flood Risk Level

Increase in Flood Level based on Elevation	Risk Area Covered (Square Meters)	Risk Area (Kilometer Square)	Areas in Percentage
5meters	4123345.433335	4.123	3.66%
10meters	14967685.054735	14.967	13.29%
15meters	25914349.142895	25.914	23.02%
20meters	38865196.792441	38.865	34.52
Total Study Area	112594177.948	112.594	100%

Source: Authors Analysis (2025)

As the floodwater level increases, the percentage of the study area susceptible to flood risk also increases this finding is also supported by [22] [16] [23] that criteria influencing flood susceptibility have been highlighted by DEM, Topographic position index amongst others. Also affirmed by [19] described Flood susceptibility as the process of identifying flood-prone areas by analyzing a series of flood-triggering and causal parameters, such as elevation, slope and rainfall levels.

4.0 CONCLUSION AND RECOMMENDATIONS

In conclusion, this study demonstrates that geospatial techniques effectively map and evaluate flood risk in Yola North LGA by integrating Land Use Land Cover (LULC) classification and Digital Elevation Model (DEM) data. The findings confirm that topography and surface characteristics significantly dictate vulnerability, with about 28% of the area facing high flood risk and potential water level rises scaling impact up to 35% under a 20m scenario. Ultimately, because built-up zones and farmlands cover a major portion of the landscape, municipal authorities must integrate elevation-based spatial models into local zoning and disaster management frameworks to protect vulnerable communities.

Based on the research findings, this research recommends incorporate flood risk into urban planning in Yola North LGA authorities to integrate flood risk level maps into urban planning and development to minimize flood risk vulnerability. The research also recommends the needs

to develop flood mitigation and preparedness strategies on the flood risk levels in Yola North LGA of Adamawa State, Nigeria.

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