

Application of Geographic Information System and Machine Learning Models for Flood Prediction in Lokoja Local Government Area, Kogi State, Nigeria

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ABSTRACT: Flooding is a developmental and environmental menace in Nigeria and the Lokoja Local Government Area (L.G.A.) has been hit hard by this owing to the fact that it lies at the intersection of the Niger and Benue Rivers. To map and predict spatial flood prone regions in the L.G.A. sharply; this paper adopted a combination of Geographic Information System (GIS) and Machine Learning (ML) model. To determine the recent trends, multi-temporal geospatial data were studied using the year 2004, 2014, and 2024, which are used to project and create maps of the 2034 and 2044 respectively. Eight geo-environmental predictor variables have been obtained, among them the Digital Elevation Model (DEM), Slope, Topographic Wetness Index (TWI), Flow Accumulation, Distance to River, Precipitation, NDVI and Land Use/Land cover (LULC). In essence, the Random Forest (RF) and the Support Vector Machine (SVM) were trained and validated using 143 historical observations of floods. The RF model had better predictive performance when compared to SVM as it achieved a classification accuracy of 86% and an Area Under the Curve (AUC) of 0.89, which is better than the performance of SVM model, that is 69% and 0.85. The analysis of feature importance has found that two features are the most powerful (DEM, 0.375, and Distance to River, 0.224): they contribute to the predictive power about 60 %, which validates the fact that the topography and the proximity to rivers are the key determinants of flood hazard. Temporal analysis showed alarming, growing faster rates of High and Severe flood risk zones between 2004 and 2024 spreading to the urbanized settlements such as Jamata and Banda. This is mostly influenced by swift and unplanned urbanization into flood plains that are at low altitude. There was a further increased in the severe flood-prone class by another 4-8% respectively from the future projections of 2034 and 2044, which required urgent and all round policy action taken. The paper was summed up by noticing that the combination of GIS and the better RF model offers the necessary and high quality geospatial intelligence and that the authorities should embrace proactive land use planning and incorporate these susceptibility maps in an effort to reduce the risks of disasters.

KEYWORDS: Geographic Information Systems (GIS), Machine Learning (ML), Random Forest (RF), Support Vector Machine (SVM), Lokoja.

I. INTRODUCTION

The most common and devastating natural disaster is known as flooding, which is considered the cause of almost 43% of recorded instances of disasters globally (Umaru and Adedokun, 2020). Its effects in terms of loss of lives and economic damage, destruction of infrastructure, displacement of communities and developmental setbacks in the long run are particularly devastating in the low and middle income countries. Along with the speedy and unplanned urbanization, climate changes keep accelerating extreme hydrological occurrences and place more people in harm's way in floods. (Mosavi *et al.*, 2018). In addition, Nigeria is one of the most susceptible countries in sub-Saharan Africa to floods because of its delicate hydro-geographical environment. The Niger and Benue rivers pass through the country and they regularly over-flow during the rainy seasons. Local human-made processes aggravate this natural tendency and include bad drainage systems, building on floodplains, deforestation, and the elimination of protective vegetation (Ahmed *et al.*, 2021). The Kogi capital, Lokoja, is situated at the confluence of the Niger and Benue Rivers and therefore it is the natural receiving basin to the upstream run-off. This leads to frequent riverine floods, since the disastrous 2012 and 2022 were extremely destructive to communities such as Ganaja, Gadumo, and Adankolo (Onyekwelu, 2024). These incidents have continued to demonstrate the lack of strength in current mitigation and preparedness measures.

Nevertheless, flood risk knowledge and prediction involve Geospatial technologies. As an example, GIS is useful in flood modelling by combining spatial information (elevation, slope, rainfall, land use, vegetation, proximity to rivers). Combined with Remote Sensing, it enables monitoring the land cover and hydrological changes on a continual basis (Ahmed *et al.*, 2021). With the introduction of Machine Learning (ML), flood prediction has been advanced further by its capability to get acquainted with non-linear relationships that are complicated to predict using historical data. Random Forest (RF) and Support Vector Machine (SVM) models have shown a high predictive capability in the various settings (Mosavi *et al.*, 2018; Youssef *et al.*, 2021). The integration of early-warning systems and the enhancement of pre and post event decision making has been enhanced by their implementation in disaster management, especially in developed countries (Garcia *et al.*, 2020; Mosavi *et al.*, 2018; Bapalu and Sinha, 2006; Adel *et al.*, 2023). To address the increasing floods challenge in Lokoja, the proposed study will use GIS-based environmental parameters such as rainfall (CHIRPS), elevation (DEM), slope, land use/land cover, closeness to rivers and vegetation (NDVI) concurrently with ML algorithms to model and predict floods in Lokoja L.G.A. The method involves the creation of high-resolution susceptibility maps and balancing them with historical data of floods to aid in urban planning, emergency operation and lasting environmental management.

Thus, the aim of the study is to apply GIS and Machine Learning techniques to predict flood susceptibility in Lokoja L.G.A and identify the best model to use in the region. In particular, the study aims to: (i.) Analyze the past trends of flood susceptibility in the research area; (ii.) Determine some of the environmental and hydrological factors that affect occurrence of floods; (iii.) Use RF and SVM models to predict future flood susceptibility; and (iv.) Compare the predictive performance of the two models to see which one is most suitable in Lokoja. Even though, there is an existing literature shift towards the analysis of Frequency Ratio (FR) and Analytical Hierarchy Process (AHP) to a more sophisticated ML prediction that has the ability to reflect complex interactions among spaces (Yousef *et al.*, 2016). SVM has been commonly applied to classify flood prone areas by identifying the optimal hyperplane boundaries (Tehrany *et al.*, 2015), and to approach high dimensional data, reduce overfitting, and measure the importance of variables with the help of the Random Forest (Chen *et al.*, 2020). These models have their theoretical basis on the

assumption of spatial stationarity that is, that the past causing factors of flood events can be applied in the future to determine future susceptibility.

Although GIS based machine learning approaches such as Random Forest (RF) and Support Vector Machine have been widely applied for flood susceptibility mapping, their application in river confluence cities with strong hydrological interaction remains limited. The study contributes by developing a Lokoja specific, multi-temporal flood susceptibility framework that integrates historical flood evidence, vegetation dynamics (NDVI), and terrain hydrological factors within a machine learning environment. Unlike previous Nigerian studies that focus on single-epoch mapping, this research evaluates susceptibility across multiple historical periods and extends the analysis to scenario bases future projections, thereby enhancing its relevance for urban planning and flood risk governance.

II. METHODOLOGY

This study used an integrated geospatial and machine learning approach for flood susceptibility mapping and prediction in Lokoja Local Government Area (L.G.A). In order to meet the research objectives, both primary and secondary data were used. The core data was the ground control points which were measured with the help of Differential Global Positioning System (DGPS) in order to improve the space precision. Multispectral satellite imagery, Digital Elevation Model (DEM), rainfall data, river network data and historical flood data were also used as secondary data derived out of reputable sources of remote sensing and geospatial data. Basically, Landsat multispectral imageries of 2004, 2014 and 2024 (Landsat 5 TM, Landsat 8 OLI/TIRS, and Landsat 9 OLI/TIRS) were obtained via the United States Geological Survey (USGS) archives provided on the Google Earth Engine (GEE) facility. The radiometric clarity and small cloud cover were used to choose these imageries in order to be reliable in land use/land cover (LULC) mapping and in determining the Normalized Difference Vegetation Index (NDVI) based on the established remote sensing standards (USGS, 2023; Jensen, 2015). Equally, 30m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model was used to for the derivation of Topographic Variables which include Elevation, Slope, Flow Accumulation, and Topographic Wetness Index (TWI) (Burrough *et al.*, 2015). Rainfall data were obtained from the CHIRPS precipitation dataset, which integrates satellite and ground station measurements to produce high-resolution rainfall estimates across Africa (Funk *et al.*, 2015). Additionally, river network layers were sourced from OpenStreetMap (OSM), while historical flood event data (2000–2024) were accessed from NEMA archives, EM-DAT, and other GEE-based flood history repositories. All datasets were clipped to the boundary of Lokoja L.G.A and resampled to a common spatial resolution of 30 meters to ensure compatibility during analysis in line with GIS preprocessing practices (Abaje and Giwa, 2007). Table I presents the details datasets used, their sources, temporal ranges, and intended purposes in the modeling workflow.

Table I: List of Dataset Acquired

Dataset	Source	Temporal Range	Purpose
Digital Elevation Model (DEM)	SRTM DEM (USGS Earth Explorer/GEE)	Static	Primary input for all terrain derivatives.
Precipitation	CHIRPS Rainfall Data (GEE Data Catalog)	Annual Averages (2000-2024)	Input factor reflecting climatic influence.
Landsat Imagery	Landsat 5, 8, 9 OLI/TIRS (USGS/GEE)	2004, 2014, 2024	Classified for LULC and derived NDVI.
River Network	OpenStreetMap (OSM) Hydrography Layer	Static	Used to calculate proximity factor.

Historical Flood Data	NEMA, EM-DAT, and Google Earth Engine (GEE) archives	2000–2024	Training and validation data set.
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Eight flood conditioning factors were subsequently integrated into the flood susceptibility modeling framework to the Lokoja Local Government Area boundary. These factors included slope, elevation, flow accumulation, and the Topographic Wetness Index (TWI) from the DEM; distance to river and precipitation representing hydrological and climatic controls; and Land Use/Land Cover and NDVI representing land surface characteristics computed using the expression of Yengoh *et al.*, (2020). Thereafter, historical flood points were compiled from past flood archives and satellite derived flood layers, producing 143 samples comprising 69 flooded and 74 non-flooded locations. These points were overlaid with the flood-conditioning factors to extract predictor variable values. The dataset was then divided into two portions: 70% for model training and 30% for validation. Two machine learning models were implemented: Random Forest (RF) and Support Vector Machine (SVM). The RF classifier was trained with an ensemble of 500 decision trees with the number of features in each split being equal to the square root of the total predictors to improve predictive stability. Moreover, Radial Basis Function (RBF) kernel was used in the SVM model to solve non-linear relationship in geospatial data. The Hyperparameters that were optimized using grid search were the Key hyperparameters such as penalty (C) and width of the kernel (g). Both models created continuous flood probability surfaces of 0 (low susceptibility) to 1 (high susceptibility) and further categorized the susceptibility into susceptibility zone with natural break intervals. Accuracy, F1-score, and the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curves were used as model performance measures. In order to identify whether the difference in the performance of the models was statistically significant, a Z-test was used at a 95% confidence level and the AUC of RF and SVM were compared.

Flood maps were made of three past time periods (2004, 2014, 2024) and extrapolated to the future time periods of 2034 and 2044. An application of the same machine learning workflow to the projected environmental conditions was used to predict the future and ensured consistency in the way factors are prepared and modeled. The future prediction was also done using Markov Chain/ Cellular Automata (CA- Markov). This methodology framework made the susceptibility results reliable and comparable in all time situations, therefore giving scientifically basing insights on the flood risk management and the early warning strategies in Lokoja L.G.A. However, it is necessary to note that the future susceptibility maps produced in this research was on scenario based projections rather than deterministic forecasts. The models assume that the relationships between flood occurrence and conditioning factors observed in the historical period remain relatively stable. But these connections may be altered over time due to changes in rainfall amount, land use changes and climate variability.

STUDY AREA

Lokoja, Kogi State capital is a place that defines most geographically important places in Nigeria since it is located at the crossroad of the Niger and Benue Rivers. Geographically, the region is located between latitudes 7°45'45''N and 8°40'45''N and longitudes 6°05'45''E and 6°48'30''E. This distinctive hydrology of Lokoja predisposes the city to regular flooding of the river due to high amounts of upstream flow experienced around the rainy season (Adetunji and Isah, 2015). The topographical features of the area of study are that the height of the area varies between 45 to 125 meters above the sea level, which gradually extending from the riverbanks toward the inland region.

The Patti Ridge is another land feature that dominates the landscape to a height of about 400 meters, which is a significant physiographic feature affecting the drainage patterns and surface runoff in the area (NIMET, 2023). Climate is usually in the form of tropical with wet and dry seasons. The amount of rainfall is 1200-1600 mm/year with a high concentration level between May and October and is very critical in hydrological processes leading to seasonal floods (Audu, 2016). More so, Lokoja experienced high urban growth, population increase and considerable land-use transformations over the years. Settlement are now taking over low flood plains and agro intensive activities and sanding along river beds have changed the natural scenery. Such actions have the influence of reducing infiltration capacity, augmenting runoff, and diminishing the terrain to withstand extreme hydrological occasions (Agunbiade *et al.*, 2021). The lack of surface storage of water in built-up regions due to increased impervious surfaces is another contributor to the surface storage of water during heavy rain.

Besides that, Lokoja being a strategic transport and commercial hub coupled with its intricate hydro-geomorphology, is amongst the most flood prone areas in Nigeria. The frequent flooding is observed in major communities like Ganaja, Adankolo, Gadumo and settlements along rivers like riverbanks, especially during high discharge periods of the river. Such repetitive occurrences provide a clear indication of the dire necessity of combined flood vulnerability analysis and predictive modeling that is based on the peculiarities of environmental and anthropogenic processes in the city. Nevertheless, Figure I provides the geographical background of the study area. Figure Ia indicates the position of Kogi State in Nigeria, Figure Ib indicates Lokoja in Kogi State and Figure Ic indicates a detailed map of Lokoja L.G.A, major communities and transportation corridors. It can be stated that to be able to model the flood patterns and interpret how the environmental variables affect the flood susceptibility, it is necessary to understand the spatial configuration of the area. Moreover, since Lokoja has frequent flood disasters and socioeconomic consequences related to it, historical trends of frequency, severity, and location are crucial to successful flood risk management. Understanding of such trends gives a basis to come up with predictive models and inform disaster preparedness at Lokoja L.G.A (Komolafe *et al.*, 2018).

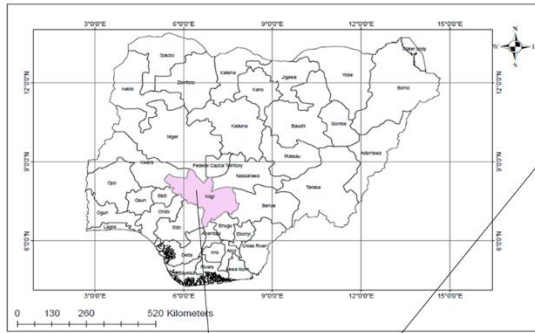


Figure Ia: Map of Nigeria Showing Kogi State

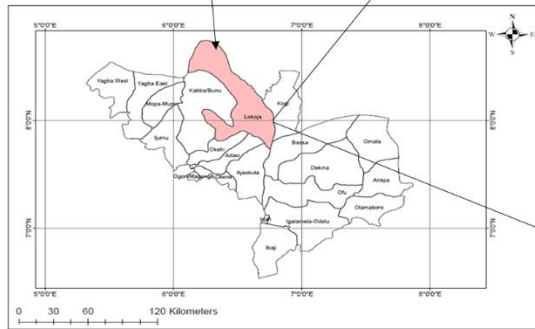


Figure Ib: Map of Kogi State Showing Lokoja LGA.

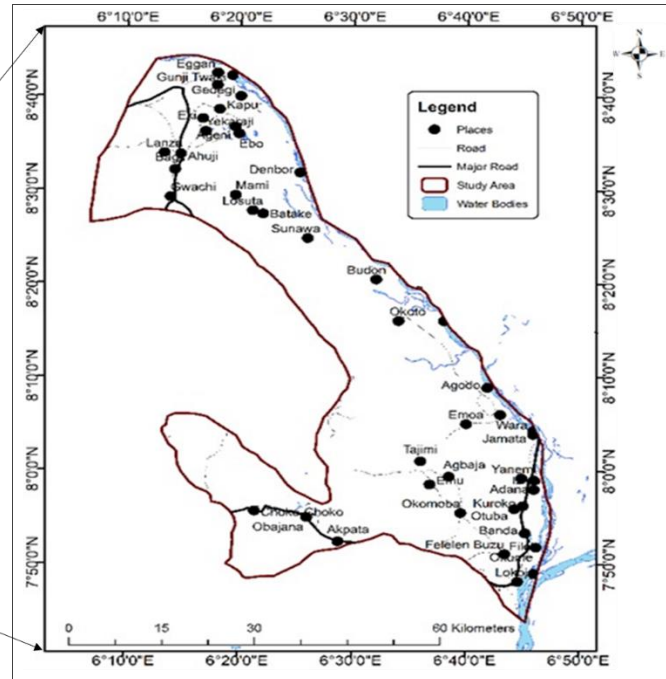


Figure Ic: Map of Lokoja LGA. showing Places

Figure I: The Map of the Study Area. (Source: Adapted from Audu, 2016)

III. PRESENTATION AND DISCUSSION OF RESULTS

Figure IIa - IIc illustrate the findings of the annual precipitation during the three periodic years (2004, 2014 and 2024). The figures indicated that there is a lot of spatial and temporal variability that directly affects surface runoff and flood risk in the study area which is steady with latest climate changeability trends reported across central Nigeria. Communities like Apata, Yenemi, and Lokoja always registered the high levels of rainfall (>1,300mm) and some areas like Kapu and Bagi registered the lowest levels. Importantly, the highest range of precipitation was observed in 2024, with an 991mm to 1,400mm range, which shows an increasing intensity of rain formation, which led to the acuity of recent floods. Such inconsistency highlights the importance of active stormwater management, such as building of retention basins as in the works of Kumar and Acharya (2016) and Abaje and Giwa (2007).

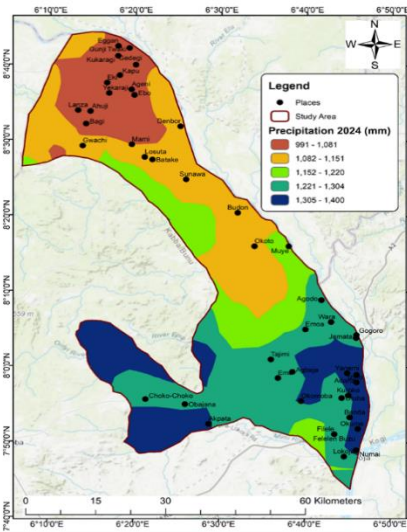


Figure IIa: Precipitation Map for 2024

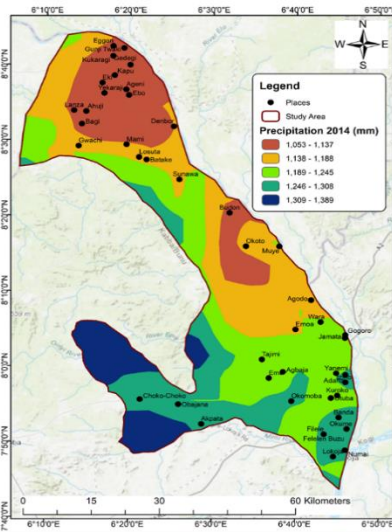


Figure IIb: Precipitation Map for 2014

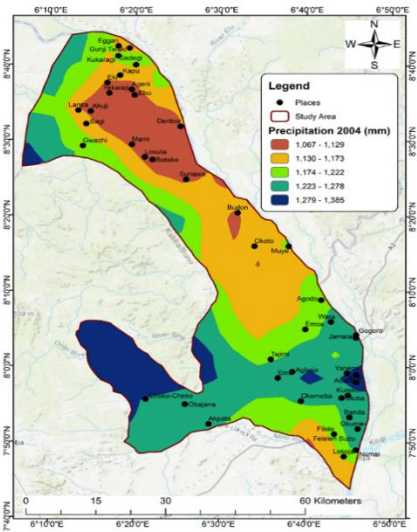


Figure IIc: Precipitation Map for 2004

Figure III - VII displays the analysis of the geoenvironmental factors that control the flood susceptibility. The Random Forest (RF) model validated the fact that terrain and hydrological flow paths determine the susceptibility to Lokoja. The most crucial factor was the Digital Elevation Model (DEM) and reveals that the lowlands (-4m to 90m) of the landforms for example, the Lokoja Town, Banda, and Ebo are prone to water stagnation and therefore highly vulnerable whereas the higher terrain (up to 582m) is a source of runoff. This is compounded further by Distance to River (RF score = 0.224) that proves that the regions nearest to the Niger and Benue confluence are at the greatest risk. Slope (RF score = 0.177) indicates that the presence of smooth slopes (0° to 6.18°) has led to long-term floods, whereas the Flow Accumulation map indicates places where the runoff is concentrated (e.g., Ebo, Budon), and therefore overwhelms the drainage. These results were further narrowed down by the Topographic Wetness Index (TWI) (RF score = 0.074) to determine the presence of persistent locations of flood hotspots in low lying, flat areas in accordance with Rahmati *et al.* (2016) and Costache *et al.* (2022). Moreso, this finding closely emulates results from flood susceptibility studies in Makurdi (Komolafe *et al.*, 2018), and Ibadan as stated by Nkeki *et al.*, 2022 and they both pinpoint low elevation and proximity to rivers as primary drivers of flood.

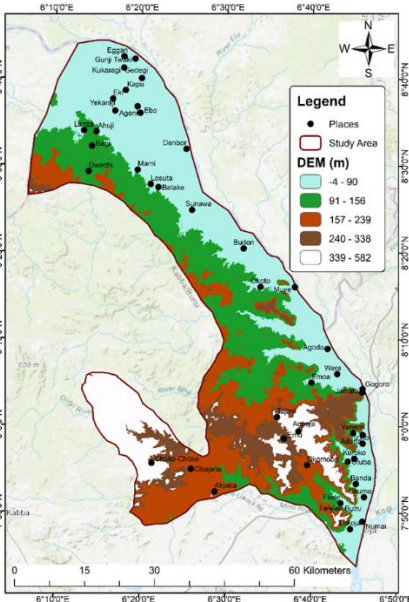


Figure III: The Digital Elevation Model of the Study Area

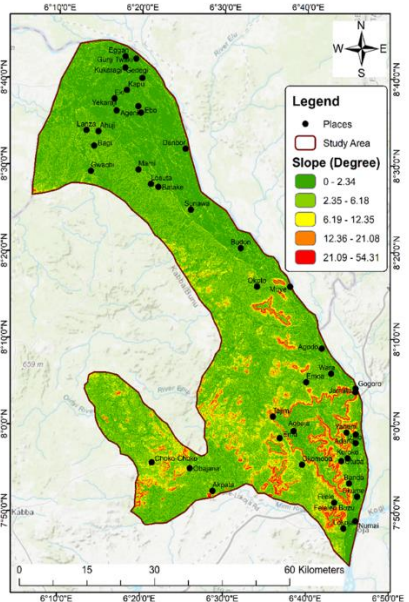


Figure IV: Slope Information of the Study Area

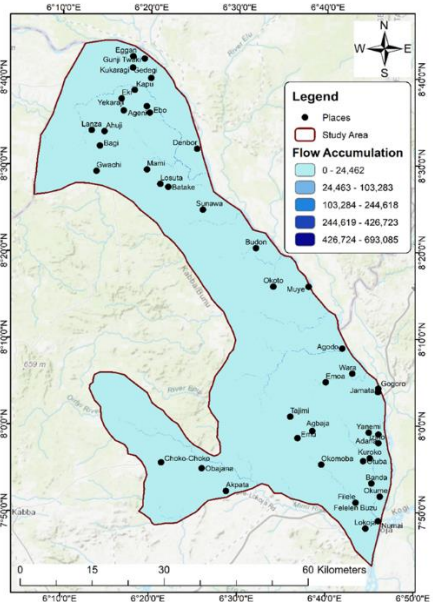


Figure V: Flow Accumulation Map

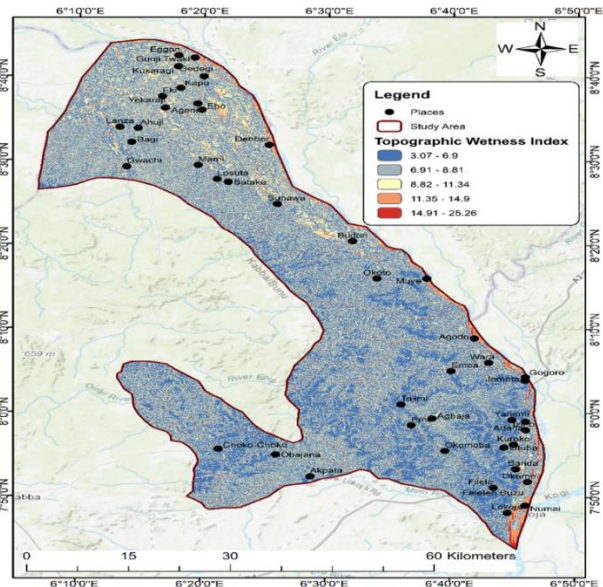


Figure VI: Topographic Wetness Index

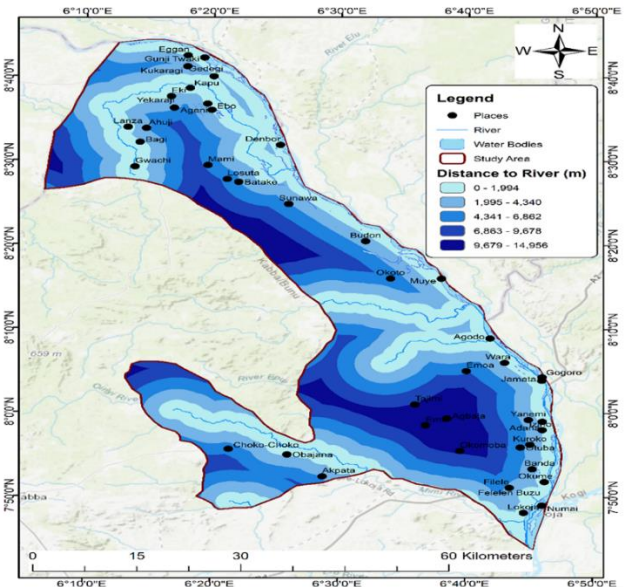


Figure VII: Distance to River

An important aspect of examining the pace of changing the risk of time is the study of the Normalized difference vegetation index (NDVI) at the three epochs, which is presented in Figures VIIIa to VIIIc. The comparison of the 2004, 2014, and 2024 NDVI maps showed that the high vegetation cover (NDVI value larger than 0.4) started to decrease gradually and significantly. It is an indicator that there has been severe deforestation and a transformation of natural permeable areas into built-up impervious areas especially around the core settlements. Although NDVI received a rather low standalone RF importance score (RF score = 0.027), its spatial change by the two decades is the major factor that correlates rapid development with the risk of floods. The shrubs and trees are destroyed, which makes the interception and infiltration slow and cause massive and rapid surface runoffs. Similar study on vegetation loss flood risk relationships have been presented in

Lagos according to Ahmed & Kranthi, (2018) and Ilorin by Louw *et al.*, (2019) where condensed interference and penetration capacity directly increased surface runoff.

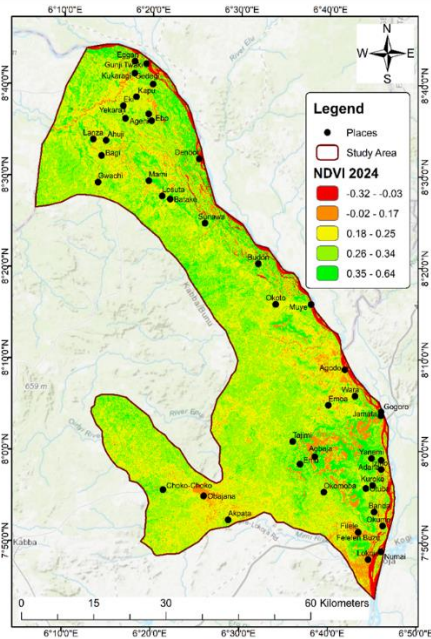


Figure VIIIa: Normalized Difference Vegetation Index (NDVI) Map for 2024

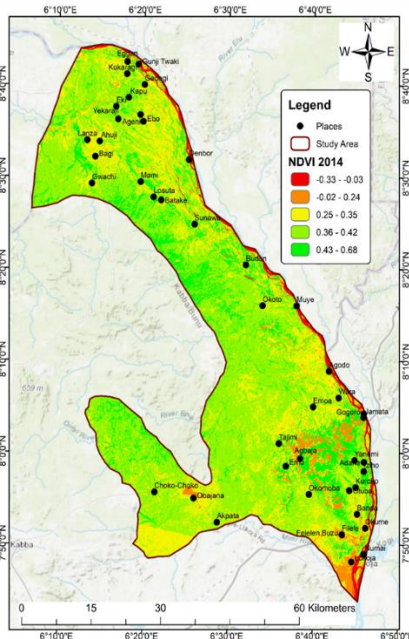


Figure VIIIb: Normalized Difference Vegetation Index (NDVI) Map for 2014

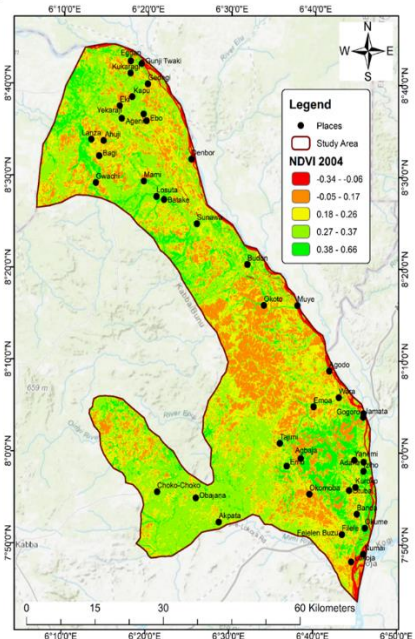


Figure VIIIc: Normalized Difference Vegetation Index (NDVI) Map for 2004

Figure IXa, IXb and IXc show the land use and land cover (LULC) distribution of 2004, 2014, and 2024 and Table II provides the area statistics. Land and vegetation, which are the cultivated products of the dominant classes, are united in a majority of the scenery. Table II explains the changes in the LULC showing the following pattern; a marked increase in Built-up area (from 4.52sq.km in 2004 to 45.99sq.km in 2024) and Water Bodies coupled with a significant decline in Vegetation cover (from 1528.87sq.km to 1130.96sq.km) over the twenty years. Such growth of impervious surfaces is a direct cause of intensified urban runoff and less infiltration, which is one of the causes in enhancing the propensity to floods. This pattern reflects urban growth trajectories detected in other Nigerian cities such as Abuja and Minna (Salami *et al.*, 2017), where unregulated development on floodplains has intensified flood impacts.

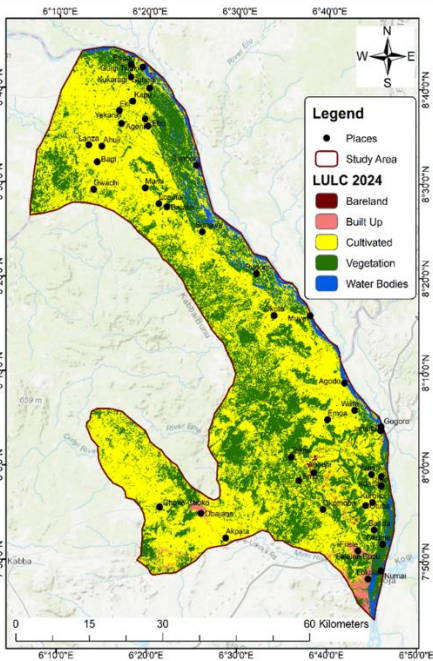


Figure IXa: Land Use/Land Cover (LULC) Map for 2024

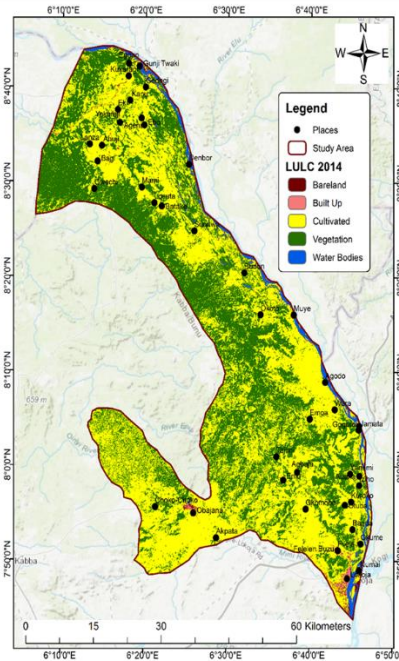


Figure IXb: Land Use/Land Cover (LULC) Map for 2014

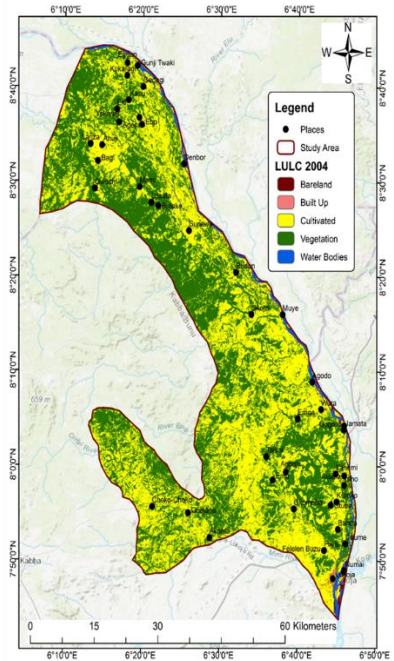


Figure IXc: Land Use/Land Cover (LULC) Map for 2004

Table II: Land Use / Land Cover Area in Sq.Km for 2004,2014, and 2024

LULC	2004 Area (Sq.km)	2014 Area (Sq.km)	2024 Area (Sq.km)
Water Bodies	66.39	83.22	108.6732
Built Up	4.52	15.46	45.99
Bare land	14.49	11.58	7.86
Cultivated	1617.02	1778.57	1937.81
Vegetation	1528.87	1342.45	1130.96

Source: Author’s Analysis

The flood susceptibility map produced by both superior RF and SVM models were categorized into five classes namely the Very Low, Low, Moderate, High, and Severe as presented figures Xa -Xc (for RF) and figures XIa - XIc (for SVM). The generated flood susceptibility maps were analyzed to identify the changes in flood susceptibility in the three epochs (2004, 2014 and 2024), and the results indicated that the flood risk increased significantly. The areas of high and severe flood prone witnessed increased and infiltrated the urbanized areas, especially in community like Jamata and Banda as illustrated in figures Xa -Xc and figures XIa - XIc respectively.

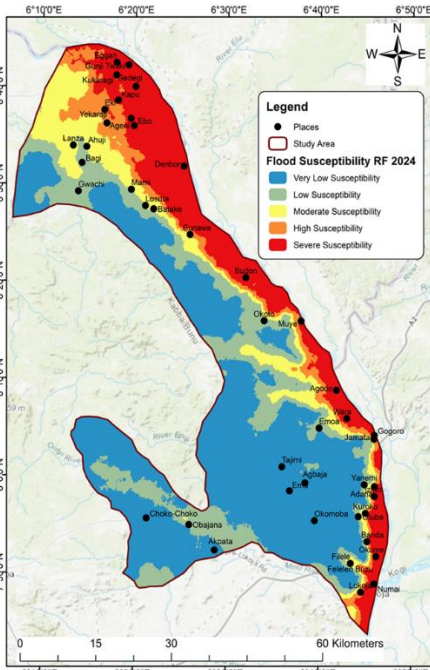


Figure Xa: Flood Susceptibility Map for year 2024 using Random Forest (RF) Model

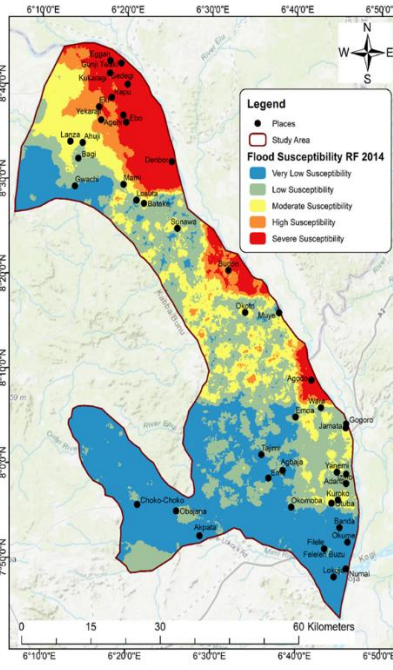


Figure Xb: Flood Susceptibility Map for year 2014 using Random Forest (RF) Model

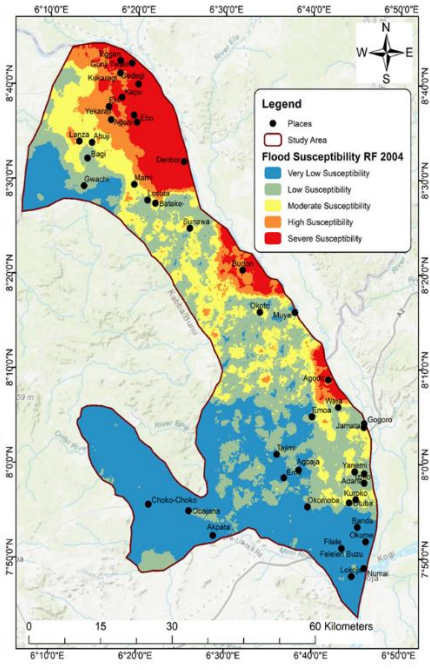


Figure Xc: Flood Susceptibility Map for year 2004 using Random Forest (RF) Model

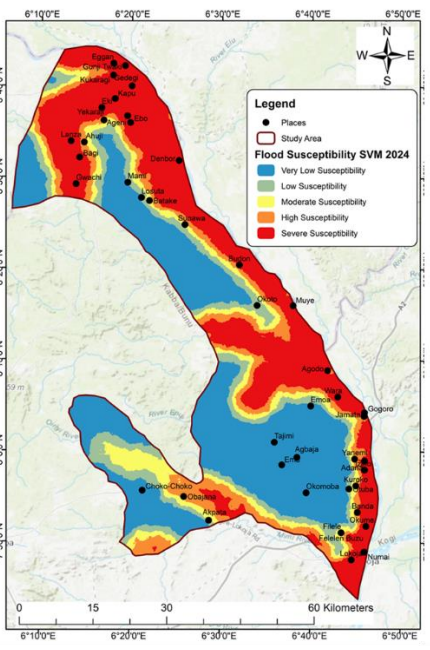


Figure XIa: Flood Susceptibility Map for year 2024 using Support Vector Machine (SVM) Model

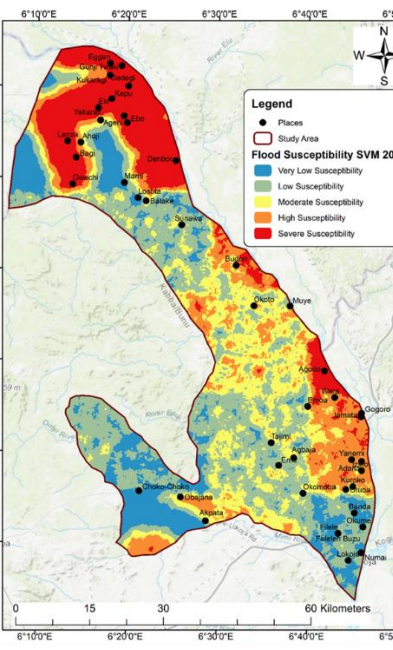


Figure XIb: Flood Susceptibility Map for year 2004 using Support Vector Machine (SVM) Model

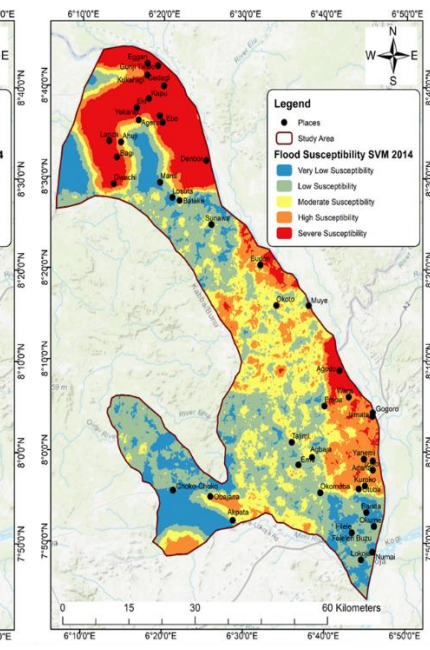


Figure XIc: Flood Susceptibility Map for year 2014 using Support Vector Machine (SVM) Model

The Future susceptibility maps were created through modeling of LULC change with a Markov Chain/Cellular Automata (CA-Markov) model in order to project urban expansion. The predictions revealed further increase in the risk of floods as illustrated in figure XIIa - XIIb and figures XIIIa - XIIIb. Figure XIIa and XIIb present the future flood susceptibility prediction for 2034 from RF and SVM respectively, moreover, figures XIIIa and XIIIb present the future flood susceptibility

prediction for 2044 from RF and SVM models respectively. The 2034 and 2044 projections indicate that an additional growth of 4-8% of the areas that are considered extreme flood-prone is likely to occur soon. The main drivers of this growth include the increasing aspects of fast urbanization and the ongoing loss of vegetation, which highlight why there is a need to create immediate policies to control development and reduce the effects of climate changes.

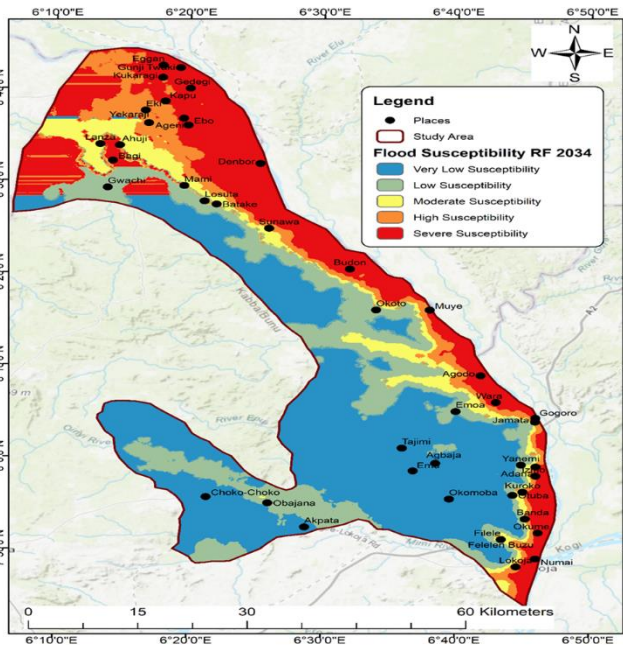


Figure XIIa: Predicted Flood Susceptibility Map for year 2034 from Random Forest (RF) Model

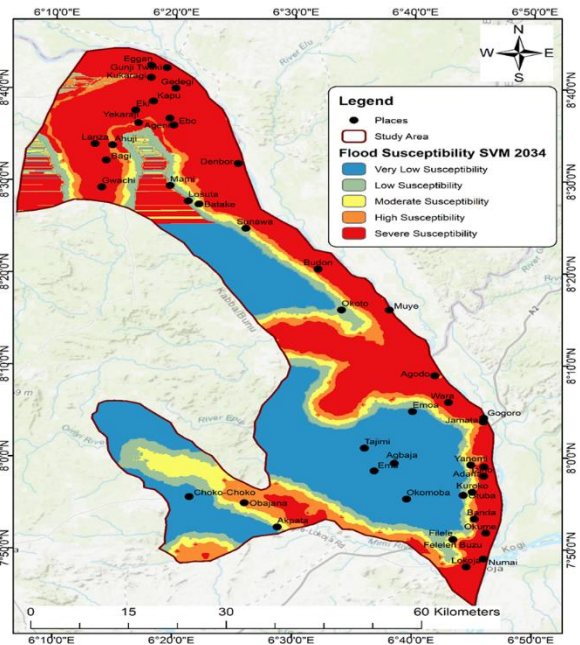


Figure XIIb: Predicted Flood Susceptibility Map for year 2034 from Support Vector Machine (SVM) Model

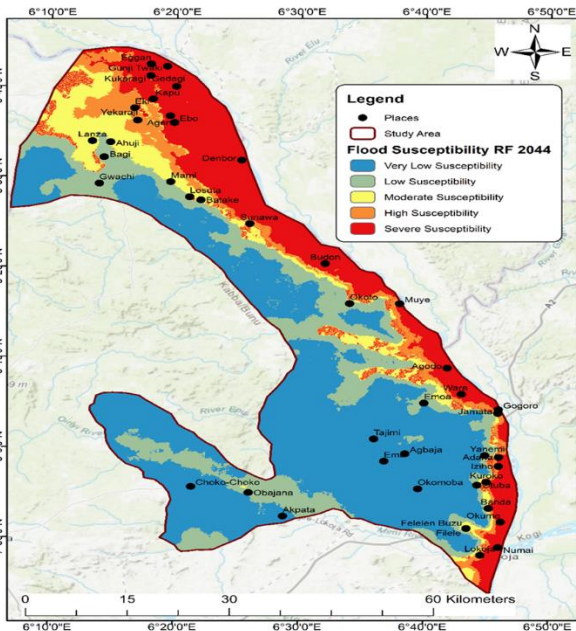


Figure XIIIa: Predicted Flood Susceptibility Map for year 2044 from Random Forest (RF) Model

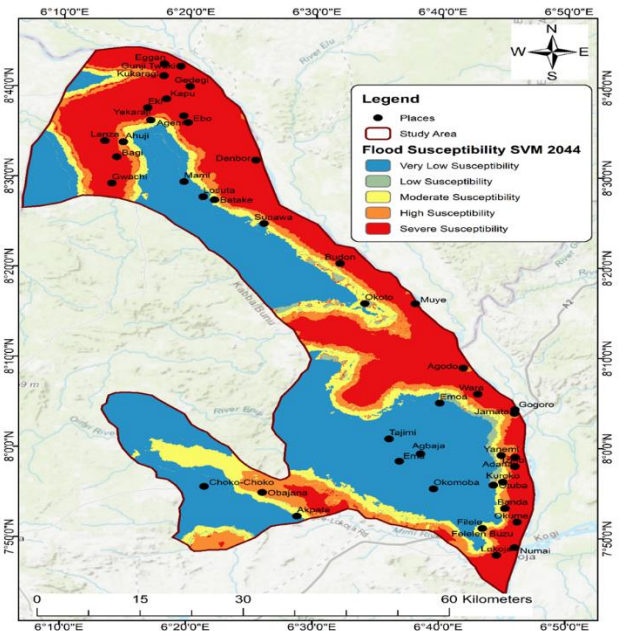


Figure XIIIb: Predicted Flood Susceptibility Map for year 2044 from Support Vector Machine (SVM) Model

In addition, the validation measures that indicate the performance of the model are showing in table III. The findings demonstrate clearly that there is a better predictive ability of the Random Forest (RF) model. RF model had greater Accuracy (86%), F1 Score (0.88) and much greater AUC of 0.89. The difference between the performance of the RF (AUC = 0.89) and the SVM (AUC = 0.85) showed statistically significant difference ($p < 0.05$) by a Z-test. It means that the RF model provided more reliable ranking of flood susceptibility and was more generalized, which proves its suitability in the creation of the final maps.

Table III: Model Accuracy Assessment for SVM and RF Models

Model	Accuracy (%)	F1 Score	ROC-AUC Score
Random Forest	86	0.88	0.89
Support Vector Machine	69	0.74	0.85

Source: Author’s Analysis

As per the above findings, the study was able to develop a high-precision, multi-temporal, flood susceptibility model for Lokoja. The high scores of Elevation, Distance to River, and Slope as the most predictive factors are hydrologically consistent and in line with the results of other fluvial systems such as Tehrany *et al.* (2014) and Costache *et al.* (2022). The research shows that the intrinsic cause of the basic flood threat of Lokoja is topographical and it is also a result of the closeness to the large rivers. The excellent outcome of the Random Forest model is in line with its performance in geospatial applications. Youssef *et al.* (2021) discovered that its ensemble character enabled it to better explain the complicated, non-linear correlation among conditioning factors relative to the SVM model. Secondly, RF delivers feature importance scores, which is an important interpretability and targeted policy making feature. The most important conclusion is the significant association between dynamic change in LULC and increasing risk of floods. The conversion of permeable vegetation to impervious built-up areas in large amounts is a major cause of the performance of the observed change in the High and the Severe susceptibility areas between 2004 and 2024. This process decreases infiltration and raises the surface runoff which directly exposes more people and assets to harm as agreed with Komolafe *et al.* (2018). The 2034 and 2044 future projections are not a prophecy, but a vivid reminder of what can and will happen to the cities in case of adopting a business-as-usual strategy in urban development. The resulting high resolution susceptibility maps are a very crucial decision support tool. They could be utilized to: (i.) implement rigorous zoning in areas that are located in High and Severe risk zones, (ii.) steer sustainable urban development towards the Low susceptibility areas, (iii.) promote the development of mitigation infrastructure such as retention ponds and better drainage, and (iv.) promote early warning systems and evacuation plans by the most vulnerable populations.

RESEARCH CONTRIBUTION

This study contributes significantly to the academic and practical understanding of flood risk modeling in the following ways:

- i. The research provides an updated spatial and temporal flood susceptibility maps for Lokoja Local Government Area (L.G.A) spanning 2004 – 2044, which serves as a critical tool for decision-making in management flood risk.
- ii. The research demonstrates the integration of GIS with Random Forest (RF) and Support Vector Machine (SVM) models for predictive flood mapping in a tropical urban setting -an innovative contribution to flood risk modeling in Nigeria.

- iii. Through advanced geospatial processing and supervised classification, the study produced high-resolution flood risk maps that can aid government agencies and stakeholders in land-use planning, early warning, and disaster preparedness in Lokoja Local Government Area (L.G.A).

CONCLUSION AND RECOMMENDATIONS

The findings of the Random Forest (RF) model were only the most reliable when it came to mapping flood susceptibility because it had the highest predictive accuracy (AUC = 0.89) when compared to the Support Vector Machine (SVM) model. The findings also revealed that it was a holistic expression of the actual susceptibility of the study area and is more reliable in spatial planning. The correlation analysis of the main factors indicated that the combination of the three factors; Elevation, Distance to River, and Slope explained the greatest predictive power in the determination of flood prone zones in Lokoja. Temporal analysis of 2004-2024 showed that the High and Severe flood prone areas were experiencing consistent and considerable increase especially encroaching on settlements like Jamata and Banda. This growth was directly associated with significant loss of vegetative cover and a significant growth in impervious built-up space. The results of the projection in 2034 and 2044 show that the extreme flood-prone lands will grow even more by about 4-8% assuming that the current land-use patterns grow.

The study recommends that:

- (a). The Random Forest model is recommended to be used because it produces high-precision flood susceptibility maps that can be incorporated as the official ground upon which land-use planning and zoning rules are made in the Lokoja Local Government Area;
- (b). No-build areas should be strictly enforced in High and Severe susceptibility areas especially along the river corridors of Niger-Benue and also in the growing flood plain along Jamata and Banda;
- (c). The urban development and growth should be intentionally channeled and only allowed to proceed in the regions assessed as Low or Very Low flood susceptibility in order to reduce the risk in the future; and
- (d). In the areas of the identified convergence zones and urban hotspots (e.g., Ebo, Budon, Lokoja Town), proactive mitigation infrastructure, e.g., detention basins and improved drainage systems, is required to resolve the issue of excess surface runoff.

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