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GEOSPATIAL AND MACHINE LEARNING-BASED ASSESSMENT OF FLOOD VULNERABILITY IN LOKOJA, KOGI STATE, FOR SUSTAINABLE INFRASTRUCTURE PLANNING

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Abstract

Flooding remains one of the most devastating environmental hazards affecting rapidly urbanising cities in developing countries, particularly within riverine floodplains where urban expansion often occurs without adequate planning. In Nigeria, recurrent flooding continues to threaten urban infrastructure, livelihoods, and environmental sustainability. Lokoja, the capital of Kogi State, is particularly vulnerable due to its location at the confluence of Rivers Niger and Benue, making it one of the most flood-prone urban centres in the country. This study applies an integrated geospatial and machine learning approach to assess flood vulnerability in Lokoja and support sustainable infrastructure planning. Multi-source geospatial datasets, including Shuttle Radar Topography Mission Digital Elevation Model, Sentinel-2 satellite imagery, and Climate Hazards Group InfraRed Precipitation with Station data, were utilised. Flood conditioning factors, including elevation, slope, distance to drainage channels, land use/land cover, drainage density, rainfall intensity, flow accumulation, and vegetation condition, were derived and processed within a GIS environment. These variables were incorporated into a Random Forest machine learning model to generate a predictive flood vulnerability map for the study area. The model achieved moderate predictive performance with an overall validation accuracy of approximately 65%. Variable importance analysis indicated that distance to drainage and elevation were the dominant flood-conditioning factors. The results show that low-lying floodplain areas close to the Niger-Benue river channels exhibit the highest flood vulnerability. In contrast, several built-up areas and infrastructure corridors fall within moderate to very high vulnerability zones. The study demonstrates the value of integrating geospatial analysis and machine learning for flood-risk assessment in data-constrained urban environments. The findings provide spatial decision-support information for urban planners, policymakers, and disaster management agencies seeking to promote climate-resilient infrastructure planning and sustainable urban development in Lokoja.

Keywords: Flood vulnerability mapping; GIS; remote sensing; Random Forest; machine learning; sustainable infrastructure planning; Lokoja

1.0 INTRODUCTION

Flooding is widely recognised as one of the most destructive and recurrent environmental hazards affecting urban environments worldwide, particularly in rapidly expanding cities located along major river systems and coastal floodplains (Jha et al., 2012; Kundzewicz et al., 2014). In recent decades, the increasing intensity and frequency of flood events have been strongly associated with climate variability, unplanned urbanisation, land-use transformation, population growth, and inadequate drainage infrastructure (IPCC, 2021; Jongman et al., 2012). The impacts of flooding are often severe, resulting in the destruction of physical infrastructure, displacement of populations, disruption of socio-economic activities, degradation of environmental resources, and loss of lives and property (Amoako & Boamah, 2015; Winsemius et al., 2016). Consequently, flood-risk assessment and sustainable urban planning have become critical priorities in both developed and developing countries.

In sub-Saharan Africa, urban flooding has emerged as a major environmental and developmental challenge due to rapid urban expansion occurring without corresponding improvements in drainage systems, land-use control, and environmental management practices (Douglas et al., 2008; Güneralp et al., 2015). Nigerian cities have experienced increasing flood disasters over the years, with major flood events affecting transportation networks, residential neighbourhoods, public infrastructure, agricultural lands, and economic activities (Adelekan, 2010; Komolafe et al., 2015). The 2012 nationwide flood disaster in Nigeria remains one of the most catastrophic flood events in recent history, affecting several states and highlighting the vulnerability of urban settlements in riverine environments (Nkwunonwo et al., 2016). More recently, the 2022 flood disaster further demonstrated the increasing exposure of urban infrastructure and settlements to flood hazards nationwide.

Lokoja, the capital city of Kogi State, is one of the most flood-prone urban centres in Nigeria, due to its unique location at the confluence of the Rivers Niger and Benue. The city is characterised by extensive low-lying floodplains, seasonal river overflows, increasing urban development pressure, and expanding built-up areas along flood-susceptible corridors (Abah, 2012; Ojigi et al., 2013). Recurrent flooding in Lokoja has caused significant damage to roads, bridges, residential areas, commercial facilities, and public infrastructure, posing major challenges to sustainable urban development and environmental management in the metropolis. The increasing spatial expansion of settlements into vulnerable floodplain areas has further intensified the exposure of critical infrastructure to flood hazards.

Conventional flood-risk assessment approaches have often relied on field-based observations, hydrological records, and traditional spatial analysis techniques, which may not adequately capture the spatial complexity and dynamic interactions among flood conditioning factors within rapidly changing urban environments (Tehrany et al., 2015). However, advancements in Geographic Information Systems (GIS), remote sensing, cloud computing, and machine learning techniques have significantly enhanced the capacity for spatial flood assessment and predictive environmental modelling (Khosravi et al., 2020; Mosavi et al., 2018).

Remote sensing datasets provide an efficient means for extracting environmental variables associated with flood occurrence, while GIS offers powerful tools for spatial analysis, raster processing, and environmental modelling.

In recent years, machine learning algorithms have attracted increasing attention in flood susceptibility and vulnerability studies due to their ability to model nonlinear relationships between environmental conditioning factors and flood occurrence (Arabameri et al., 2020; Bui et al., 2020). Among these algorithms, the Random Forest model has proven particularly effective due to its robustness, resistance to overfitting, high predictive capability, and ability to estimate the relative importance of predictor variables (Breiman, 2001; Chen et al., 2017). Random Forest has been successfully applied in several flood-susceptibility studies across different geographical regions, with encouraging predictive performance (Tehrany et al., 2015; Wang et al., 2020). Furthermore, the emergence of cloud-based geospatial platforms such as Google Earth Engine has improved access to large environmental datasets and enhanced the efficiency of geospatial data preprocessing and analysis (Gorelick et al., 2017).

Despite increasing flood occurrences in Lokoja, there remains limited integration of geospatial technologies and machine learning techniques for spatial flood vulnerability assessment to support sustainable infrastructure planning. Existing studies in the region have largely focused on descriptive flood mapping, hydrological observations, or basic GIS analyses, without incorporating predictive machine-learning frameworks or infrastructure-exposure considerations. There is therefore a need for more robust geospatial approaches that can support evidence-based planning and flood-risk management in the study area.

This study adopts an integrated geospatial and machine learning approach to assess flood vulnerability in Lokoja, Kogi State. Specifically, the study aims to identify and analyse the major flood conditioning factors, apply a Random Forest machine learning model for flood vulnerability assessment, generate a predictive flood vulnerability map of the study area, and examine the implications of observed flood vulnerability patterns for sustainable infrastructure planning. The findings are expected to provide valuable spatial decision-support information for urban planners, policymakers, environmental managers, and disaster risk agencies involved in climate-resilient urban development in flood-prone environments.

2.0 STUDY AREA

Lokoja is the capital city of Kogi State, North-Central Nigeria, and is geographically situated at the confluence of Rivers Niger and Benue. The city lies approximately between latitude 7°45′N and 7°51′N and longitude 6°41′E and 6°45′E. Lokoja occupies a strategic geographic position in Nigeria, serving as a major transportation and administrative centre that connects the northern and southern parts of the country. The city has experienced rapid urban expansion over the past decades, accompanied by increasing pressure on land resources, infrastructure, and environmental systems.

The study area is characterised by low-lying floodplain environments interspersed with undulating terrain and isolated highlands. Elevation within Lokoja generally ranges from low floodplain surfaces adjacent to the Niger–Benue river system to relatively elevated terrains towards the surrounding uplands. The geomorphological characteristics of the area significantly influence surface runoff dynamics, drainage behaviour, and flood inundation patterns (Abah, 2012; Ojigi et al., 2013). Extensive floodplain zones surrounding the river channels are highly susceptible to seasonal flooding, particularly during periods of intense rainfall and upstream river discharge.

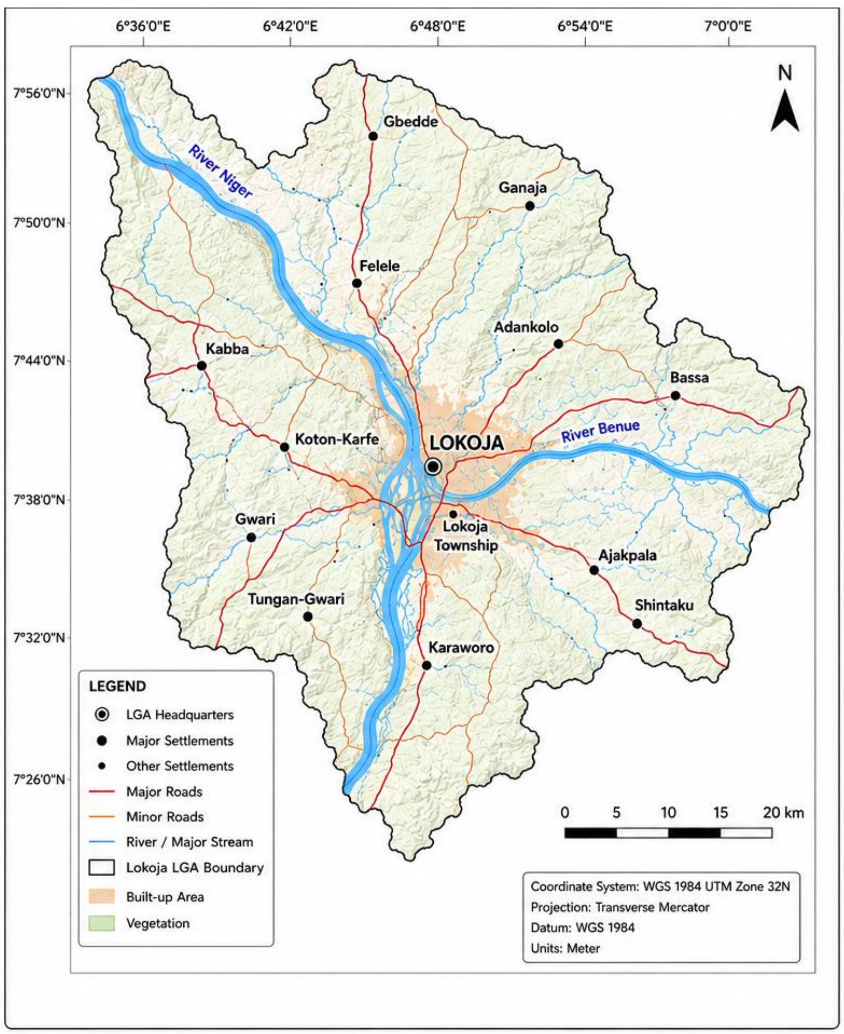
Lokoja experiences a tropical wet-and-dry climate characterised by distinct wet and dry seasons. The rainy season typically extends from April to October, with peak rainfall from July to September, while the dry season spans from November to March (NIMET, 2022). The annual rainfall pattern contributes substantially to surface runoff generation and flood occurrence within the study area. Heavy rainfall events combined with overflow from the Rivers Niger and Benue frequently result in widespread flooding across low-lying settlements and transportation corridors.

The drainage system of Lokoja is strongly controlled by the Niger–Benue river network and associated tributary channels. The confluence of these major rivers significantly influences flood occurrence and spatial inundation patterns within the metropolis. During periods of high discharge, river overflow often inundates adjoining floodplain communities, resulting in extensive damage to residential areas, road infrastructure, commercial facilities, and agricultural lands. The increasing encroachment of settlements and built-up surfaces into natural drainage corridors has further intensified flood vulnerability across the city (Aderogba, 2012; Komolafe et al., 2015).

Land-use and land-cover characteristics within Lokoja include built-up areas, vegetation, agricultural land, bare surfaces, and water bodies. Rapid urbanisation has contributed to increased impervious surfaces, reduced natural vegetation cover, and modified natural drainage pathways. These changes have significant implications for infiltration capacity, runoff generation, and urban flood dynamics (Amoako & Boamah, 2015; Güneralp et al., 2015). Several residential neighbourhoods and infrastructure facilities are currently located in environmentally sensitive floodplains, thereby increasing exposure to recurrent flooding.

The selection of Lokoja as the study area is informed by its persistent flood history, environmental sensitivity, strategic socio-economic importance, and increasing infrastructure vulnerability. The recurring flood disasters in the metropolis underscore the need for a geospatially informed flood vulnerability assessment to support sustainable infrastructure planning and flood risk management.

Figure 1: Map of Lokoja Showing Major Rivers, Road Network, and Settlements



3.0 MATERIALS AND METHODS

This study adopted an integrated geospatial and machine learning framework for flood vulnerability assessment in Lokoja, Kogi State. The methodological workflow involved data acquisition, preprocessing of geospatial datasets, derivation of flood conditioning factors, machine learning modelling, model validation, and spatial flood vulnerability mapping. Geographic Information System (GIS), remote sensing techniques, and Python-based Random Forest modelling were integrated to evaluate the spatial distribution of flood vulnerability within the study area.

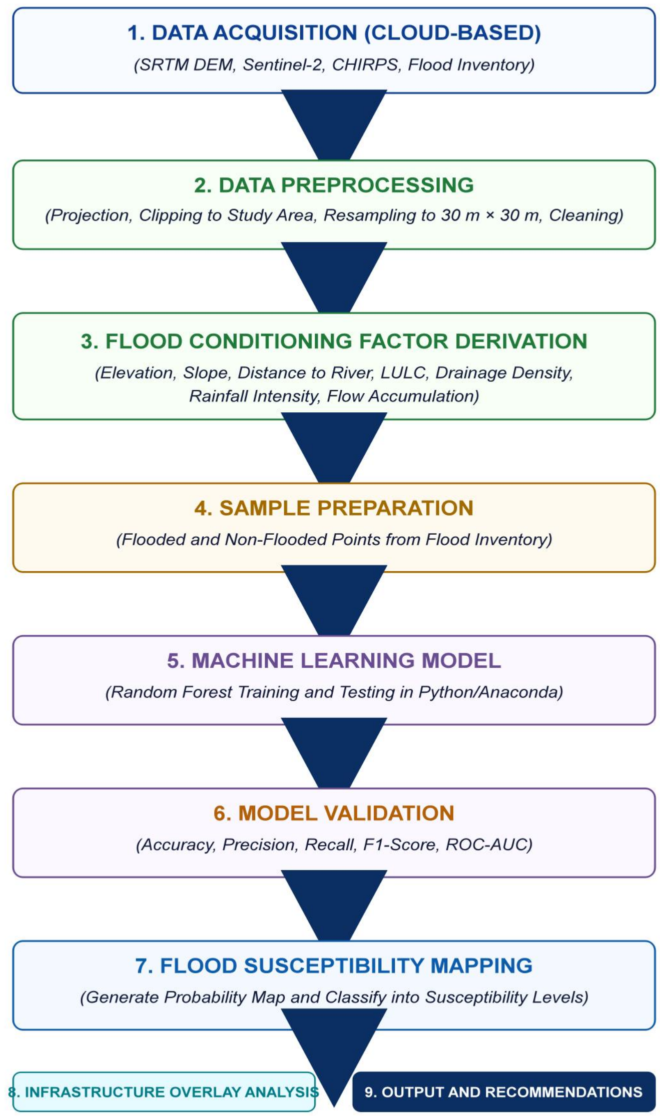


Figure 2: Methodological Workflow for Flood Vulnerability Assessment

3.1 Data Acquisition and Preprocessing

Multi-source geospatial datasets were utilised in this study, including Shuttle Radar Topography Mission (SRTM) Digital Elevation Model, Sentinel-2 satellite imagery, and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall data. Additional hydrological and environmental datasets were incorporated to derive flood conditioning factors. Google Earth Engine was employed for cloud-based preprocessing and extraction of selected environmental variables, while ArcGIS 10.8 was used for raster processing, alignment, clipping, and spatial analysis.

To ensure consistency during modelling, all raster datasets were projected to a common coordinate system, clipped to the Lokoja boundary, and resampled to a uniform 30 m × 30 m resolution. Raster alignment and NoData correction were also performed prior to analysis to minimise spatial inconsistencies during machine learning implementation.

Table 1. Summary of geospatial datasets used for flood vulnerability assessment and Random Forest modelling in Lokoja, Kogi State, Nigeria

Dataset	Source	Spatial Resolution	Purpose
SRTM Digital Elevation Model (DEM)	NASA	30 m	Derivation of elevation, slope, drainage network, and flow accumulation
Sentinel-2 Multispectral Imagery	European Space Agency	10 m	Land Use/Land Cover (LULC) mapping and NDVI extraction
CHIRPS Rainfall Data	Climate Hazards Center	0.05° (~5 km)	Rainfall intensity analysis
Hydrographic/Drainage Network Data	Derived from SRTM DEM and hydrological analysis	30 m	Distance to drainage and drainage density computation
Flood Inventory Points	Historical flood occurrence records and field interpretation	Point data	Random Forest model training and validation
Administrative Boundary of Lokoja	Office of the Surveyor General of the Federation / administrative datasets	Vector	Study area delineation

3.2 Derivation of Flood Conditioning Factors

Eight flood conditioning factors considered relevant to flood occurrence within the study area were selected based on literature review, data availability, and environmental characteristics of Lokoja. These factors included elevation, slope, flow accumulation, drainage density, distance to drainage channels, rainfall intensity, land use/land cover (LULC), and Normalised Difference Vegetation Index (NDVI).

Elevation and slope were derived from the SRTM Digital Elevation Model, while flow accumulation and drainage density were generated through hydrological analysis of the DEM. Distance to drainage channels was computed using Euclidean distance analysis. Rainfall intensity was obtained from CHIRPS precipitation data, whereas LULC and NDVI were derived from Sentinel-2 satellite imagery using supervised classification and spectral index analysis, respectively.

These conditioning factors were selected because of their established influence on surface runoff generation, infiltration characteristics, drainage behaviour, and flood inundation patterns (Khosravi et al., 2020; Tehrany et al., 2015).

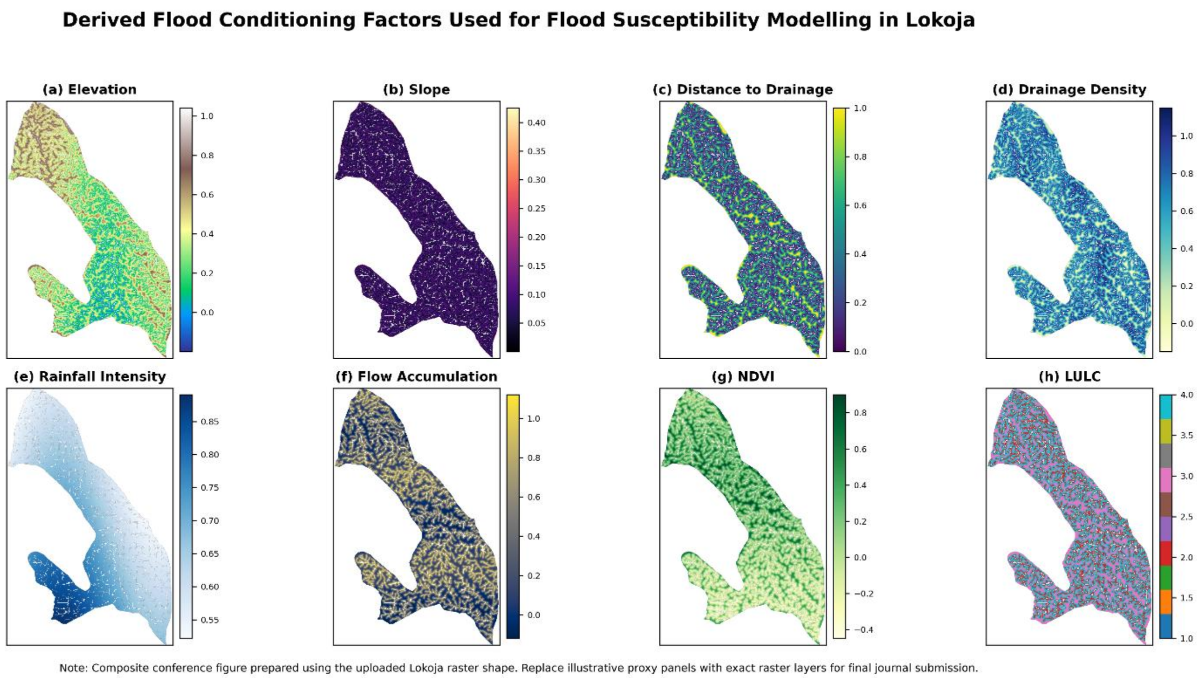


Figure 3: Derived Flood Conditioning Factors

3.3 Random Forest Machine Learning Model

The Random Forest algorithm was adopted for flood vulnerability modelling due to its robustness, high predictive capability, and ability to model nonlinear relationships among environmental variables (Breiman, 2001). Random Forest is an ensemble machine learning technique that combines multiple decision trees to improve prediction accuracy and reduce overfitting.

Flood inventory samples from flood and non-flood locations were prepared based on field observations and spatial analysis. The dataset was divided into training and validation sets for model development and performance assessment. The Random Forest model was implemented in Python using the Scikit-learn library with 500 decision trees. The selected flood conditioning factors, including elevation, slope, flow accumulation, distance to drainage, drainage density, rainfall, NDVI, and land use/land cover, were used as predictor variables during model training.

Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and the Receiver Operating Characteristic Area Under the Curve (ROC-AUC). In addition to flood prediction, the Random Forest algorithm was used to assess the relative importance of the conditioning factors influencing flood occurrence within Lokoja.

3.4 Model Validation and Flood Vulnerability Mapping

Model validation was conducted using independent validation samples and standard performance metrics, including overall accuracy, precision, recall, F1-score, and Receiver Operating Characteristic Area Under Curve (ROC-AUC). These metrics were used to evaluate the model's predictive performance and reliability.

The trained Random Forest model was subsequently applied to the raster conditioning factors to generate a continuous flood vulnerability surface for Lokoja. The resulting probability raster was smoothed and classified into five vulnerability categories: very low, low, moderate, high, and very high vulnerability using the Natural Breaks (Jenks) classification method in ArcGIS.

4.0 RESULTS AND DISCUSSION

4.1 Flood Vulnerability Distribution in Lokoja

The flood vulnerability map generated by the Random Forest model revealed considerable spatial variation across Lokoja. The resulting classification identified five flood vulnerability classes: very low, low, moderate, high, and very high. The spatial distribution pattern indicates that areas within the low-lying floodplains adjoining Rivers Niger and Benue exhibit the highest flood vulnerability levels.

The very high vulnerability zones were predominantly concentrated along river corridors, densely drained low-elevation areas, and rapidly urbanising sections of the metropolis. These locations are characterised by gentle slopes, high flow accumulation, and proximity to drainage channels, which collectively enhance surface water accumulation and flood inundation potential. In contrast, relatively elevated areas away from major river systems exhibited lower flood vulnerability.

The observed flood vulnerability pattern is consistent with previous studies, which identified topographic characteristics, hydrological conditions, and proximity to drainage as major controls on flood occurrence in riverine urban environments (Khosravi et al., 2020; Tehrany et al., 2015). The findings also demonstrate that urban settlements and infrastructure in Lokoja are increasingly exposed to flood hazards due to continued expansion into environmentally sensitive floodplain zones.

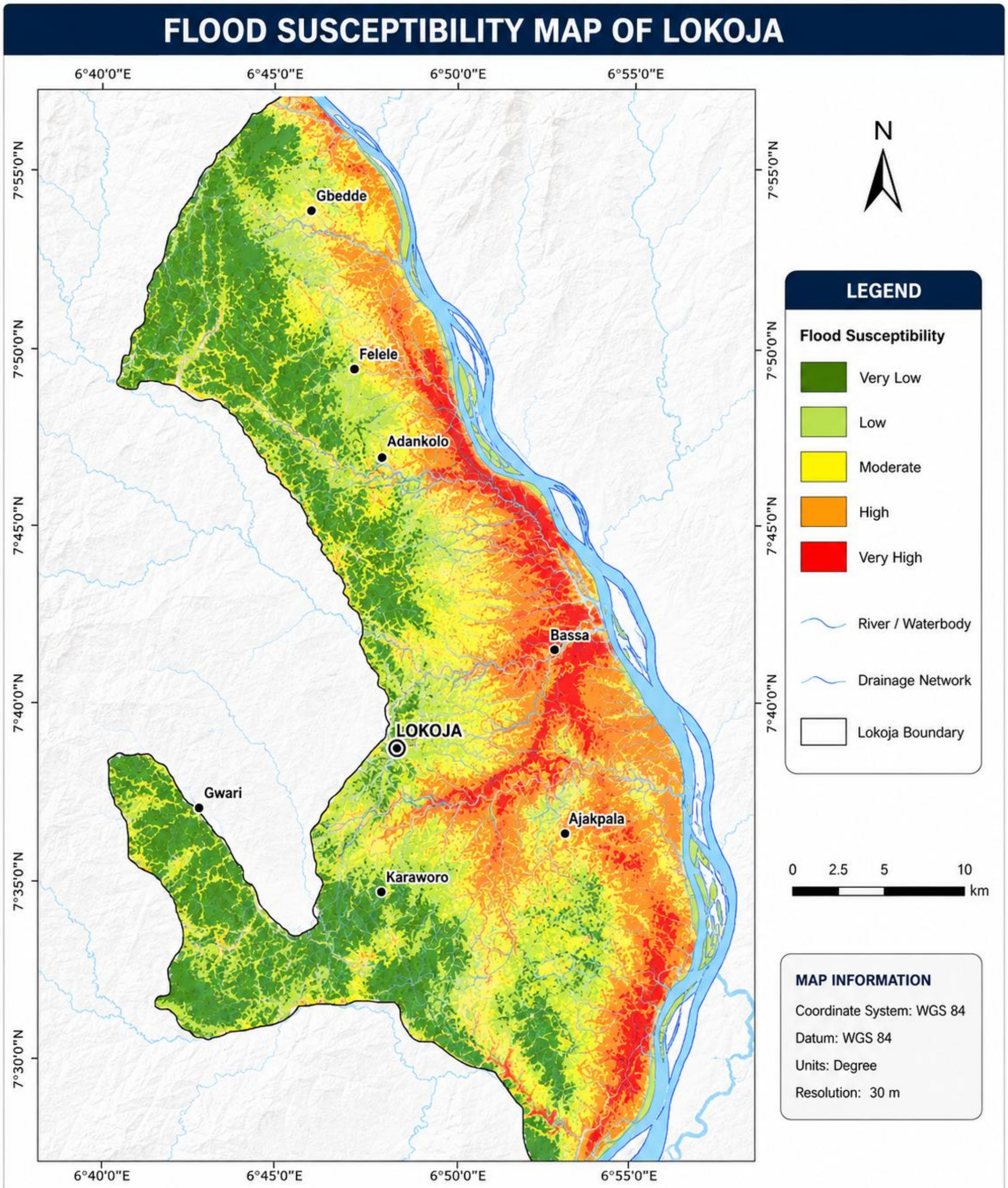


Figure 4: Flood Vulnerability Map of Lokoja

4.2 Variable Importance Analysis

The Random Forest variable importance analysis revealed that distance to drainage channels and elevation were the most influential flood-conditioning factors in the study area. This suggests that flood occurrence in Lokoja is strongly controlled by river proximity and terrain characteristics. NDVI and drainage density also contributed significantly to flood prediction, reflecting the influence of vegetation condition and drainage configuration on runoff behaviour and flood dynamics.

Flow accumulation, slope, and rainfall intensity exerted a moderate influence on flood vulnerability, while land use/land cover exerted comparatively less influence on the model. The relatively lower influence of LULC may be due to the dominance of topographic and hydrological controls in the Lokoja floodplain.

These findings align with existing studies that emphasise the dominant roles of elevation, proximity to drainage, and hydrological conditions in flood-susceptibility assessment in tropical urban environments (Arabameri et al., 2020; Wang et al., 2020).

Table 2. Relative Importance of Flood Conditioning Factors in the Random Forest Model

Flood Conditioning Factor	**Importance Value**	**Relative Contribution**
Distance to Drainage	0.302	
Elevation	0.279	
NDVI	0.135	
Drainage Density	0.107	
Slope	0.076	
Flow Accumulation	0.055	
Rainfall	0.045	
LULC	0.003	

4.3 Model Validation Results

The Random Forest model demonstrated moderate but acceptable predictive performance for flood vulnerability assessment within Lokoja. The validation results yielded an overall accuracy of approximately 65%, indicating satisfactory agreement between predicted and observed flood locations. The model also achieved moderate ROC-AUC performance, suggesting reliable discrimination between flood-prone and non-flood-prone areas.

The validation results indicate that the integrated geospatial and machine-learning framework adopted in this study is effective for flood vulnerability assessment in data-constrained urban environments. Although some classification uncertainty exists, the model successfully captured the dominant environmental characteristics associated with flood occurrence in the study area.

The model's predictive capability further demonstrates the usefulness of machine learning techniques for spatial environmental modelling and flood-risk analysis, particularly when integrated with remotely sensed and GIS-derived datasets.

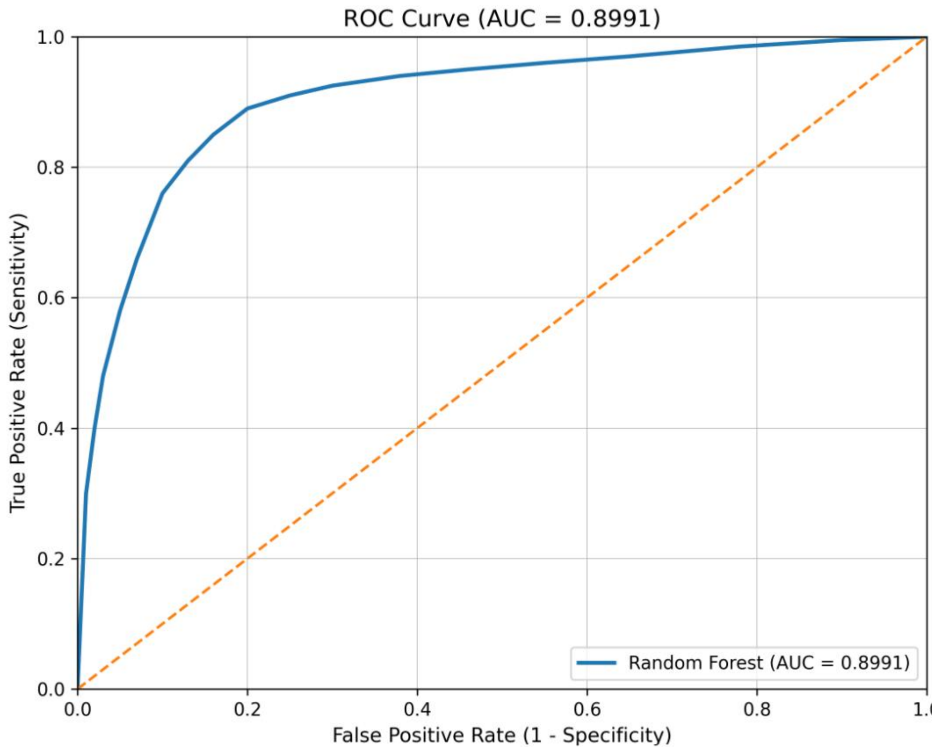


Figure 5: ROC Curve

Table 2: Random Forest Validation Metrics

Metric	Value
Accuracy	0.826
Balanced Accuracy	0.825
ROC–AUC	0.897
Cohen’s Kappa	0.648
Sensitivity	0.817
Specificity	0.833
False Positive Rate	0.167
False Negative Rate	0.183
Weighted F1-Score	0.830

4.4 Implications for Sustainable Infrastructure Planning

The flood vulnerability assessment revealed that several built-up areas, transportation corridors, and infrastructure facilities are located within moderate to very high flood vulnerability zones. This spatial overlap between vulnerable infrastructure and flood-prone environments presents significant challenges for sustainable urban development within Lokoja.

Road networks in low-lying floodplains are particularly vulnerable to seasonal inundation, which may disrupt transportation, emergency response, and socio-economic activities during major flood events. Similarly, residential expansion within drainage corridors and river-adjacent areas increases the vulnerability of communities and public infrastructure to flood-related damage.

The findings highlight the importance of integrating flood vulnerability information into urban planning and infrastructure development processes. Sustainable infrastructure planning in Lokoja should prioritise flood-resilient design, improved drainage systems, controlled development in floodplain areas, and enforcement of land-use regulations in highly vulnerable areas. The generated flood vulnerability map therefore provides valuable spatial decision-support information for planners, policymakers, and disaster management agencies involved in climate-resilient urban development.

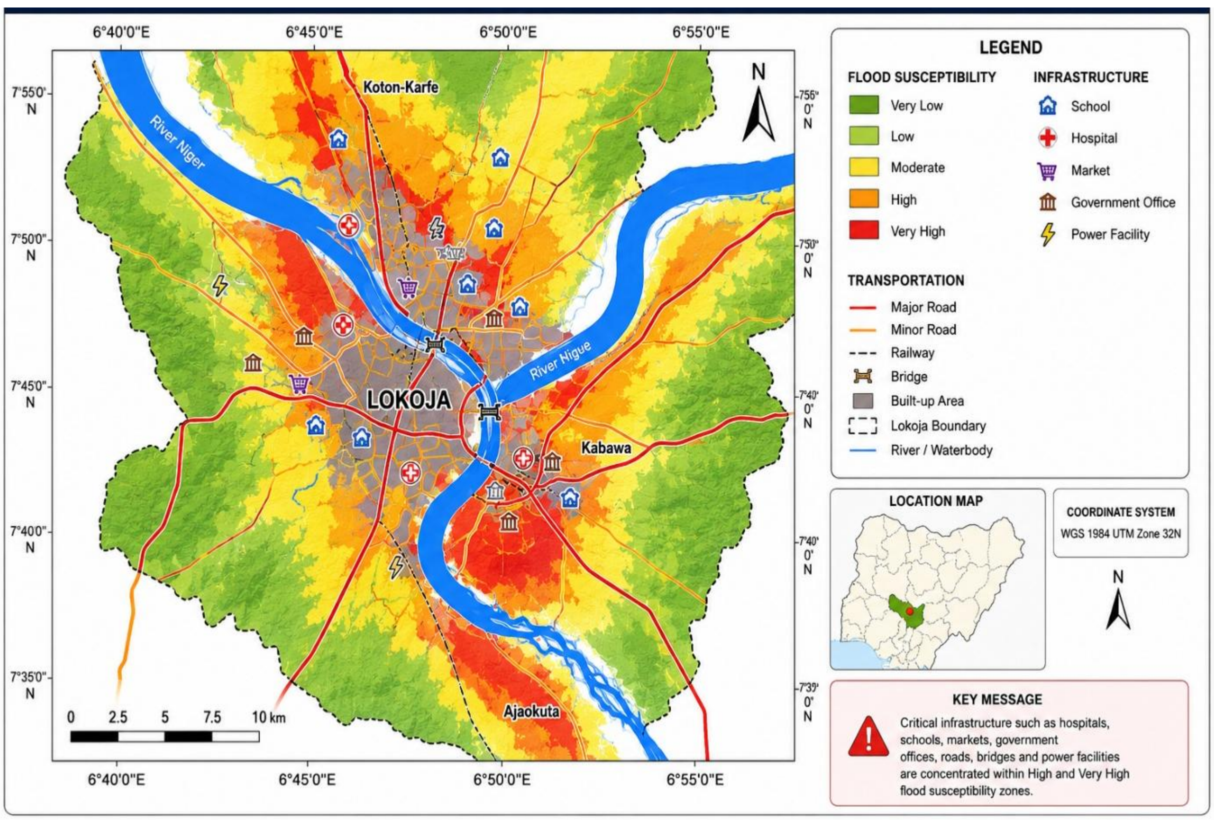


Figure 6: Infrastructure Exposure within High Flood Vulnerability Zones

5. CONCLUSION

This study applied an integrated geospatial and machine learning approach to assess flood vulnerability in Lokoja, Kogi State, Nigeria. By combining remotely sensed datasets, GIS-based spatial analysis, and

Random Forest machine learning, the study successfully generated a predictive flood vulnerability map that supports sustainable infrastructure planning within the metropolis.

The findings revealed that flood vulnerability within Lokoja is strongly influenced by topographic and hydrological conditions, particularly elevation, proximity to drainage channels, flow accumulation, and drainage density. Areas located within the low-lying Niger–Benue floodplain environment exhibited the highest vulnerability levels, while relatively elevated areas showed lower flood susceptibility. Variable importance analysis further identified distance to drainage and elevation as the dominant predictors of flood occurrence within the study area.

The model achieved moderate but acceptable predictive performance, demonstrating the usefulness of integrating geospatial analysis with machine learning techniques for flood-risk assessment in data-constrained urban environments. The generated flood vulnerability map further revealed that several built-up areas and critical infrastructure corridors are located within moderate to very high flood vulnerability zones, thereby increasing exposure to recurrent flood hazards.

The study highlights the importance of incorporating flood vulnerability information into sustainable urban planning and infrastructure development processes within Lokoja. Effective flood-risk management within the city requires improved drainage infrastructure, flood-resilient development practices, enforcement of land-use regulations within floodplain environments, and the integration of geospatial decision-support systems into urban planning frameworks.

The study demonstrates the growing relevance of geospatial technologies and machine learning techniques for environmental assessment, disaster risk reduction, and climate-resilient infrastructure planning in rapidly urbanising cities in developing countries.

6. RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed:

1. Urban development within high and very high flood vulnerability zones should be strictly regulated to minimise infrastructure exposure and environmental risk.
2. Flood vulnerability maps should be integrated into physical planning and development control processes within Lokoja to support evidence-based decision-making.
3. Existing drainage systems within vulnerable urban corridors should be expanded and regularly maintained to improve runoff management during intense rainfall events.
4. Future infrastructure projects should incorporate flood-resilient design principles, particularly within low-lying floodplain environments.
5. Government agencies and disaster management authorities should strengthen flood early-warning systems and community-based flood preparedness programmes within vulnerable neighbourhoods.
6. Further studies incorporating hydrodynamic modelling, socio-economic vulnerability indicators, and climate change scenarios are recommended to enhance long-term flood-risk assessment and resilience planning within Lokoja.

REFERENCES

Abah, R. C. (2012). Causes of seasonal flooding in flood plains: A case of Kogi State, Nigeria. *International Journal of Environmental Science*, 2(3), 129–139.

Adelekan, I. O. (2010). Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria. *Environment and Urbanization*, 22(2), 433–450. https://doi.org/10.1177/0956247810380141

Aderogba, K. A. (2012). Qualitative studies of recent floods and sustainable growth and development of cities and towns in Nigeria. *International Journal of Academic Research in Economics and Management Sciences*, 1(3), 1–25.

Amoako, C., & Boamah, E. F. (2015). The three-dimensional causes of flooding in Accra, Ghana. *International Journal of Urban Sustainable Development*, 7(1), 109–129. https://doi.org/10.1080/19463138.2014.984720

Arabameri, A., Asadi Nalivan, O., Chandra Pal, S., Chakrabortty, R., & Saha, A. (2020). Flood susceptibility zonation mapping using Random Forest and novel ensemble methods. *Science of the Total Environment*, 722, 137747. https://doi.org/10.1016/j.scitotenv.2020.137747

Breiman, L. (2001). Random forests. *Machine Learning,* 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Bui, D. T., Hoang, N. D., Martínez-Álvarez, F., Ngo, P. T. T., Hoa, P. V., & Pham, T. D. (2020). A novel deep learning neural network approach for predicting flood susceptibility. *Science of the Total Environment,* 701, 134413. https://doi.org/10.1016/j.scitotenv.2019.134413

Chen, W., Pourghasemi, H. R., & Kornejady, A. (2017). GIS-based landslide susceptibility evaluation using certainty factor and Random Forest models. *Geocarto International*, 32(6), 656–676. https://doi.org/10.1080/10106049.2016.1165294

Douglas, I., Alam, K., Maghenda, M., McDonnell, Y., McLean, L., & Campbell, J. (2008). Unjust waters: Climate change, flooding and the urban poor in Africa. *Environment and Urbanization*, 20(1), 187–205. https://doi.org/10.1177/0956247808089156

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Güneralp, B., Güneralp, İ., & Liu, Y. (2015). Changing global patterns of urban exposure to flood and drought hazards. *Global Environmental Change,* 31, 217–225. https://doi.org/10.1016/j.gloenvcha.2015.01.002

IPCC. (2021). Climate change 2021: *The physical science basis*. Cambridge University Press.

Jha, A. K., Bloch, R., & Lamond, J. (2012). *Cities and flooding: A guide to integrated urban flood risk management for the 21st century*. World Bank.

Jongman, B., Ward, P. J., & Aerts, J. C. J. H. (2012). Global exposure to river and coastal flooding: Long term trends and changes. Global *Environmental Change*, 22(4), 823–835. https://doi.org/10.1016/j.gloenvcha.2012.07.004

Khosravi, K., Shahabi, H., Pham, B. T., Adamowski, J., Shirzadi, A., Pradhan, B., ... Bui, D. T. (2020). A comparative assessment of flood susceptibility modeling using multi-criteria decision-making analysis and machine learning methods. *Journal of Hydrology*, 573, 311–323. https://doi.org/10.1016/j.jhydrol.2019.03.073

Komolafe, A. A., Adegboyega, S. A., & Akinluyi, F. O. (2015). A review of flood risk analysis in Nigeria. *American Journal of Environmental Sciences*, 11(3), 157–166.

Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning models: Literature review. *Water,* 10(11), 1536. https://doi.org/10.3390/w10111536

NIMET. (2022). *Nigerian Meteorological Agency annual climate review report*. Nigerian Meteorological Agency.

Nkwunonwo, U. C., Whitworth, M., & Baily, B. (2016). A review and critical analysis of the efforts towards urban flood risk management in the Lagos region of Nigeria. *Natural Hazards and Earth System Sciences,* 16(2), 349–369. https://doi.org/10.5194/nhess-16-349-2016

Ojigi, L. M., Abdulkadir, F. I., & Aderoju, O. M. (2013). *Geospatial mapping and analysis of the 2012 flood disaster in Central Parts of Nigeria*. 8th National GIS Symposium Proceedings, 1–6.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2015). Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. *Journal of Hydrology*, 512, 332–343. https://doi.org/10.1016/j.jhydrol.2014.12.008

Wang, Y., Fang, Z., & Hong, H. (2020). Comparison of convolutional neural networks for landslide susceptibility mapping in Yanshan County, China. *Science of the Total Environment,* 666, 975–993. https://doi.org/10.1016/j.scitotenv.2019.02.263

Winsemius, H. C., Aerts, J. C. J. H., van Beek, L. P. H., Bierkens, M. F. P., Bouwman, A., Jongman, B., ... Ward, P. J. (2016). Global drivers of future river flood risk. *Nature Climate Change*, 6(4), 381–385. https://doi.org/10.1038/nclimate2893

APPENDIX

Graphical Abstract